A Novel Co-operative AI Model for Future Fall Prediction in the Elderly

Deepika Mohan

A thesis submitted to

Auckland University of Technology

in fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD)

School of Engineering, Computer and Mathematical Sciences

New Zealand

2025

Abstract

Senior citizens are one of the significant proportions of healthcare service users, with approximately 12% of public sector, primary care, and hospital services utilized by this demographic. Senior Citizens living alone, without adequate monitoring, are at a higher risk of severe consequences from sudden falls caused by slips, trips, or underlying health conditions. In New Zealand, approximately one-third of people over 65 years fall each year. Among those who experience a fall, 22–60% sustain injuries, 10–15% suffer serious injuries, 2–6% experience fractures, and 0.2–5% sustain hip fractures. People in their 80s and above are particularly at high risk of falling. Overall, half of all ACC claims and costs in this age group result from falls, amounting to estimated costs of NZ$443 million annually. The majority of these incidents go unreported in time for emergency interventions, causing critical delays in treatment. This affirms the necessity of trustworthy and affordable e-health technologies to support independent living among older adults. In the modern era, Artificial Intelligence (AI) and Machine Learning (ML) have significantly impacted daily life, proving instrumental in various domains. In this context, AI can serve as a vital companion for older adults, providing continuous health and behaviour monitoring and early fall prediction capabilities.

The focus of this thesis is on leveraging AI to forecast potential falls in older adults by identifying abnormalities in their health and behavioural patterns. The proposed approach termed the Co-operative AI model for future fall prediction in the Elderly, employs Fuzzy logic and deep learning networks and algorithms such as Deep Belief Networks (DBN) for the development of two AI models that are combined using a Meta-Model to provide the Future Fall Risk Prediction Outcome. AI-1 model utilizes vital sign parameters such as Blood Pressure, Heart Rate, and Oxygen Saturation as input and employs Fuzzy Logic to predict potential fall risk in older adults. The AI-2 model, on the other hand, uses Activities of Daily Living (ADLs) such as Sitting, Standing, Walking, Running, and Jumping as input parameters and employs a Deep Belief Network (DBN) for fall risk prediction. The input dataset for both AI-1 and AI-2 models was collected from PhysioNet – a Public Repository. The outputs from AI-1 and AI-2 models are then integrated using a Meta-Model which uses a Random Forest with continuous learning features, which provides a comprehensive prediction of impending falls in older adults.

The thesis has the following main contributions:

- A detailed background analysis was done in terms of health, behaviour, and environmental factors, and the critical parameters that lead to an abnormality in older adults were analyzed.
- The system architecture consists of 3 AI models (AI-1 model, AI-2 model, and Meta-

model) where each model works independently to assess fall risks with different factors, then works collaboratively by learning from each other to generate a promising final fall risk prediction result.

- Data is collected from the public repository for both the AI models. The system continuously monitors health and behavioural parameters, processes the information through deep learning models, and predicts early indicators of fall risk. By analyzing these parameters in real time, the model effectively identifies abnormalities that signal potential fall risks.

In a nutshell, this thesis proposed the research findings and model development which highlights the significant potential of advanced deep learning techniques to evaluate the severity of risks, to improve future fall risk prediction, and finally to predict and reduce fall occurrences. This innovative technology provides a transformative approach, enabling timely interventions that improve the safety and well-being of elderly people while potentially saving lives.

Contents

Abstract ii
List of Figures vii
List of Tables ix
List of Appendices x
List of Abbreviations x
Attestation of Authorship xiv
Co-Authored Works xv
Acknowledgments xvi
Ethics Approval xviii
Chapter 1. Research Motivation, Direction, and Thesis Organization 1
1.1. Introduction 1
1.2. Need for Fall Prediction System 1
1.3. AI/ML Development in Healthcare Applications 3
1.4. Motivation for Driving towards Fall Prediction using AI 7
1.5. Research Gap, Questions, Aims and Objectives 8
1.6. Scope of Research 10
1.7. Thesis Organization 11
1.8. Conclusion 13
Chapter 2. Literature Review 14
2.1 Introduction 14
2.2 Categories of Falls in the Elderly 14
2.3 Health-Based Analysis 16
2.3.1 Body-Worn Sensors 17
2.3.2 Health Monitoring Systems 19
2.3.3 Exercise Programs 20
2.4 Behaviour-Based Analysis 21
2.4.1 Computer Vision 22
2.4.2 Human Activity Recognition 24
2.4.3 Activities for Daily Living (ADLs) 25
2.5 Posture-Based Analysis 27
2.5.1 Gait and Posture Sway 27
2.5.2 Balance Tests 30
2.5.3 Fall Risk Assessment Tools 30
2.6 Emotion-Based Analysis 31
2.6.1 Depression and Stress 32
2.6.2 Anxiety and Fear of Falling 33
2.7 Analysis of AI-Based Smart Devices 34
2.8 Summary of Reviewed Systems and Methodologies 37
2.9 Conclusion 39
Chapter 3. Methodology Used 40
3.1 Introduction 40

3.2 Methodology and Model Development Phase 41
3.3 Simulation Tools for AI/ML Modelling and Development 45
3.4 Visual Studio-Based AI Simulation 50
3.5 Conclusion 52
Chapter 4. Proposed AI-1 Model: Fuzzy-Based Fall Risk Prediction System 54
4.1 Introduction 54
4.2 Vital Signs Monitoring 54
4.2.1 Blood Pressure 56
4.2.2 Heart Rate 57
4.2.3 Blood Oxygen Level ($SpO2$): 58
4.3 Rationale behind Selected Vital Health Metrics 59
4.4 Existing Works on AI and Fuzzy Logic 60
4.5 Proposed Vital Sign-Based Fall Risk Prediction Model 63
4.6 Fuzzy-Based Rule Generation 65
4.7 Membership Function and Rule Weighting 67
4.8 Evaluation of AI-1 Model 73
4.8.1 Evaluation Metrics 73
4.8.2 Data Collection – Vital Sign Data 73
4.8.3 Morse Falls Scale (MFS) 74
4.8.4 Verification of the Developed AI-1 Model with Theoretical Analysis 75
4.8.5 Evaluation of the AI-1 Model with Data from a Public Repository and Existing Work 76
4.8.5.1 Source – 1 Validation: Datasets obtained from Elderly 85 years old with Multiple History of Falls [180] 77
4.8.5.2 Source – 2 Validation: Datasets obtained from PhysioNet based on an eICU Collaborative Research Database [181] 79
4.8.5.3 Source – 3 Validation: Datasets obtained from PhysioNet based on Early Prediction of Sepsis Clinical Data [182] 80
4.8.5.4 Initial Testing of the Developed Model- Smart Watch Integration Using Fuzzy Logic 81
4.9 Conclusion 84
Chapter 5. Proposed AI-2 Model: Deep Belief Network-Based Fall Risk Prediction System ... 85
5.1 Introduction 85
5.2 Behaviour-Based Monitoring 85
5.3 Importance of ADLs 90
5.4 ADL Parameter Selection 91
5.5 Deep Belief Networks (DBN) 92
5.6 Proposed DBN-Based 3-Stage Fall Risk Prediction System 95
5.7 Evaluation of the AI-2 Model 101
5.7.1 Evaluation Metrics 101
5.7.2 Data Collection – ADL Data 101
5.7.3 Evaluation of the AI-2 Model with Data from Public Repository and Existing Work 105
5.7.3.1 Verification of Proposed AI-2 Model with Ground Truth 105
5.7.3.2 Accuracy Comparison of the Developed Model with Existing Works 108
5.8 Conclusion 111

Chapter 6. Novel Co-operative AI-Based Fall Risk Prediction Model 112
6.1 Introduction 112
6.2 Comparator Analysis 112
6.2.1 Weighted Average or Score Fusion 113
6.2.2 Rule-Based Fusion Method 114
6.2.3 Decision-Tree Approach 115
6.2.4 Ensemble Learning 115
6.3 Novel Co-operative AI-based Fall Risk Prediction Model Architecture Overview 117
6.4 AI-Based Co-operative Meta-Model Fall Risk Prediction Algorithm 120
6.5 Data Collection and Ground Truth Selection 121
6.5.1 Evaluation Metrics 122
6.6 Evaluation of the Developed AI-Based Meta Model with MFS 122
6.7 Conclusion 126
Chapter 7. Conclusion and Future Directions 128
7.1 Introduction 128
7.2 Conclusion 128
7.3 Future Directions 130
References 134
Appendices: 149
A. AI-1 and AI-2 Model Development Analysis: 149
A.1 AI-1 Model - Formulated Fuzzy Rules (111- Fuzzy rules) 149
A.2 AI-2 Model - Raw Data to ADL Conversion 152
A.3 AI-2 Model - Long-Term Movement Monitoring Database 154
B. Result Evaluation and Dataset Information: 155
B.1 AI-2 Model - GT Evaluation 155
B.2 Meta-Model -Training Data (15 Participants) 156

List of Figures

Figure 1.1: Dimensions Leading to a Fall in Older Adults. 2
Figure 1.2: AI-IoT in Healthcare. 3
Figure 1.3: Categories for Detecting and Predicting Falls in Older Adults. 7
Figure 1.4: AI in Healthcare without Human Intervention. 8
Figure 1.5: Chapter's Technical Connection Representation 11
Figure 2.1: Risk Factors of Fall. 15
Figure 2.2: Fall Prediction and Prevention Classification. 16
Figure 2.3: Health-Based Analysis for Fall Prediction and Prevention in Older Adults. 16
Figure 2.4: Behavioural-Based Analysis in Elderly Fall Prevention [67]. 22
Figure 2.5: Posture-Based Analysis Classification. 27
Figure 2.6: Emotion-Based Analysis on Elderly Fall Prevention. 32
Figure 2.7: Classification of AI-Based Smart Devices. 34
Figure 2.8: Cognitive Device Analytics. 35
Figure 2.9: Smart Devices Utilization Metrics. 36
Table 2.10: Fall Prevention comparison using AI, ML, and other methods. 37
Figure 3.1: Workflow Process of Research Methodology. 41
Figure 3.2: Context of Research. 43
Figure 3.3: Framework of the Proposed Approach. 45
Figure 3.4: HR Sample Datasets. 47
Figure 3.6: Physical Activity HR Datasets after Normalization. 48
Figure 3.7: Data Visualization Results after Smoothing Physical Activity Datasets. 48
Figure 3.8: Sample Data Model Obtained from FitaBase. 48
Figure 3.9: Parameter and Classifier Selection. 49
Figure 3.10: Comparison Analysis of HR and Normal Activity. 49
Figure 3.11: Weka Classifier Training. 50
Figure 3.12: Final Classification Outcome. 50
Figure 3.13: Simulation Processes of AI-2 Model using Visual Studio Code. 51
Figure 3.14: Terminal Window Output of Visual Studio Code. 52
Figure 3.15: Graphical Analysis of Fallers using Visual Studio Code. 52
Figure 4.1: Vital Sign Parameters. 55
Figure 4.2: Logical Balance Structure of Fuzzy Logic. 61
Figure 4.3: Vital Sign-Based Fall Risk Prediction Model. 63
Figure 4.4: Architecture of AI-1 Fuzzy-Based Fall Risk Prediction Model. 65
Figure 4.5: Membership Function for Heart Rate (bpm). 68
Figure 4.6: Membership Function $SpO2$ Level in Blood (%). 69
Figure 4.7: Membership Function for HBP (mmHg). 70

Figure 4.8: Membership Function for PP (mmHg). 71
Figure 4.9: Fuzzy Rule Evaluation Metrics. 72
Figure 4.10: MFS Calculator. 75
Figure 4.11: Fall Risk Prediction Evaluation Results. 76
Figure 4.12: Simulated Results from the Developed Model. 78
Figure 4.13: Predicted Risk Score from the Developed Model. 78
Figure 4.14: Results from MFS Assessment Tool. 79
Figure 4.15: Model of Tuya-Enabled Smartwatch. 82
Figure 4.16: Smart Watch Integration Using Physical Prototype. 82
Figure 4.17: Risk Alert Notification through Physical Prototype. 83
Figure 5.1: Behaviour-Based Monitoring Smart Devices. 86
Figure 5.2: Worldwide Statistics of Fall Detection and Prediction Research:2020-2024. 89
Figure 5.3: Behaviour Parameter Selection. 91
Figure 5.4: DBN Overview. 93
Figure 5.5: Architecture of the Developed 3-Stage DBN-Based Fall Risk Prediction System. 96
Figure 5.6: Network Structure of Proposed 3-Stage DBN-Based Fall Risk Prediction System. 96
Figure 5.7: Workflow Structure of Developed DBN Model. 98
Figure 5.8: Raw Accelerometer Signal obtained from PhysioNet. 103
Figure 5.9: 3D Accelerometer Numerical Signal Values. 103
Figure 5.10: Six Signal Categories of the Accelerometer Data Obtained from Participant C2.104
Figure 5.11: 3D Accelerometer Data of Participant C2. 104
Figure 5.12: DBN-Based Fall Risk Prediction Evaluation Results. 107
Figure 5.13: Accuracy Comparison between Different Fall Risk Prediction Models. 109
Figure 6.1: Comparator Analysis. 113
Figure 6.2: Final Predictions Derived from the Rule-Based Fusion Method. 114
Figure 6.3: Model of Ensemble Learning. 117
Figure 6.4: Architecture of an AI-based Co-operative Meta-Model for Fall Risk Prediction. 118
Figure 6.5: Simulation Results for Participant P1. 124
Figure 6.6: Simulation Results for Participant P9. 124
Figure 6.8: Confusion Matrix Outcome. 125
Figure 7.1: Integration of AI-1 Model with Smart App and Voice Models. 130
Figure 7.2: Combined Integration Structure of Future Work. 131
Figure 7.3: Fall Risk Prediction Model using Transfer Learning – Future Directions. 132

List of Tables

Table 2. 1: Fall Prevention comparison using AI, ML, and other methods. 37

Table 4. 1: Blood Pressure Chart 56

Table 4. 2: Average Resting HR for Elderly above 60 years [153] 58

Table 4. 3: Target and Max. HR from Age 60-100 [153] 58

Table 4. 4: Different Levels of $SpO2$ in Older Adults 59

Table 4. 5: Vital Metrics for AI-1 Model 60

Table 4. 6: Fall Risk Prediction Metrics 74

Table 4. 7: Comparative Result Analysis using Source 2 80

Table 4. 8: Comparative Result Analysis using Source 3 81

Table 5. 1: Evaluation Metrics 101

Table 5. 2: Description of Participants' Recordings – PhysioNet 102

Table 5. 3: TUG and MFS for GT Formation in Fall Risk Prediction 106

Table 5. 4: Comparative Result Analysis using GT 106

Table 5. 5: Confusion Matrix Layout 108

Table 5. 6: Comparative Result Analysis with the Existing Work 110

Table 6. 1: Weight Assignment for AI-1 and AI-2 Models 114

Table 6. 2: Score Fusion Metrics 114

Table 6. 3: Decision Tree Approach Predictions 115

Table 6. 4: Weights assigned to each risk level of AI-1 and AI-2 Models 117

Table 6. 5: Comparative Result Analysis on the Meta Model and MFS Prediction 123

List of Appendices

A.1 AI-1 Model - Formulated Fuzzy Rules (111- Fuzzy rules) 149
A.2 AI-2 Model - Raw Data to ADL Conversion 152
A.3 AI-2 Model - Long-Term Movement Monitoring Database 154
B.1 AI-2 Model - GT Evaluation 155
B.2 Meta-Model -Training Data (15 Participants) 156

List of Abbreviations

AAL_RSS	Ambient Assisted Living - Received Signal Strength
ABC	Activities-Specific Balance Confidence Scale
ACC	Accident Compensation Corporation
ADL	Activities of Daily Living
AEMM	Self-Operating Elderly Movement Monitoring
AI	Artificial Intelligence
AL	Assisted (aided) Living
ANN	Artificial Neural Networks
AP	Anterior-Posterior
AR	Augmented Reality
BADL	Basic Activities of Daily Living
BBS	Berg Balance Scale
BD	Big Data
BERT	Bidirectional Encoder Representations from Transformers
BHS	Beck Hopelessness Scales
BLE	Bluetooth Low-Energy
BMI	Body Mass Index
BP	Blood Pressure
BT	Bluetooth
CDC	Centre for Disease Control and Prevention
CGA	Comprehensive Geriatric Assessments
CHD	Coronary Heart Disease
CNN	Convolutional Neural Networks
ConvLSTM	Convolutional Long Short-Term Memory
Cx	Non-Fallers
DBN	Deep Belief Networks
DBN-FRPA	DBN-based Fall Risk Prediction Algorithm
DBN-TSK-FC	Deep Belief Networks-based Takagi-Sugeno-Kang Fuzzy Classifier
DBP	Diastolic Blood Pressure
DCNN	Deep Convolutional Neural Networks
ECG	Electrocardiogram
EHR	Electronic Health Records
EI	Emotional Intelligence
EMG	Electromyography
ESP32	Espressif32

FAP	Functional Ambulatory Profile
FARAO	Fall Risk Assessment in Older Adults
FES	Fall Efficacy Scale
FES-I	Fall Efficacy Scale-International Standard
FIS	Fuzzy Inference System
FL	Fuzzy Logic
FLAA	Fuzzy Logic Based Adaptable Autonomy
FMS	Fall Management System
FN	False Negative
FP	Fall Prediction
FPA	Fall Prediction Algorithm
FSST	Four-Square Step Test
Fx	Fallers
GDS	Geriatric Depression Scale
GPS	Global Positioning System
GPT	Generative Pre-trained Transformer
GT	Ground Truth
HAR	Human Activity Recognition
HBK	Human Body Kinematics
HBP	High Blood Pressure
HM	Healthcare Monitoring
HR	Heart Rate
HRV	Heart Rate Variability
IADL	Instrumental Activities of Daily Living
IIHS	IoT-Based Intelligent Health System
IMU	Inertial Measurement Sensor
IoHT	Internet of Healthcare Things
IoT	Internet of Things
IR	InfraRed
KNN	K-Nearest Neighbors
LBP	Low Blood Pressure
LR	Logistic Regression
LSTM	Long Short Term Memory
MAP	Mean Arterial Pressure
MF	Membership Function
MFES	Modified Fall Efficacy Scale
MFS	Morse Falls Scale
MHLW	Ministry of Health, Labour, and Welfare

ML	Machine Learning
MMSE	Mini-Mental State Examination
Mobi-Fall	Mobile Fall
NDNQI	National Database of Nursing Quality Indicators
NHS	National Health Services
NLP	Natural Language Processing
OCI-DBN	Optimally Configured and Improved Deep Belief Networks
OH	Orthostatic Hypotension
OSF	Open-Source Files
PCS	Physical Component
PIR	Passive InfraRed
PPA	Personal Profile Analysis
RBM	Restricted Boltzman Machine
RFID	Radio Frequency Identification
ROI	Region of Interest
RPA	Robotic Process Automation
SAFE	Steps to Avoid Fall in Elderly
SBR	Spontaneous Blink Rate
SBP	Systolic Blood Pressure
SF12	Short Form Survey
SHAP	SHapley Additive Explanations
SOC-ER	Selection, Optimization, and Compensation with Emotion Regulation
STEADI	Stopping Elderly Accidents, Deaths & Injuries
SVM	Support Vector Machine
TAFETA	Technology Assisted Friendly Environment for Third Age
T-Fall	Temporal Fall
TILDA	Irish Longitudinal Study on Ageing
TMMS	Trait Meta-Mood Scale
TN	True Negative
TP	True Positive
TUG	Timed up and Go
VR	Virtual Reality
VS	Visual Studio
WEKA	Waikato Environment for Knowledge Analysis
XAI	Explainable Artificial Intelligence
XGBOOST-CNN	Extreme Gradient Boosting- Convolutional Neural Networks

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgments), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

03/04/2025

Signature Date

Co-Authored Works

Peer-Reviewed Journals

1. **D. Mohan,** D. Z. Al-Hamid, P. H. J. Chong, K. L. K. Sudheera, J. Gutierrez, H. C. B. Chan, and H. Li, "Artificial Intelligence and IoT in Elderly Fall Prevention: A Review," *IEEE Sensors Journal*, vol. 24, no. 4, pp. 4181-4198, Feb. 2024, doi: 10.1109/JSEN.2023.3344605.
2. **D. Mohan,** D. Zuhair Al-Hamid, P. H. J. Chong, J. Gutierrez, and H. Li, "Fall Prediction in Elderly Through Vital Signs Monitoring—A Fuzzy-Based Approach," *IEEE Internet of Things Journal*, vol. 11, no. 20, pp. 33439-33449, 2024, doi: 10.1109/JIOT.2024.3429516.
3. **D. Mohan,** P. H. J. Chong, and J. Gutierrez, "A novel cooperative AI-based fall risk prediction model for older adults," *Sensors*, vol. 25, no. 13, p. 3991, 2025, doi: 10.3390/s25133991.
4. **D. Mohan,** P. H. J. Chong, J. Gutierrez, and M.M. Baig, "DBN-Based ADL Monitoring for Fall Risk Prediction in Older Adults," – **Submitted to *IEEE Trans on Emerging Topics in Computing,* in January 2025.**
5. **D. Mohan,** M.M. Baig, P. H. J. Chong, J. Gutierrez, D. Zuhair Al-Hamid, and C. Hobson, " Systematic Review of Artificial Intelligence-based Falls Prediction Applications for Older Adults: Challenges and Strategies," **Submitted to *IEEE Intelligent Systems*, in July 2025.**

Peer-Reviewed Conferences

1. **D. Mohan,** D. Z. Al-Hamid, P. H. J. Chong, J. Gutierrez, and H. Li, "Fuzzy based Fall Risk Prediction in Older Adults," in *Proc. 2024 3rd Int. Conf. Artificial Intelligence for Internet of Things (AIIoT)*, 2024, pp. 1-6, doi: 10.1109/AIIoT58432.2024.10574676.
2. **D. Mohan,** P. H. J. Chong, J. Gutierrez, and D. Z. Al-Hamid, "Fall Risk Prediction in Older Adults through Daily Activity Monitoring – A DBN-based Approach," *in IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES2024)*, Penang, Malaysia, Dec 2024.
3. **D. Mohan,** P. H. J. Chong, J. Gutierrez, D. Z. Al-Hamid, and N.Khan, "A Novel AI-based Co-operative Meta Model for Fall Risk Prediction in Older Adults," in *4th IEEE International Conference on Micro/Nano Sensors for AI, Healthcare, and Robotics (IEEE-NSENS - 2025),* Kuala Lumpur, Malaysia, March 2025**.**

Acknowledgments

The PhD journey requires patience and determination from the candidate, but at the same time motivation, inspiration, guidance, and support from the supervisors, mentors, and loved ones.

I would like to start by expressing my deep and sincere gratitude to Prof. Peter Chong, Associate Head of School (Research) at the School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, for his invaluable supervision, advice, encouragement, and guidance from the very early stages of this research. I am especially thankful for the extraordinary experiences he provided throughout this journey. Above all, his unwavering support and continuous motivation were crucial to the success of this work. His scientific intuition and passion for engineering have been a constant source of inspiration, enriching my research skills and fuelling my enthusiasm to work even smarter and harder.

I would like to extend my deepest gratitude to my second supervisor, Prof. Jairo Gutierrez, School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology for his invaluable insights, constructive feedback, practical ideas, and dedicated supervision, particularly in supporting the data collection process. His mentorship has been pivotal in shaping the direction and success of my research.

My deepest gratitude goes to Dr. Duaa Zuhair Abduljabbar Al-Hamid, whose unwavering mentorship, guidance, and encouragement have been invaluable throughout this journey. She has not only been a dedicated mentor but also a well-wisher and a true friend, always supporting me with her wisdom, kindness, and positivity. Her continuous presence and reassurance have played a crucial role in helping me overcome challenges and stay motivated, for which I remain sincerely thankful.

I would also like to thank Callaghan Innovation and Smartlife NZ (R &D team - Mentors, Guide, and Industrial hands) for initially supporting this research work from March 2022 to November 2023 and guiding me with the model development and mentoring. I sincerely thank my family and friends for their unwavering encouragement, understanding, and belief in me, which have been a constant source of strength throughout this journey. A special thanks goes to my father, mother, husband, and to my dear son Dhashvin Balaji, who have always stood by my side, offering moral support and cheering me on from the beginning to the completion of this research. I am also deeply grateful to my colleagues and peers for sharing their knowledge and ideas and fostering a stimulating and collaborative academic environment.

My sincere thanks go to the members of the Postgraduate Research Programmes Office for their outstanding service and support. This research was made possible with financial assistance, equipment, and personnel support provided by the AUT Doctoral Scholarship, the School of Engineering at AUT, and the Summer Research Award from the Faculty of Design and Creative Technologies at AUT. A special note of thanks to Jamie Protheroe and Maata Vakalahi for their constant support and mentorship during my administrative role at the school. Their guidance and encouragement greatly contributed to my professional growth and confidence in this role. Finally, I would like to extend my appreciation and thank myself (Deepika Mohan) for the hard work and sincere dedication to not giving up and aiming to achieve my goals despite balancing the family situations and being a sincere and good mother to my son. I thank everyone who contributed to the successful completion of this thesis. Thank you for your invaluable support.

Ethics Approval

This research involves all data collected from the public repository – **PhysioNet.** AI-1 model uses data from the PhysioNet – eICU database and Sepsis study. Similarly, the AI-2 model uses data from the long-term monitoring database obtained from PhysioNet.

Chapter 1. Research Motivation, Direction, and Thesis Organization

1.1. Introduction

This chapter includes a general overview of falls in the elderly, the number of injuries faced because of falls, and the strategies that have been taken place to handle this issue. One of the most important aspects of this chapter lies in the incorporation of Artificial Intelligence (AI) in fall prediction which describes how sophisticated algorithms learn from the datasets of older adults, integrating proactive measures, and tailoring fall prevention strategies. The research gap, research questions, aim, and objectives for this study are then set out to provide a roadmap to make sure that the goals and purpose will result in meaningful outcomes. Also, the boundaries within the scope of research for this study have been established. To enhance understanding, the outline of the thesis, particularly the rest of the chapters that are to come and their significance to the main topic of this research is synthesized. The chapter ends with an overview by recalling important issues that have been dealt with so far and previews the following chapter which will have an extensive literature review.

1.2. Need for Fall Prediction System

Demographic aging is a universal issue faced by most countries worldwide. This situation is expected to intensify due to the prolonged life expectancy. From the analysis data provided by the United Nations in [1], the aging population above 65 will increase from 9.3% to 16% in 2050. As age increases, older adults face age-related problems like sensory and cognitive impairments, reduced muscle strength, imbalance, psychological distress, chronic pain, unsteadiness, limited Activities of Daily Living (ADL), and other coexisting health problems that result in falls. One of the serious hurdles that is faced by the healthcare sector throughout the world is the fall in older adults. Falls can happen to people at any age but for an elderly person, the fall occurs due to loss of balance or health conditions which becomes a major risk to life or permanent disability. According to the STEADI analysis (Stopping Elderly Accidents, Deaths & Injuries) conducted by the Centre for Disease Control and Prevention (CDC), older adults fall every second in a day [2], which leads to minor or major injury and sometimes loss of life. Health injury surveys conducted in [2, 3] conclude that there will be a further increase in healthcare expenses till 2060, especially in addressing fall-related injuries in the aging population. It has been estimated that roughly around $31 billion or more are being spent on handling fall injuries each year in older adults and this is the same in western Pacific regions.

Among the western Pacific regions, New Zealand holds the largest investment in promoting healthy aging care resulting in enhanced improvements in quality living [3]. Today the elder generation has an active and positive approach towards their lifestyle but there are still many conditions like impaired limb function, depression, environmental threats, low blood pressure, dizziness, etc., that cause a risk of falling in them. Hence majority of them opt to stay at home for a longer time, with almost 3% living alone. An average of 30% of elderly individuals above 65 years fall more than once a year and approximately 5% of them resulting in fracture and hospitalization [4]. In New Zealand, around 4000 senior citizens fall every year, and most of the falls result in severe hip fractures, and almost 4% resulting in death. As the age rises over 75, the fall rates seem to be doubled [5]. The cost of all active claims in 2024 for fall-related injury was NZ $2,538,647,751 (9,71,596 active claims) out of which the highest number of Accident Compensation Corporation (ACC) was claimed by elderly aged 60+ (2,53,464 claims) due to accidental falls [6]. The government is also implementing certain fall risk programs to create awareness for the elderly based on strength and balance exercises, but those programs are not fully utilized by everyone in the community. In the fast-paced world, where families have been reduced to smaller sizes, most of the older adults prefer to live alone, hence it is vital to monitor them to save their lives and limit their risk of falling.

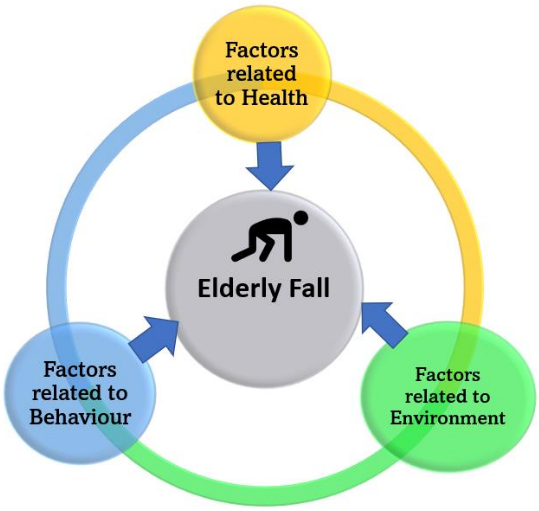


Figure 1.1: Dimensions Leading to a Fall in Older Adults.

Over 400 or more factors contribute to a fall in the elderly, and all are classified under 3 main dimensions namely behaviour, health, and environment [7]. When an interaction occurs between these 3 dimensions, it results in a fall as shown in Figure 1.1. Unlike typical activity prediction tasks such as walking, sitting, or running, fall detection and prediction present unique challenges. Activities of daily living (ADLs) generally follow repetitive and structured motion patterns, which makes it easier to model and classify using wearable sensors or vision-based approaches. In contrast, falls are rare, unstructured, and highly variable events. A fall can occur suddenly, within a fraction of a second, and may be triggered by multiple factors such as loss of balance, health conditions, environmental hazards, or unexpected movements. This makes it difficult to capture consistent patterns leading to a fall. Another challenge is the imbalance of data: large datasets exist for normal activities, but fall events are limited due to safety and ethical concerns during data collection. As a result, prediction models may become biased towards recognizing normal activities while underperforming on falls. Furthermore, unlike activity recognition, fall prediction requires anticipating an event before it occurs, which means models must identify subtle precursors such as gait instability, hesitation, or physiological changes that precede a fall. These signals are often weak and easily confused with normal variations in movement, adding another layer of complexity.

Therefore, while activity prediction focuses on identifying well-defined, repetitive tasks, fall detection and prediction involve modelling rare, unpredictable, and high-risk events that demand both high sensitivity and robustness. This distinction underscores why falls are significantly harder to predict than other activities and why specialized models are required. To prevent these accidents and minimize the consequences, it is obvious that a fall detection, prediction, and avoidance system is needed, especially for older people living alone. Initially, Fall Detection is the method of discovering a fall (finding out) upon its occurrence and sending alerts to the concerned caretaker or family member or emergency services for assistance, whereas Fall Prediction is identifying the fall risk factors earlier through continuous monitoring and notifying the concerned elderly or carer or health care professional about the future risk of fall and to prevent it before it occurs [8, 9]. A fall risk and its consequences can be reduced if it is identified, predicted, or (detected) earlier or on time. There is much research conducted based on Fall Detection but only a few studies were conducted to predict future falls (Fall Prediction).

1.3. AI/ML Development in Healthcare Applications

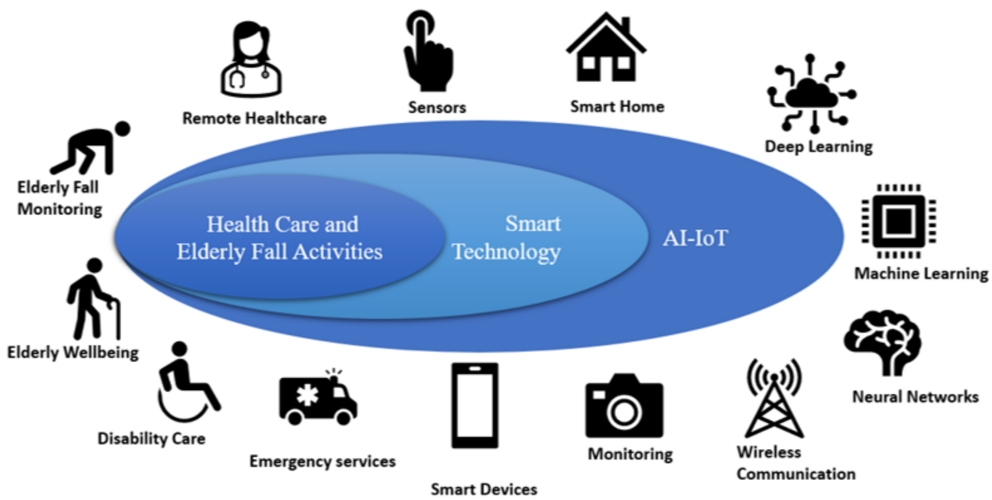


Figure 1.2: AI-IoT in Healthcare.

One of the promising solutions for predicting and preventing elderly falls based on their daily activities is through Artificial Intelligence (AI) and the Internet of Things (IoT). These techniques are suitable for both Aided (assisted) Living (AL) and Healthcare (protection and management) Monitoring (HM) in older adults, which compares the previous and current data to provide future outcomes. It makes predictions, which is the ability to gather information and learn from its environment and one of its advancements is Machine Learning (ML) which involves programming that learns from its experience [9]. From the amount of available data and with a combination of natural language processing and algorithms, the AI application becomes more useful in all domains, especially in healthcare, where the patient's records and data can be obtained, stored, and processed to predict their health status [10]. By combining AI and IoT, many new advancements can be developed, especially in the healthcare industry [11]. A summary of this new emerging technology is shown in Figure 1.2. Since AI and IoT in elderly healthcare is a young field, more research and developments are currently in process but from the completed research works and proven analysis, it can be identified that AI can predict future falls in the elderly, and it can also offer more solutions to eldercare enabled smart homes.

Most of the older adults live a restricted lifestyle, their social life and daily activities are limited due to fear of falling which leads to health and psychological illness. The increasing fall-related injury rates have created a greater impact worldwide and more research is being done to safeguard the lives of older adults. According to [12] a fall is an uncontrolled collapse or plunge of the body to a lower level and this overall fall period can be divided into 4 phases,

- *Pre-Fall Phase:* ADLs are carried out in this phase (sudden running, walking, or sitting).
- *Critical-Fall Phase:* abrupt imbalance and the body declines to the ground within 2 seconds.
- *Post-Fall Phase:* no movement or activity when the body is at rest (ground).
- *Recover Phase:* body recovered to pre-fall either with or without external assistance.

When phases 1, 2, and 3 are identified, it is referred to as Fall Detection and alerts for assistance are transmitted via smart devices. However, while continuous monitoring in Phase 1, the older adult receives information about the possibility of a future fall (Phase 2), which eliminates Phases 3 and 4 is “Fall Prediction”. A home-based self-operating system is required to track the health and wellness of the senior individuals (indoors). Due to the advanced evolution of wireless sensor networks and their related application uses in health management, this technology has acquired more and more recognition in recent years. Every smart device embedded in home monitoring related to health indicators, security, or surveillance interacts with each other through wireless communication [13]. This smart technology improves the affordable and portable health sensing devices and wearable sensors to effectively measure the important parameters in the elderly. The IoT device is intelligent enough to interact with the cloud and provides good-quality data and information to medical services [14]. IoT-enabled health monitoring devices with unique identifiers can be easily identified by communication protocols as they connect to the physical and digital world.

A novel individual healthcare and critical assistance wearable structure called WAITER was developed in [15]. It uses small wearable sensors to steadily acquire active data signals from the older adult. It transmits the signal to the mobile phone through Bluetooth technology, which can be used for storage and health evaluation. Using the integrated motion sensor in the wearable device, the body movements are monitored, and if a fall is discovered then an alert message is transferred to the emergency services. In a similar vein, iCare is an elderly mobile health monitoring system that was developed in [16, 17] to use wireless body-worn detectors (Sensors) and smartphones to monitor the health of older adults. A record of personal health information is also collected to provide medical guidance to the elderly through the communication platform and once, an emergency is detected, it will send an alert text to the pre-assigned people, and the elderly. Additionally, the developed model is effective enough to track location and for sending reminders. Modern technology growth and innovations enhance the lifestyle of mankind via smart applications, sensors, wireless communication networks, etc. For all those advancements, the Internet is the foundation that provides intelligent processing like retrieving and delivering data through the IoT. By positioning the sensors in a specific region, the information features are collected in the IoT environment. It receives data depending on the defined framework for the IoT devices. Although these devices may have some limitations such as sensitivity, energy constraints, distance, etc., they collect data from the surroundings and transmit it to the central node to evaluate the data and then the essential information is switched to other nodes. Based on the choice of the end user, these applications and resources could be formulated in IoT. The enhancement in data gathering modules and their use improves the lifestyle drastically. Hence handling, organizing, and assessing such information via IoT is a current research trend.

The use of AI in healthcare consists of two primary branches: virtual and physical. The virtual module constitutes Machine Learning, (also called Deep Learning (DL)) in which mathematical algorithms are used for enhancing learning through experience. The physical part includes physical entities, medical devices, and robots taking part in the distribution of care units. As in [17], AI is thoroughly used in elderly care which handles the electronic medical records of the patient where specified algorithms are used to identify subjects with a background history of an inherited disease or an increased risk of a chronic disease. Machine learning is a primary tool for AI techniques used in healthcare. It supports IoT devices with advanced capabilities for data inference, data analytics, and intelligence. ML has become a competent and efficient solution for several Internet of Healthcare Things (IoHT) technology contexts.

The Technology Assisted Friendly Environment for Third Age (TAFETA) group in [18] developed a smart home for older adults that utilizes integrated sensor technology for communicating and processing information. Intelligent sensors, magnetic switches, accelerometers, Radio Frequency Identification (RFID), pressure mats, microphone arrays, and smart grab bars were used for this development to monitor elderly activities. The data is collected and forwarded to the AI Expert system, and by using classification algorithms the anomaly patterns were categorized as mild, caution, high alert, and emergency and it informs the concerned services based on the severity. The data-driven prediction models in [19] are becoming prominent among medical professionals due to improvements in computational algorithms. The prediction models can suggest diagnosis, prognosis, and treatments. These systems are developed via ML for data analysis and identifying patterns to provide prediction outcomes. A study in [20] was conducted based on fall injury and prevention using 2 classification ML algorithms such as Random Forest (RF) and Decision Tree, both predicted the fall outcome with 54% and 66% accuracy. Deep learning permits the modelling of computational systems which consists of multiple layers resulting in more powerful models. Because of its complex feature calculations and directly dictated data, the quality of model predictions is more accurate. Moreover, no initial knowledge is required for developing new models, so it is useful to co-relate DL techniques to traditional ML methods.

Healthcare technology is a fast-growing field compared to other technologies. This fast improvement, along with the indistinct nature of falls in older adults, builds the need for various strategies and creative technologies such as Fuzzy Logic (FL) or its conjunction with other AI techniques as mentioned in [21]. Studies on ordering and clustering, classification, pattern recognition, feature selection, and performance comparison can all serve as the foundation for FL. Fuzzy clustering, rule-based methods, pattern-matching methods, and fuzzy relations techniques are the main approaches in visual pattern recognition that are associated with this field. Fuzzy systems are therefore employed in many real-world situations. There are now more opportunities to combine mental health data with preliminary knowledge about an elderly person's behaviour to predict a fall because of the development of IoT and mobile technologies [22].

More dependable and effective healthcare systems can be created because to advancements in sensor technology, computer vision, and communication networks. There is numerous sensor-based monitoring (non-wearable) or wearable devices available to detect falls, monitor the health of the elderly, and track their location, which can be identified by their family members; however, one problem is that they need to be worn all of the time [23]. Other IoT-based smart devices such as motion sensors, cameras, etc. help with continuous monitoring, but they will not predict a future fall. Generally, a fall in older adults can be monitored under 4 groups namely health-based, behavioural-based, posture-based, and emotion-based as shown in Figure 1.3. Several methods are being proposed for predicting and preventing falls in the elderly and it is quite complicated to prevent a fall but with long-term monitoring analysis, predicting a future fall can be achieved.

Figure 1.3: Categories for Detecting and Predicting Falls in Older Adults.

1.4. Motivation for Driving towards Fall Prediction using AI

Falls occur across the world for older adults, and from [24] it is speculated to be 9% until 2016 and it has increased to about 30% recently. The fall can end up in severe injuries resulting in death and it mostly occurs with elderly over 60 years. For Māori elders in New Zealand, the issue is particularly concerning due to health disparities and physical size, as they report falls at slightly higher rates than non-Māori [6]. An average of 37% of Māori people reported a fall in the preceding year, and 7% of those had four or more falls. Of the people who fell, 35% were injured and 10% sustained a fracture [25]. Therefore, monitoring the health and well-being of older adults is an important aspect and hence the core idea of this research work is to protect older adults including the Māori population who have a high risk of health and fall issues due to their physical size and lifestyle. Conventional fall detection or prediction systems for the elderly, use cameras and sensors to track a person's movement and then send the collected data to a server for validation. When a fall event is identified from the collected data, the server notifies the emergency services or carer via text message about the occurrence [26]. From the above-mentioned explanations, it can be understood that most of the discussions were based on Fall risk management, fall detection, and prediction but many researchers suggest exercise programs for balance have resulted in good accuracy. Fall prevention in elderly monitoring needs to be brought into the limelight with good and reliable technology that does not require much human intervention as shown in Figure 1.4. Over the last few decades, AI and ML have created a substantial impact on our daily lives.

Figure 1.4: AI in Healthcare without Human Intervention.

As prevention is better than cure, fall prevention research targets predicting a future fall in older adults by identifying the abnormalities in health and behavioural patterns and alerting them about the risk of a fall earlier. One major advantage of AI is its contribution towards improving the quality of life through advanced technology: especially in healthcare areas [27]. The Fall prediction model will be developed in such a way that it will be more useful for people with disabilities where their health and ADLs can be monitored continuously through the devices they access regularly [28]. Finally, the fundamental concept of this research work is to protect older adults as they have a high risk of health and fall issues due to aging and lifestyle [29].

1.5. Research Gap, Questions, Aims and Objectives

In many similar research based on Fall detection and prediction discussed in Section 1.2 and Chapter 2, it has been identified that the background of the existing work lacks one of the following criteria,

- Some of the developed models in the existing work are not suitable for supporting multiple profiles.
- In some cases, the pre-trained model can only understand a fixed dataset. When a change occurs, it does not learn from the changes or provide an outcome based on the changes.
- Most of the Deep Learning algorithms used in the system model for Fall prediction are not transparent, uncontrollable, and tend to be opaque.

The field of fall prediction research has been dominated predominantly by computer vision-based approaches [30-32] and gait analysis [33, 34] for the detection and prediction of falls in elderly individuals. Computer vision-based detection of falls performs well compared to other approaches [35, 36] but lacks predictive power. Gait-based fall prediction, although efficient, necessitates a large infrastructure and wearable sensors, which are perhaps impractical and uncomfortable for the elderly. Advanced gait analysis employs AI models with an accuracy of 90% or more but is still limited by sensors and other hardware, limiting its suitability for the elderly. In addition, both computer vision and gait-based models operate independently, processing one modality of data pattern at a time. Also, they are not scalable and need large amounts of data gathering and preprocessing, which poses grand challenges to real-world deployment in healthcare.

The preceding information and background on falls in elderly individuals, as well as the work based on fall detection and prediction analysis, raises the following question, which served as the foundation for this research work:

- What are the areas, causes, factors, when, and under what conditions older adults tend to feel unconscious?

- How can a Co-operative model be infused with a prediction model to review and analyze the present and past data to forecast the risk of future falls in older adults without making the system opaque?

- What impact does the developed AI model have on predicting future falls when it is designed to cope with environmental changes?

This research aims to understand the key factors related to fall risk, which is critical for enhancing prediction performance. This study introduces a Novel Co-operative AI Model for Future Fall Prediction in Older Adults, designed to foresee future falls by monitoring health and behavioural parameters and detecting abnormalities through continuous monitoring based on AI analysis.

The following are the research goals for achieving the aforementioned aim:

- To have a deep knowledge of how AI technology can be applied to enhance and predict falls in older adults, especially in identifying future fall risks.

- To conduct research on deep learning models with controlled parameters and improved understanding of self-learning capabilities.

- To explore the possibility of the combined analysis and to utilize different data in the AI models and to provide a better solution for future fall prediction in older adults by enhancing AI learning capability.

1.6. Scope of Research

The significance of this research is to identify a future fall in older adults before it occurs based on continuous monitoring through smart devices. This research focuses on the elderly 60 years and above as they have a high chance of falling risks. Data on the health and behaviour of the elderly is obtained from a public database. This information is subsequently calculated by two AI models based on different strategies for computation to predict the likelihood of future falls. The first model, AI-1, applies Fuzzy Logic in combination with a pre-existing set of fuzzy rules to compute the risk of a fall. With these rules applied, the model is capable of accepting the uncertainties present in physiological data, such that rather than a straightforward binary choice, it can provide a rich, qualitative risk assessment. Fuzzy Logic's flexibility makes it possible for AI-1 to pick up very small variations in an individual's physiological measures and is therefore highly beneficial when dealing with inaccurate or incomplete data.

On the other hand, the second model, AI-2, employs Deep Belief Networks (DBNs), which is a deep learning model that excels at hierarchical feature learning and classification. Training DBN consists of two stages: pre-training and fine-tuning. Under pre-training, the model is trained in an unsupervised fashion to learn a structured data representation through Restricted Boltzmann Machines (RBMs). This allows the network to expose underlying, latent factors relevant to fall prediction. The fine-tuning process further fine-tunes the pre-trained model through supervised learning with backpropagation and optimization in maximization of the accuracy of classification. With the application of fine-tuning and pre-training, AI-2 can learn advanced, non-linear patterns in the data and therefore become a good tool in classifying fall. These two AI frameworks are combined, where AI-1 generates an interpretable rule-based decision-maker and AI-2 utilizes the power of deep learning to enhance predictability. The combination offers flexibility and a complete system for fall risk classification, with provision for identifying visible rule-based patterns as well as hidden dependencies in the data.

The results from the 2 AI models are then combined using a Meta-Model which then generates the final fall risk prediction result. The developed AI model will continuously sense and monitor the health and behaviour patterns and when an abnormality leading to a fall risk is identified, the model categorizes the fall risk level (*Low, Moderate, or High*) based on the severity of the detected abnormality. The obtained results are then sent to the elderly and to their direct links through the physical prototype to alert them on the risk of future falls.

In this study, two individual AI models are developed that can perform separately and also work together as they learn from each other and understand previous data. This makes the research novel with each model supporting one another to produce reliable outcomes. The developed model will also be suitable for integrating with multiple users as it has a combination of controllable data from Fuzzy Logic (risk level prediction) and self-learning ability from DBN (comparison of the input parameters), which can predict future falls in the elderly with good accuracy.

Different from conventional approaches that employ a single predictive model, this proposed research explores the synergistic collaboration of three AI models to enhance accuracy and flexibility. The Co-operative model employs fusion technology to integrate two distinct AI models based on Deep Belief Networks (DBN) and Fuzzy Logic-based AI such that they can coexist and collaborate. No previous study has employed multi-aspect AI models to predict future falls in older people. The AI models each operate in different dimensions and finally, they are integrated using a meta-model that refines the result significantly improving predictive accuracy. A major limitation in existing research is the dependence on a single data pattern, typically electronic health records (EHRs), which may not fully capture the behavioural and contextual factors contributing to falling risk. In contrast, the research elaborated in this thesis integrates multiple dataset patterns, including real-time sensor-based physiological data, and long-term activity tracking collected from the wearable devices, providing a holistic and personalized assessment of fall risk. Furthermore, these proposed models interact dynamically, continuously learning from both past and present predictions. This iterative learning process enhances adaptability, making our approach more robust and effective in real-world fall prediction scenarios.

1.7. Thesis Organization

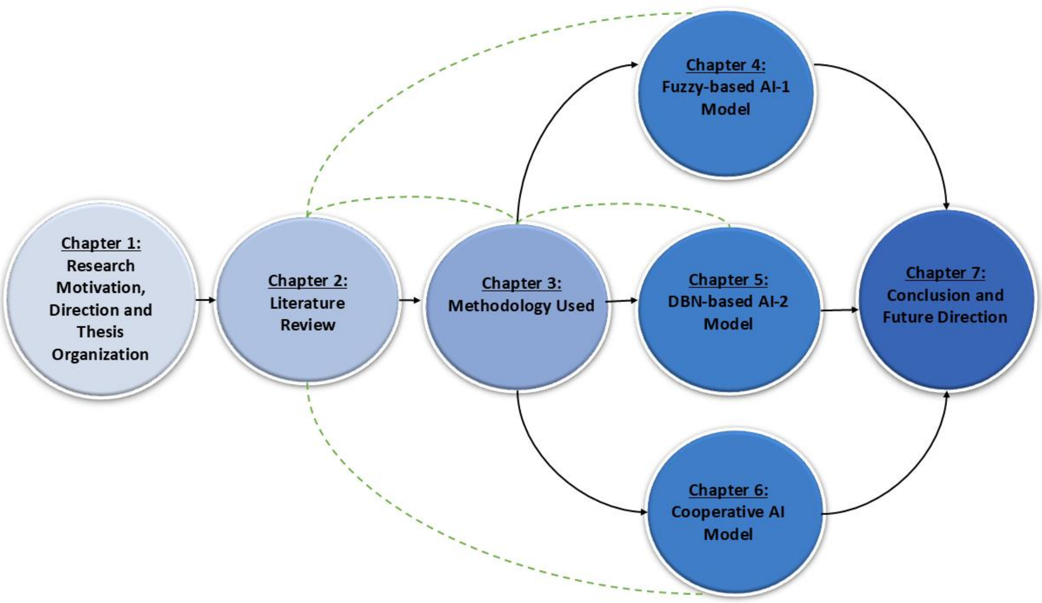


Figure 1.5: Chapter's Technical Connection Representation

Chapter **1** gives an overview of the problem of falls among older adults and the need for fall prediction systems. The use of IoT and AI in healthcare and its applications, and research done to detect and predict falls in the elderly are discussed. The background area outlined in this chapter includes the solutions to minimize falls in older adults and motivation for driving toward fall prediction using AI. The research gap, motivation, research problem statements, research aim, and objectives are also discussed which highlights the novelty of this research work.

Chapter **2** provides an insight into the related literature to the important aspects associated with this research. The chapter begins with a discussion of the different factors leading to a fall in older adults, then elaborates on the detailed analysis of its sub-categories, and existing works related to fall prediction in older adults. The analysis of AI-based smart devices used in healthcare monitoring and their pros and cons are discussed in detail and the chapter concludes with a summary of the reviewed systems and the solutions to overcome the drawbacks through the novel findings from this research work.

Chapter **3** elaborates on the methodology, step-by-step framework analysis for data processing, model development phase, modelling, and implementation tools employed towards concept development and testing. It provides an insight into the ability of various available tools including software and hardware to investigate the concept of an AI-based fall risk prediction system. Visual Studio and Python compilers are discussed in detail in this chapter.

Chapter **4** introduces the essential vital sign parameters used in the AI-1 model's development. The proposed Fuzzy-based fall risk prediction system (AI-1 model) is described in detail. This chapter discusses the rationale behind the proposed approach's core components, including parameter selection, vital sign-based fall prediction model design, fuzzy rule generation, membership function, and rule weighting. The chapter also focuses on the data gathering and evaluation of the AI-1 model. The Morse falls scale (MFS) is utilized as the ground truth to validate the fuzzy-based fall risk model, and the findings are compared with three publicly available sources. From a performance perspective, the chapter focuses on the construction, testing, and assessment of the AI-1 Model for predicting future falls in older adults.

Chapter **5** introduces the essential behaviour parameters used in the AI-2 model's development. The suggested DBN-based fall risk prediction system (AI-2 model) is described in detail. This chapter discusses the rationale behind the proposed approach's core components, including parameter selection, ADL-based fall prediction model design, and a 3-stage fall risk prediction system. The chapter also focuses on the data gathering and evaluation of the AI-2 model. The Morse falls scale (MFS) and Timed up and Go (TUG) are utilized as the ground truth for the validation of the DBN-based fall risk model, and the findings are compared with existing works. From a performance perspective, the chapter focuses on the construction, testing, and assessment of an AI-2 model for forecasting future falls in older adults.

Chapter **6** presents the network modelling of the novel Co-operative AI-based fall risk prediction model. The comparator analysis is presented along with its subcategories, and a summary of the fully developed system is discussed in depth. This chapter also discusses the data collection mechanism and how the final model is evaluated using ground truth. A comparison between the current and existing work is highlighted.

Chapter **7** summarises the research work, and addresses some of the limitations faced during the model development. A description of the solutions to overcome this limitation has been discussed in this chapter and finally concludes with the advancements in Transfer learning which highlights the future work. A detailed connection between the chapters is elaborated in Figure 1.5.

1.8. Conclusion

This chapter provides a diverse associated introduction describing the risk of falls for the aging population, paying particular attention to how injuries from falls are multifaceted problems that are magnified within the healthcare system. The issues related to fall prevention and the need for more coordinated efforts to reduce them are pointed out in this chapter. One of these efforts is predicting falls, which is useful for exploring ways to avert them. This chapter has built the case for seeking a predictive model for identifying future fall risk. This study also strives to consider these shifts in the level of falls and devise for the elderly an appropriate data-based advanced method of prediction. The application of AI and IoT in healthcare was also discussed. Moreover, the chapter describes the research gap, research questions, research aims, and research objectives, which will navigate toward designing an accurate fall prediction model in this study. The novelty of this study has also been discussed, and justifications are provided on how it is distinct from other fall prediction methods. The chapter concludes by detailing the research scope and thesis organization.

Chapter 2. Literature Review

2.1 Introduction

The absence of real-time tracking, monitoring, and data transmission exacerbates the challenges of managing fall risk in older adults in healthcare settings [37]. In many research based on Fall detection and prediction, it has been identified that the developed model or the background of research lacks one of the following criteria that was discussed in Section 1.5, Chapter 1 under research gap in which,

- Certain developed models lack the ability to save numerous user histories.
- In some circumstances, pre-trained models are limited to a static dataset, making them ineffective for tracking dynamic changes or producing outputs depending on changing data.
- Most Deep Learning approaches used in fall prediction models are black-boxed, difficult to interpret, and uncontrollable.

These difficulties necessitate creative approaches to the organization of healthcare monitoring systems, which must be able to function with limited resources, such as system performance, and respond dynamically to the occurrence of falls. Thus, this chapter aims to conduct a comprehensive literature review to clarify the key aspects of developing a flexible and uncontrollable monitoring system for fall prediction and prevention. This section intends to elaborate on cutting-edge technologies, including AI and sensor-based predictive models, IoT devices, wearable and non-wearable technologies, data mining, and real-time analytical processes for the rapidly evolving environment. The focus of this literature review is mainly on methodologies used in fall prediction, as well as assumptions based on motion detection, machine learning, deep learning, and other rule-based systems. Multifaceted approaches to fall prediction and risk factor detection that are challenging when used by the elderly are also highlighted. Furthermore, the performance of AI-IoT-based models is compared to typical, non-AI models to illustrate that the AI-integrated systems offer improved performance, accuracy, and effectiveness compared to the non-AI methods. Hence, from the Literature analysis, it can be determined that ML and AI can detect and predict elderly falls with good accuracy.

2.2 Categories of Falls in the Elderly

Different categories of falls result in various types of injuries in older adults, for instance, a backward fall or a slip may cause a more severe injury than a forward fall or a trip. [38]. Future falls could be avoided with a good understanding of the different kinds of falls and by continuously monitoring the activities of older adults. Fall risk factors are generally categorized into Intrinsic, which is person-specific, and Extrinsic, which is based on environmental factors [39]. From [40], the intrinsic risk factors are individual-specific and include patient features, comorbidities, and medication management difficulties. Intrinsic factors associated with an elevated risk of falls are classified into four states, namely, mental status, mobility, urinary problems, and common factors such as exhaustion and a history of falls. Extrinsic risk factors include environmental considerations (building design, flooring quality, and lighting), Organizational and personnel issues (shift changes and communication problems), and Socioeconomic factors (social engagement and health status) [40]. Figure 2.1 elaborates on the two main categories of risk factors leading to falls in older adults.

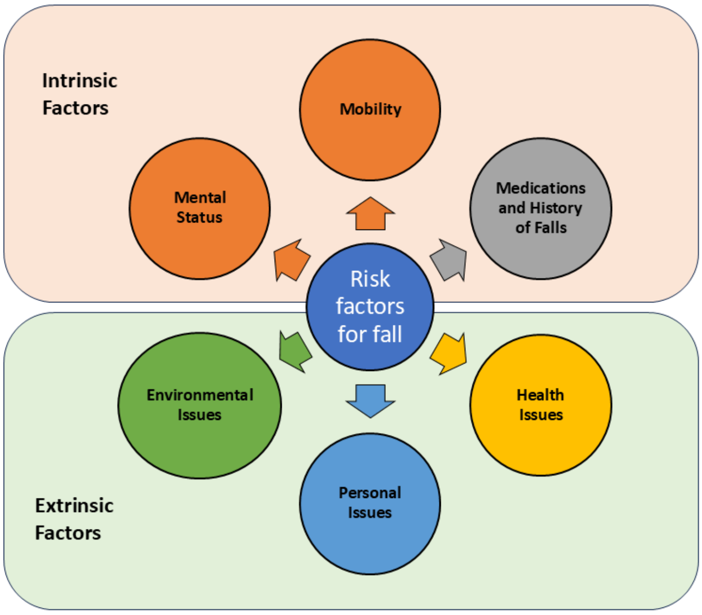


Figure 2.1: Risk Factors of Fall.

Fall prediction research in [41] uses approaches such as predictive and prescriptive analytics in wearable sensors, home environments, IoT, computer vision, AI, machine learning, video monitoring, exergames, alarm technology, and so on. Using efficient and reliable technology, particularly in the living context, has the potential to allow older adults to maintain their independence while participating in clinically supervised measures, particularly in predicting a fall. The progress of advanced technology in healthcare needs outlined in [42] represents a genuine collaborative work among engineers, healthcare professionals, and administrators in identifying the cause of a fall in an individual and what treatments can significantly impact the results.

Fall Prediction and Prevention in Older Adults can be broadly classified into four categories based on their nature and actions in real-time. Health-based monitoring, Behavioural-based monitoring, Posture-based, and Emotion-based monitoring help in predicting a future fall. Since each monitoring category has its sub-classifications and functions, internally, all are interlinked with each other and provide the best results in Fall Prediction. The classification in Figure 2.2 compares research on fall prediction and prevention with and without AI. As this study focuses on Elderly Fall Prediction with AI and IoT, numerous healthcare-related AI-IoT developments and benefits are discussed and compared with research efforts that do not employ AI.

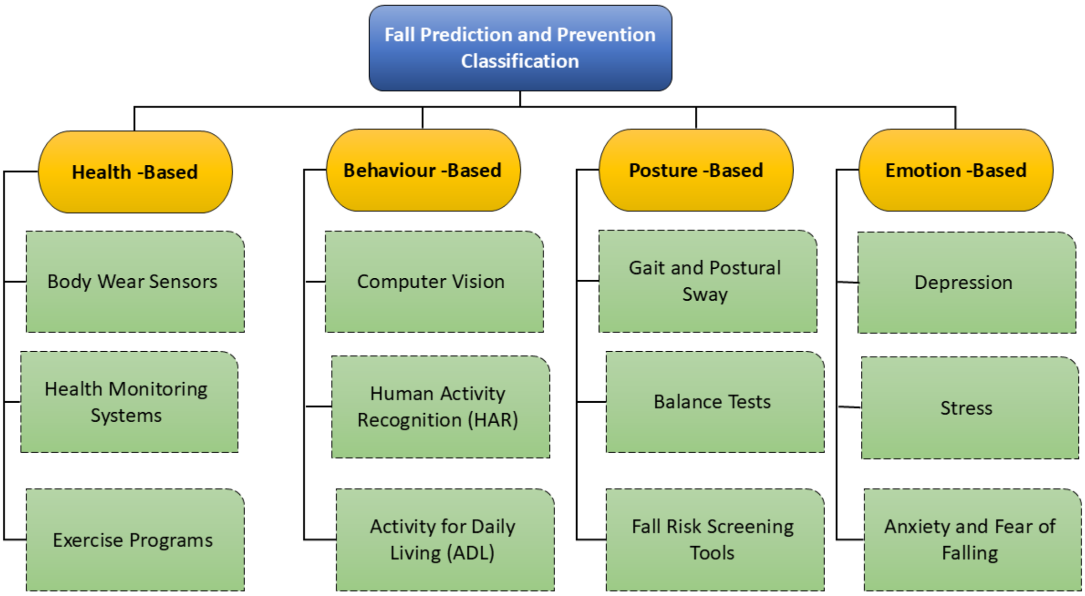


Figure 2.2: Fall Prediction and Prevention Classification.

2.3 Health-Based Analysis

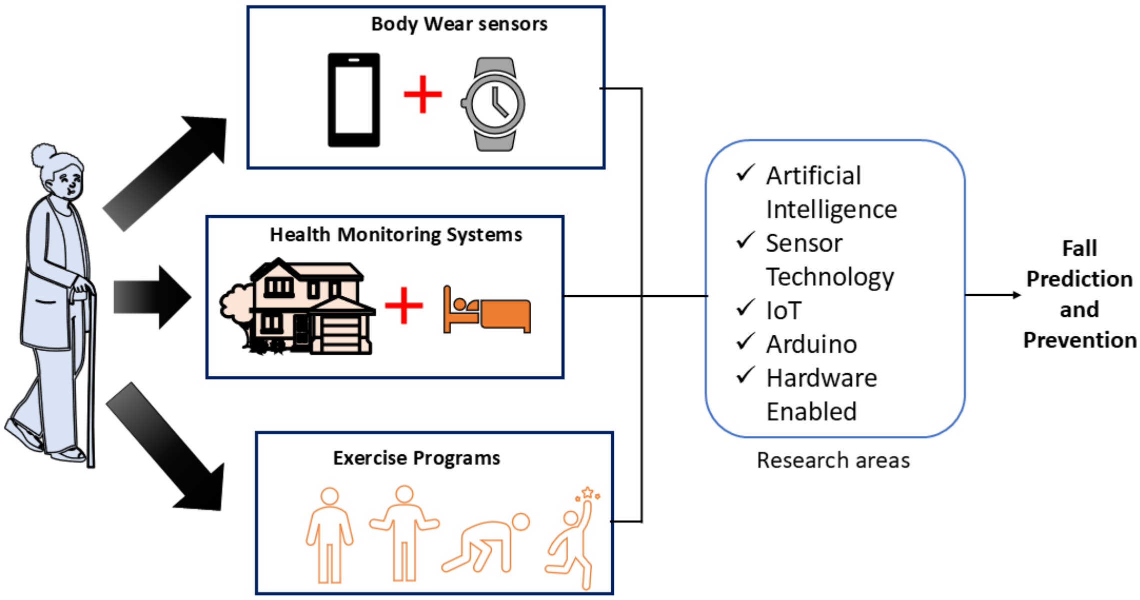


Figure 2.3: Health-Based Analysis for Fall Prediction and Prevention in Older Adults.

Individuals frequently track health-related information using wearable technology, as shown in [43]. They enable continuous monitoring of critical body parameters such as blood pressure, heart rate, electrocardiogram (ECG) signals, body temperature, oxygen saturation of the blood

(SpO_2), blood glucose level, and other critical physiological measurements. Wearable sensors are extremely crucial in healthcare for the elderly, enabling immediate feedback regarding a person's condition, which is beneficial for early detection of threats to their health. One of the significant advantages of wearable sensors is their low power, miniaturization, and low cost. As they are light in weight and have minimal or no visibility, they can be worn every day without any discomfort. As they are low power, they can be worn for long periods and are therefore appropriate for long-term monitoring and continuous data logging.

The health-based analysis is further divided into three main categories, such as Body-worn sensors, Health monitoring systems, and Exercise Programs, which examine numerous research and real-time initiatives in fall prevention. Body-worn sensors capture real-time physiological information by directly measuring physiology. Healthcare monitoring systems incorporate wearable devices and cloud analytics or artificial intelligence analytics to identify patterns and anomalies and utilize them for improving disease management and prevention. Concurrently, exercise programs make use of wearable sensors to track movement patterns, posture, and activity levels, and play a significant role in rehabilitation and preventing falls in older adults. In order to compare more effectively the impact of monitoring technology on elder care, an additional cluster analysis was conducted, bifurcating individuals according to monitored health measurement and activity category. The cluster analysis performed derived from the health monitoring of the elderly is shown in Figure 2.3 which indicates, a veritable trove of information used to develop target health monitoring plans for enhancing fall prevention planning, as well as overall wellness for older individuals.

2.3.1 Body-Worn Sensors

Using Sensors, IoT, and Hardware: One of the most common methods for obtaining motion data is through an Inertial Measurement Unit (IMU), which employs two or more sensors to predict, detect, and measure the activity of the body through a wearable device. Normally, the accelerometer, gyroscope, magnetometer, barometer, and many other sensors defined in [44] fall under the IMU category and employ either threshold-based values or context to classify fall prevention problems. Even though the fall risk evaluation and intervention tools are meant to identify and reduce fall risk, they do not address sudden falls. The model in [45] employs a wearable airbag that expands once when the older adult experiences a pre-impact fall. The technology is particularly beneficial for older adults who are susceptible to bone fractures from falls, resulting in hip fracture, which significantly affects mobility and quality of life. Threshold-based algorithms are employed, which analyze data obtained in real time from natural activity to differentiate normal motion and fall-like motions. The pre-impact fall detection algorithm detects the start of a fall (i.e., loss of balance, downward acceleration, and abnormal posture transitions) before impact. In the event that a fall path is determined, the system will activate the airbag inflation system to inflate the airbag in milliseconds to cushion the body and minimize the impact forces. This first intervention enhances fall protection through a lessening of the impact of injury before the ground effect. Threshold-based systems are suitable for real-time fall detection but may be restrictive in flexibility and accuracy. They employ pre-determined acceleration and angular velocity thresholds that are unlikely to detect body motion change, other falls, or environmental change.

Advanced technologies, such as machine learning-based fall-detecting algorithms, could potentially enhance the pre-impact fall prediction sensitivity using learning from high-density movement patterns and activity profile-dependent adaptive updates of the thresholds. Overall, the wearable airbag system is a new-generation elderly fall prevention system that combines real-time motion monitoring and quick response protection to reduce the likelihood of serious injury. In [26], an elderly fall monitoring IMU sensor for spectacles was developed to prevent and detect falls. The model employs an accelerometer and a gyroscope to monitor falls, and through the user's head movement, the fall can be predicted or identified; therefore, if a fall is identified, an alarm is activated to alert the environment. The model employs a threshold-based algorithm, and forecasts fall with 95.44% accuracy. Furthermore, by employing AI, the fall prediction mechanism can be implemented.

Using AI and ML: Recently, ML algorithms appear to be an improved option for accurate fall prediction as mentioned in [46], thus preventing future disasters when compared to threshold-based systems. These health-related data statistics are obtained using ML algorithms and IoT applications, as described in [47]. The statistical data can be used by the caretaker, physician, or family to monitor the health of the older adult, and early fall prevention treatment can also be provided. An in-house intelligent patient monitoring system was constructed in [48], which collects important data from sensors and uses Extreme Gradient Boosting- Convolutional Neural Networks (XGBoost-CNN) algorithms to categorize irregularities as low, medium, or high risk of falls. This ML classifier attained an accuracy level of approximately 98%. More research is being conducted on context-sensitive systems and wearable devices for post-fall detection to seek immediate assistance, but due to the emergence of AI as stated in [49], the focus has shifted to fall prediction and prevention approaches that are dependent on fall interventions and risk assessments. Wearable devices, IoT-based smart homes, and AI-enhanced rehabilitation programs are integrating into these predictive systems, ensuring that fall prevention is not merely reactive but also proactive and dynamic. Briefly, while post-fall detection is an important aspect of geriatric care, the evolution of AI technologies has propelled research into fall prediction and prevention strategies. The AI-driven approaches are focused on early risk detection, real-time intervention, and adaptive monitoring, a paradigm shift in fall management among the elderly. Another AI-based fall prevention method termed the hybrid deep neural network with Long Short Term Memory (LSTM) architecture, was proposed in [50] and leverages public datasets to identify pre-impact falls. The method identified True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) and provided realistic results with 93% sensitivity and 94% specificity in detecting true pre-impact falls.

2.3.2 Health Monitoring Systems

Using Sensors, IoT, and Hardware: A fall recognition system was developed in [51], employing smart sensors with accelerometers that interact with an Android application (smartphone) over Bluetooth (BT). This wearable sensor monitors heartbeats per minute and has a threshold below 45 and above 120 beats. If the beat range falls below or rises above the pre-set value for more than one minute, the caretaker receives an alert about the irregularity. The hardware device arrangement was built around the Atmega 328p microcontroller. The threshold-based method achieves an accuracy of 97.6%. Older adults with impairments face more obstacles to taking care of their health. They must be observed every second and must be given special attention. A smart automobile system was developed in [52] specifically for the elderly with disabilities, which includes body temperature and heart rate measurement metrics. Sensor technology is utilized to record health factors such as temperature, blood pressure, and heart rate, which are then processed using Arduino. It alerts the caretaker by text message when an indicator goes below the threshold level or if a fall or irregularity is observed. In [53], a tailored health monitoring system was developed that uses pulse, gas, and temperature sensors to examine the elderly's health as well as to detect CO, CO_2, and humidity in the room. The acquired data is routed to the Espressif32 (ESP32) hardware board, which transmits data to the care unit over Wi-Fi using a web platform and User Interface. The developed model was evaluated in real-time and achieved a success rate of 95%.

Using AI and ML: In [54], a fall occurrence-based detection method was created that uses both threshold-based and ML approaches to record falls and estimate their direction. Using a tri-axial accelerometer that detects motion along the x, y, and z axes, the device tracks six categories of falls: walking, standing, sitting, ascending/descending stairs, lying on a bed, and jumping. The obtained data is then processed using these two fall detection methods to precisely determine the fall direction and develop a suitable response strategy. The outcomes of this developed algorithm are 99.83% sensitivity, 98.44% specificity, and 99.19% accuracy. Similarly, in [55], an efficient healthcare monitoring system was developed that includes IoT body sensor networks, data pre-processing, data classification, and a remote health monitoring database. The data was classified and processed to the monitoring care system using a neural network model to evaluate the older adult's health and identify abnormal changes that could result in falls, and the proposed model achieved a 95% accuracy rate. Fuzzy logic can be used to process and monitor health-related parameters such as blood pressure, pulse rate, and kidney function. A Fuzzy Inference System (FIS) was developed in [56] that uses input data and fuzzy set rules to perform risk analysis based on health risk variables, resulting in an 83% prediction rate for health abnormalities.

2.3.3 Exercise Programs

Training programs using Sensors and IoT: Fall prevention measures described in [57] are used in hospitals and residential homes and include elderly monitoring technologies, alarms in elderly accommodation, location and identification tracking, safety and precaution procedures, and elderly and family education. According to [58], the National Database of Nursing Quality Indicators (NDNQI) conducted a survey in 2017 that included an average of 80 hospitals and care homes, as well as 60 manager nurses. The poll focused on vision and recognition, bed adjustment, ongoing elderly monitoring, subject protection, and education. According to the results of the study and data acquired by older adults, the most desired techniques indicated by participants were restructuring (70%), constant monitoring (68%), and fitness programs (60%). The research in [5] identified critical interventions, particularly clinical tests, and risk reduction variables, along with exercise programs incorporating balancing exercises, that are required for the elderly to adopt new behaviours. Older Adults will be encouraged to take part in fall prevention programs with the help of family and friends, as well as personal assistance from a health care provider. The most effective method of fall prevention is through exercise programs, which can reduce falls by up to 24%. Additionally, completing standing activities can result in a steady balance, which can reduce falls. A cost-effective analysis was carried out in [59] to investigate community-related fall interventions that are effective, flexible, and create positive results. According to these criteria, three exercise programs were chosen: the Otago Exercise Programme, Tai Chi - Moving for Better Balance, and Stepping On. The Otago program focuses on individual muscle strengthening and balancing exercises, while the Tai Chi approach focuses on warm-up and cool-down intervals, and stepping on is linked to pharmaceutical and behavioural programs that use hip protectors. The study emphasizes community-based intervention to prevent falls in older adults with a focus on multidimensional exercise programs that have physical as well as a cognitive benefit. Individualized strengthening of muscles is the basis of the Otago Exercise Programme, balance, and fluent movement become the hub of Tai Chi, and behaviour and medical strategies are included as the base of Stepping On to enhance the prevention of falls. From a cost-effectiveness point of view, the interventions are cost-saving in the long term by reducing hospitalizations for falls, saving healthcare expenditures, and improving overall quality of life. The findings support that a combination of structured physical activity, medication review, and behavioural training is the most comprehensive approach to fall prevention in the elderly. Therefore, the implementation of such programs within community settings, senior centres, and home care can be key in reducing fall rates and enabling elderly independence.

Using AI and ML: To avoid falls and become independent, fall prevention exercises and physical criteria development are promoted, with a focus on balance and support training. With the advanced development of modern technologies, it is expected that wireless and cloud computing will help older adults live better lives, particularly in terms of health monitoring and assessment. An IoT-based intelligent health system (IIHS) using smart devices was set up in [60] by combining IoT, fog computing, and AI to improve health monitoring systems, strategic planning, and forecasting. IIHS allows older adults to work on fall prevention and safety exercises and strengthen their balancing abilities to achieve ongoing health improvement. The findings indicated that older adults gained more confidence, security, and independence after utilizing balance boards. The ML can be effectively employed to train the proposed IIHS and improve performance in determining the ideal posture during exercise. Fuzzy expert systems (FES) are one type of computer-based technology that facilitates medical decision-making. FESs have proven to be quite effective for medical diagnosis, as they are based on quantitative analysis and qualitative evaluation of medical data, resulting in accurate results.

Discussion: The wearable sensor-based system, which uses body-worn sensors to measure health indicators for analysis of personal health and everyday activities, is the most desired health monitoring technology. Even though it is an effective technique for gathering health-related data, wearing it all the time is one of the most difficult challenges. There are numerous fall prevention programs for the elderly, including home-based training, food feedback, fall prevention tests, behaviour guidelines, fall-avoidance counselling, alarms, and development programs [61]. Out of these, multi-factorial fall prediction and prevention programs for the elderly appear to provide good results and are the best option for fall prediction and prevention. Several trials noted in [62] involve workbooks or films, conversations, and goal setting but did not result in improved fall prevention results. However, combining all these health programs utilizing AI may be a beneficial activity for the elderly to live a balanced life with constant monitoring, which can help predict and prevent falls.

2.4 Behaviour-Based Analysis

Several countries, including the United Kingdom, the United States, and Germany, are more interested in structuring new approaches and software for in-person homes, as the majority of them suffer from health issues and solitary deaths [63]. To resolve the issue raised in [64], a variety of approaches are used to intelligently recognize resident (older adults living alone) activities. Considering that over 30% of the elderly are digitally ignorant, and due to chronic conditions, such as dementia, computer vision-based approaches were used to monitor the occupant's behaviour. The well-known IoT systems are smart homes, that are equipped with several devices and sensors to track the home environment. The advancements vary depending from simple and low-cost devices such as infrared (IR) and sensors to complicated technologies such as Wi-Fi, RADAR (Radio Detection and Ranging), RFID, and Bluetooth Low-Energy (BLE) [65]. Computer vision-based behaviour recognition is widely employed in elderly monitoring, and it can be divided into three categories: 3-D, 2-D, and specific shape models, as described in [66]. In the predictive analysis and behaviour recognition, ADLs can be defined as the developed understanding of sensor information under situations that can be analyzed to predict behaviour patterns.

The behavioural abnormalities can initially be identified and analyzed by creating a baseline of normal behaviour patterns. This involves connecting ADLs and other routine activities to the system, which enables the detection of variations that may signal abnormal behaviour. It is also vital to keep track of any deviations from behavioural designs, as this can indicate that the elderly are at risk of falling or experiencing another unsafe event. Behavioural-based analysis can be divided into three categories: Computer Vision, Human Activity Recognition (HAR), and Activities for Daily Living (ADLs). Figure 2.4 shows the classification of behavioural monitoring in older adults.

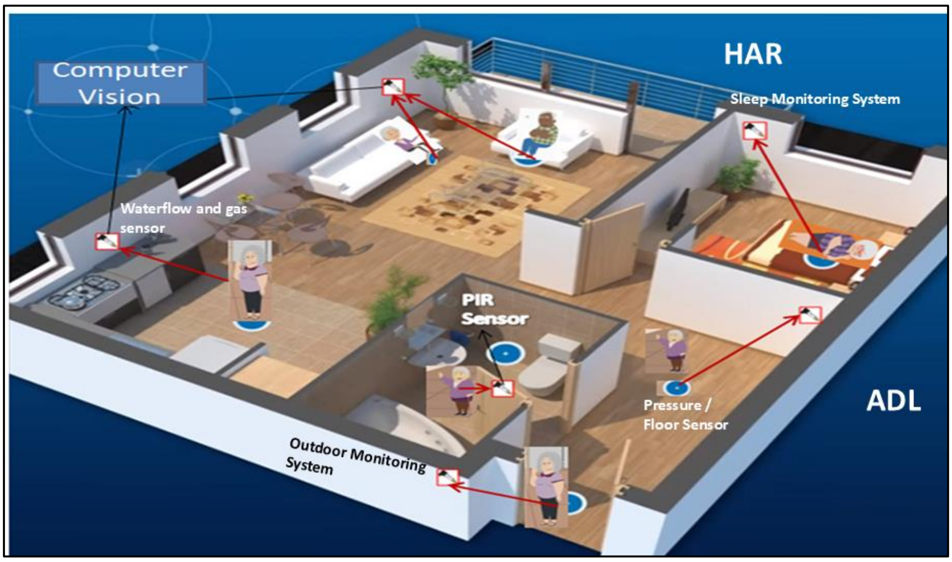


Figure 2.4: Behavioural-Based Analysis in Elderly Fall Prevention [67].

2.4.1 Computer Vision

Using Sensors, IoT, and Hardware: Illustration, segmentation, and recognition of human movement involving hand and body gestures as well as facial expressions are the foundations of vision-based approaches. As a result, computer vision investigates a variety of methods in both spatial and temporal dimensions. To prevent and identify falls in older individuals, a context-aware representative model that tracks the behaviour of elderly people living alone was presented in [68]. Four agent groups are included in the created system for distinct duties. The first group is in charge of gathering data on the activities (behaviour) of the older adults, the second group interprets the data; the third group assesses the behaviour ability and notifies the elderly; and the last group looks for anomalies and takes emergency action. This model can effectively distinguish between a disabled person and a healthy person; however, the four agent groups employ various algorithms, which produces disappointing results. Only the Region of Interest (ROI) surrounding the topic is detected by the holistic or image-based representation; in contrast, an example-based embedding method that employs Euclidean embedding spaces and concentrates on the visual elements was proposed in [69], which uses Euclidean embedding spaces and focuses on the visual components. Ten actions are used to compute the distance of the acquired image, and 93.6% of the photos are successfully recognized using clustered sequences.

Using ML and AI: A study conducted in [70] to classify the categories of falls in the elderly using smartphones and an accelerometer belt worn by 15 subjects. 4 different categories of falls, such as left fall, right lateral, forward trips, and backward slips were validated through the x, y, and z-axis of the accelerometer and the belt on 3 directions (up, left, and backward). Five machine learning classifiers were used, and the comparison results show that the Support Vector Machine (SVM) and Logistic Regression classifiers predicted the fall type with 99% accuracy. One disadvantage of this study was that smartphones were used in a stable position but this work on data collection and fall classification can be extended for prediction of future falls through continuous analysis and monitoring. A Sphere (SPH) monitoring-based approach was developed in [71] using deep learning and sound recognition to identify serious emergency incidents in residential care. The occupant behaviour was monitored, and the emergency sounds were classified based on CNN, LSTM, and DL models. Based on sound patterns, the DL-based sound recognition model recognizes a person's behaviour, classifies them for prompt action, and notifies the environment through calls, alerts, or alarms (severe emergencies or death). In real-time, the model generated results with an average precision (accuracy) of 90.8%. Even while health and behaviour-based monitoring of the elderly has advanced significantly, some researchers concentrate on combining the two methods. Given that behaviour and health are the two most crucial factors that can be used to identify an individual's initial irregularity, it's also critical to concentrate on combining the two approaches in order to broaden the scope of monitoring older adults.

To examine the vital signs and biological and behavioural changes of an older adult a health monitoring system was proposed in [72] which works on the combination of wearable sensors and online context to evaluate the older adult's health function and to provide accurate monitoring methods for fall prediction. A wearable sensor-based health monitoring system coupled with context-aware analytics is a breakthrough in fall prediction. Merging real-time physiological information with external environmental and behavioural information, the system offers an integrative means of elderly health assessment. Using AI-driven personalization to improve prediction models, improving sensor accuracy, and further enhancing remote healthcare capabilities are some research directions that could be pursued in the future to empower older adults with proactive fall prevention. In order to prevent fall injuries, a Fall Management System (FMS) that emphasizes learning cycles was put into place [73]. This strategy seeks to create an intelligent environment that will help older people act better by helping them recognize fall hazards and reduce their likelihood of falling. Four modules make up the developed FMS:

- Preparation, Training, and Learning, which deals with fall information.
- Sensor Systems, which gather information through body movements, visual detection (video, infrared, motion detection), and gait balance.
- Analysis and Machine Learning.
- System, feedback, which offers recommendations and feedback based on the analysis.

The combination of training, movement tracking in real-time, and prediction of risk through artificial intelligence makes it a stronger force for reducing falls and creating safer habits in the elderly. By employing continuous learning and adaptive interventions, the system not only recognizes impending falls but also helps individuals alter their behaviour to avert them. Future technologies can include further refining AI models for increased accuracy, improving sensor performance, and integrating the system into a home and wearables automation technologies to further enable fall prevention. In [74], a Fuzzy logic-based adaptable autonomy (FLAA) model was deployed in a self-operating elderly movement monitoring (AEMM-Care) system, which monitors the movements of the elderly through sensory data and position coordinates. Eleven fall posture groups were categorized, and the fall risk was determined using fuzzy logic. The success percentage of this created model in preventing falls is 64.07%. Based on machine vision, 2D and 3D body model patterns were also created in [75]. A 2D model that achieves 100% accuracy is used to record behavioural recognition techniques, while a 3D model is used to estimate motion capture. According to [68], a supervised system often makes use of a camera, which requires pre-training in the form of datasets with image sequences and human behaviours. The SVM classifier then uses the acquired images to make predictions. The IR sensor or IR cameras are also used for recognizing human activities which calculate the captured data from a distance and compares that data using the meta-classifier which recognizes the action with an accuracy of 84.36%.

2.4.2 Human Activity Recognition

Using Sensors, IoT, and Hardware: With many older adults striving to maintain their independence, a smart home-based solution would be most adapted to relieve human health services and offer constant awareness of the risk of falling [76]. Activity recognition is a key criterion for identifying actions based on older adult's behaviour. Its goal is to analyze the event sequence in human activity, as well as to assist in the prediction and monitoring of repeating models to get further information. Significant activity identification is important in self-managed healthcare because it serves as a foundation for predicting subjects' behaviour and decision-making skills. Activity recognition is possible with basic dual sensors. As detailed in [77], changes in sensor monitoring occur as the user walks around indoors and uses specific spaces and/or gadgets. The wearable sensors are affixed to the older adult as in [78], and the data is gathered and processed by integrating devices that transfer the data to the communication protocol to calculate the risk of falls. In [79], a health and human activity monitoring system was developed that uses acceleration activity, wireless ECG, Global Positioning System (GPS), and a temperature sensor placed on the elderly body. The details are collected and transmitted to a medical database using built-in algorithms, which are then analyzed by the caretaker to track behavioural patterns.

Using ML and AI: The Hidden Markov Model and the Conditional Random Field are the two most used models for activity recognition, both of which involve wearable or perception-based sensors on users. A HAR system described in [80] can be either supervised, which requires prior training with specialized datasets, or unsupervised, which operates on a set of rules during the building process. The HAR system often employs machine learning methods to create behavioural patterns for data identification and analysis. Future advancement of HAR systems should emphasize hybrid solutions that use supervised pre-training and unsupervised adaptation to improve accuracy and versatility. Additional integration of edge computing, real-time processing, and advanced deep learning models can make it possible to improve HAR system performance for enhanced usability in health monitoring, geriatric care, and fall prevention. In [81], the training sets are given as input (human activities) and compared to the gathered data. The Waikato Environment for Knowledge Analysis (WEKA) is a good ML tool for HAR models, as it includes a variety of learning algorithms that analyze the data using cross-validation and random split. The kinetic sensors in [82] use an infrared projector and a camera capable of detecting 20 joints in the human body for activity classification. The kinetic skeletal tracking coordinates use pixels in body parts to detect human behaviour and track facial movements to anticipate elderly activities, therefore a Linear Deformable Model was developed that uses alignment points to track elderly activity with an accuracy of 74.7%.

2.4.3 Activities for Daily Living (ADLs)

Using Sensors, IoT, and Hardware: In the majority of elderly in-home monitoring cases [83], abnormal activities that disrupt the established sequence of events can be identified as harmful. This can be caused by taking too long to finish an ADL, switching patterns in an ADL, missing a step, or forgetting about the main ADLs. Possible falls are detected using a mathematical formula that connects heart rate and foot pressure to ADLs. In [84], a Peder system was developed that measures the load between shoe and foot using operating modes predicts potential falls, and alerts the elderly depending on daily activities. The three typical daily activities of the elderly (living alone), such as urination, physical hygiene, and kitchen labour, were monitored continuously, even at night, using non-contact sensor systems and water flow sensors linked to the water pipe. The monitoring system in [23] included RFID tags, an infrared motion sensor, and a computer with an RFID reader connected to the attached sensor. Depending on water usage and motion detection, the physical health of the elderly is recognized, and the data is predicted and shared with a local nursing facility.

Using ML and AI: IoT combined with (AI) presents a significant pattern that recognizes human control and investigates the causes of human habits. According to the research in [85], Deep Convolutional networks are the best fit for feature extraction, so a general deep framework activity recognition based on LSTM and convolutional methods was proposed, which extracts human activity and improves itself by 15% when combined with wearable sensors. Fall activity can be tracked using sensing devices in smartphones equipped with accelerometers, magnetometers, and gyroscopes, which forecast falls using a threshold-based algorithm with an 85% accuracy. The quality and quantity of sleep can also determine the behaviour of older adults. In [86], a simple environment was developed that uses a Passive Infrared (PIR) sensor and a highly sensitive accelerometer on the bed; data is collected based on sleep-wake conditions, and their sleep quality is assessed using a multilayer feed-forward neural network, which produces an accurate fall prediction of 94.2%. A simple sensor-based ADL model was created in [87], which collects data from sensors placed under armchairs and/or beds to evaluate older people's activity and then highlights abnormal occurrences during the day or night.

The patient's activity is processed by a light algorithm, and the results are kept locally on the device. The sensor system transmits the data over a Bluetooth (BT) wireless link to a smartphone running a specific application. This created technology predicts potential falls based on ADL and sitting posture with 70% accuracy and informs the elderly through smartphones. In [88], multiple AI strategies are examined to spontaneously identify between various types of falls and ADLs, and 22 distinct AI-based classification algorithms under a fivefold cross-validation learning policy are used to characterize which method is more suited for this set of data. The binary results show that the ensemble-based approach and K-Nearest Neighbours (KNN) have the highest grading accuracy at 86.0%.

Discussion: Security cameras are an effective way to continuously monitor geriatric behaviour, but they cannot foresee emergency scenarios and have privacy concerns. Passive devices are commonly employed to collect behavioural data through changes in sensor monitoring in response to activities and abnormal events. Behavioural monitoring can be based on the elderly's behaviours, movements, or unusual changes. 2D, 3D, and skeleton modelling can predict superior behaviour statistics with face recognition, while the full body and alignment posture are still being developed. AI may be a superior option for predicting geriatric behaviour and preventing falls. When combined with Radio Detection and Ranging (RADAR), 2D, 3D, or skeletal modelling, the system learns about its environment, including ageing features, and continuously improves itself for better results. There are more AI-based analyses that utilize behaviour models, but just a few are deployed in real-time, and most of the developed models are only evaluated in labs or on younger people.

2.5 Posture-Based Analysis

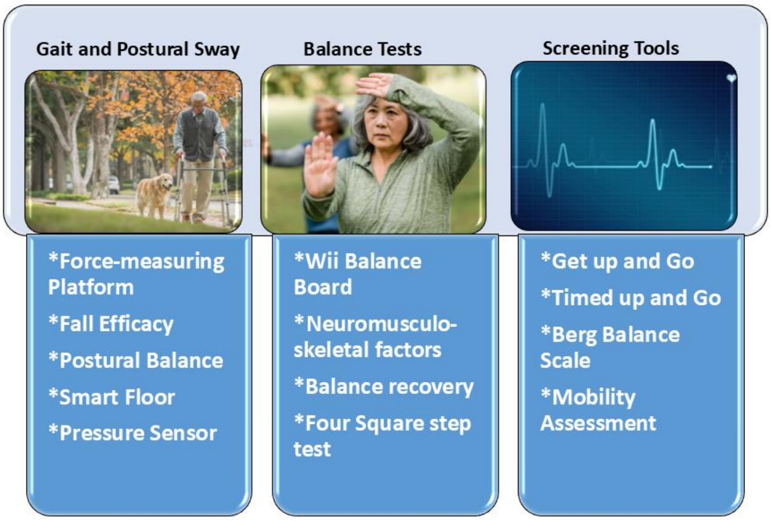


Figure 2.5: Posture-Based Analysis Classification.

A fall while walking creates a major risk to individuals, particularly to older adults [89]. While there are numerous methods for tracking behaviour and health, postural-based monitoring is also a crucial component to take into account. According to [90], the primary daily living activity for older adults with impaired postural balance - the primary cause of future and near falls is controlling and managing their balance. By utilizing self-initiated corrective body movements in response to gravity, the static posturography mentioned in [91] can assist in achieving balance while walking, standing, or sitting and avoid falls. Typically, the center of pressure movements is monitored by the force plates, while an elderly individual stands on a flat board and focuses on a fixed place during posturography testing. To detect postural sway, the test is conducted with both eyes open and closed. Additional extensions of the postural-based analysis include screening tools, gait and postural sway tests, and balance assessments. Figure 2.5 shows a detailed analysis based on posture monitoring in older adults.

2.5.1 Gait and Posture Sway

Using Test Boards and Screening Tools: To distinguish between non-recurrent and recurrent fallers, a study based on Postural Sway and testing conditions was presented in [92]. Based on their fall history, more than 150 older adults (65 and older) were divided into four groups. They were then asked to stand comfortably for 60 minutes in a comfortable position over the force-measuring platform, with their eyes open and closed. The current state of the recurrent and non-recurrent fallers was assessed using Logic Regression, and the center of pressure data was computed using both conventional and fractal metrics. With a 75% accuracy rate for Medi-Lateral sway, it was determined that fallers are at a higher risk of falling. Elderly individuals with low fall efficacy (low self-confidence in performing everyday activities without falling) are more likely to fall and have poor postural balance, but this is even greater for people with strong fall efficacy (overconfidence). A review of the relationship between fall efficacy, postural balance, and fall risk was undertaken in [92] using the clinical trial subsidiary SAFE (Steps to Avoid Fall in Elderly), which consists of home-based programs. This study has indicated the necessity for multidisciplinary fall intervention programs that consist of physical, psychological, and environmental interventions. New advances with AI-powered monitoring, wearable sensing technology, and personalized rehabilitation strategies hold the key to more enhanced predictive and preventative capabilities against falling, along with increased mobility, safety, and quality of life for older individuals.

A similar study in [93] included 247 volunteers (over the age of 65) who were evaluated over 9 months using 14 Modified Fall Efficacy Scale (MFES) Questionnaires and a digital posturography using the Nintendo Wii Balance Board. The data obtained is measured on a scale from 0 (worst) to 12 (best), and from the research, it was discovered that the elderly with poor postural balance and high efficacy had a greater risk of falling than individuals with low fall efficacy. The data collected is measured on a scale of 0 (worst) to 12 (best), and the analysis revealed that the elderly with poor postural balance and high efficacy were more likely to fall than those with low fall efficacy. This is due to overconfidence, as the elderly may tend to walk quickly and perform all ADLs without taking any precautions, resulting in a higher fall risk. A fall risk assessment was built for caretakers to examine the gait parameters and other elements using clinical testing to prevent falls. In [94], a simple fall risk assessment system was designed to continuously monitor the elderly's risk of falling. The system that was developed uses a smart floor with pressure sensors to monitor gait metrics such as speed, stride length, and step breadth, and walking segments are recorded using skeletal visualization. The motion similarity technique is utilized to categorize the acquired data, and the walking segments are monitored using Microsoft Kinetic by the obtained skeletal information. The pressure data from the proposed model matches the pose data with 80% accuracy.

Using ML and AI: ML approaches are frequently utilized in gait studies to assess fall risk categories. A study was undertaken in [95] to assess gait balance in the elderly, with 46 healthy volunteers. Wearing sports shoes and a safety harness, they all completed a walking trial at a steady but uneven speed. Each participant had an average of 8.9 trials out of 10, and the models were evaluated using a deep-learning network. The walking behaviour was predicted with 96.3% accuracy, which can be used for fall prevention and fall risk intervention approaches. In [96], a robust posture detection system was proposed, which detects human presence under various ambient stimuli and subsequently extracts posture-based information using Fuzzy Logic. The proposed model collects 62 image sequences from various situations and then uses Fuzzy Logic to extract human body features and classify posture based on the space between the camera and the subject. This created method can recognize the posture of an older adult with an accuracy of up to 74.29%. A machine learning-based floor-mounted pressure sensor system was devised in [97] to measure gait metrics and detect abnormal behaviour. The data is acquired using body-worn sensors and cameras, which are linked to the pressure sensor. A machine learning algorithm was utilized to predict fall risk and improve gait performance employing data acquired by the characteristic chart. Similarly, another gait monitoring model was built in [98] employing pressure monitoring floor sensors to gather walking data, and the acquired information is classified using a Support Vector Machine to predict deviation in walking patterns, with an accuracy of 92.96%.

A Spatio-Temporal Graph Neural Network for Fall Prediction with Inertial Sensors was proposed in [99] which develops a novel approach to address the challenge of accurately predicting falls, which are highly variable events involving complex body poses and movements. Using wearable inertial sensors, the authors developed a Spatio-Temporal Graph Neural Network (ST-GNN) that models both spatial dependencies between body joints and temporal dynamics of motion, enabling more effective recognition of fall-related patterns. To further improve consistency, a human body orientation estimator focusing on lower-limb positioning was incorporated, ensuring a more accurate representation of global body posture. The model was evaluated on two benchmark datasets and one in-house dataset, where it significantly outperformed existing state-of-the-art methods, demonstrating its potential as a powerful and privacy-preserving solution for fall prediction in real-world applications.

A similar study in [100] utilizes deep neural networks to predict human fall risk by analyzing balance patterns obtained from force-plate time series data. The research introduces a specialized architecture called the One-One-One Neural Network, which combines Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and One-Dimensional Convolutional Neural Networks (1D-CNN). This hybrid approach is designed to effectively capture both temporal dependencies and spatial features present in the force-plate signals. The dataset includes participants from diverse age groups and health conditions, ensuring the broad applicability of the model. The results demonstrate outstanding performance, achieving an accuracy of 99.9% at the 12th training epoch, highlighting the model's effectiveness in predicting fall risk based on balance metrics. Overall, the One-One-One Neural Network provides a robust and computationally efficient framework that outperforms traditional clinical assessment tools in both accuracy and practicality, making it a promising solution for early detection and intervention in fall prevention.

2.5.2 Balance Tests

Balance Methodologies: A comprehensive study was conducted [101] using force-platform static posturography, and four different balance measures were detected between fallers and non-fallers. This study was classified more broadly in [102], with an emphasis on data collection utilizing anterior-posterior (AP) and medial-lateral pressure (center) among fallers, single-fallers, multi-fallers, and non-fallers. 100 participants aged 65 and older participated in this study, with 76 being non-fallers who had not fallen in the previous six months and the remaining 24 being fallers who had fallen more than once in the previous six months. The test was carried out with both eyes open and closed, and the results were acquired using the Wii Balance Board. It was discovered that the majority of subjects had a higher likelihood of falling in the AP range while their eyes were closed. Finally, the overall result indicates that there is a substantial risk of falling owing to visual input in the aged, particularly among multi-fallers in AP, with a cut-off score of 0.541 and an accuracy of 84.9%. The aging constraint described in [103] is based on lateral balance recovery information about the significant risk of falling owing to imbalanced stepping, which results in a fracture. To assess the danger of falling, cross-sectional research on the elderly was carried out in [104], focussing on medial-lateral careful stepping performance, hip abduction, and trunk mobility trials. The study discovered novel predictor values associated with neuromusculoskeletal aspects that contribute to lateral balance stability.

Using ML and AI: A 12-month extensive study on forward loss balancing and recovery was conducted in [105], which used lean magnitude to predict future falls. The participants (aged 65 to 90) used the balance recovery protocol mechanism to obtain data on their whole-body kinematics. Based on the data collected, the individuals were classified as single, mixed, or multi-steppers after four recovery trials. The data from various balancing tests, such as TUG, Berg, and Personal Profile Analysis (PPA), was categorized using logistic regression analysis to determine independent predictors of future falls. The future fall was predicted for all participants based on these stabilizing steps carried out in repetition with advancing instability.

2.5.3 Fall Risk Assessment Tools

Questionnaire and Experiments: The fall risk screening questionnaire is crucial for detecting future falls in older adults. In [106], 1563 older persons were tracked for 11 months and completed 13 surveys, including a fall risk screening tool, Get Up and Go Test, Timed Up and Go Test, Berg Balance Scale, Performance Orientated Mobility Assessment, and Cognitive Testing. The collected data was analyzed to forecast sensitivity and specificity in fallers, and it was discovered that independent-living older adults had a higher risk of fall history and future falls, yielding an accurate prediction record of more than 89.4%. The Four-Square Step Test (FSST) was conducted in [107] with solitary older adults over the age of 65 and the performance-based balance tool was utilized to precisely differentiate between non-fallers and multiple fallers. The FSST consists of four single-point cones to step over in a cross-configuration, and it accurately recognized numerous fallers and non-fallers with an 86% predictive value. Despite the positive results, the FSST is not a useful approach for predicting and averting falls in older adults who use walkers.

Using ML and AI: The introduction of low-cost motion sensors has resulted in greater breakthroughs in tracking gait variances. A two-part study conducted in [32] to predict fall risk using AI, involving 73 elderly care home patients over the age of 65. Participants (fallers and non-fallers) performed a 6-minute walk test and a Time Up and Go (TUG) test while wearing an IMU sensor over 6 months. The sensor data was trained with an AI (Deep learning) algorithm, and the TUG findings indicated an improvement in gait from 68 to 76%, with a fall prediction metric of 75%. In [104], a Fall Risk Assessment in Older Adults (FARAO) group research was carried out, collecting data on fall risk scenarios in the elderly through questionnaires, physical tests, and wearable sensors. The findings revealed that Deep Learning models employing single task learning strategies were more accurate in identifying participants. However, when paired with multi-task learning, the created models only moderately outperformed the baseline method, with deep learning models obtaining 75% performance. As a result, DL models, particularly multitask learning, successfully forecast fall risk using screening tools and wearable sensor data.

Discussion: Doctors and nurses in Toronto retirement homes ensure that there is always a strong relationship between patient status and posture [108]. Using an intelligent system that can forecast a prospective fall, or a future fall based on hand and leg movement, sitting posture, walking or running pace, can effectively help the older adult be aware of their current condition and potentially adjust their postural status to avoid a fall. More AI research based on posturography should be conducted to benefit the senior population.

2.6 Emotion-Based Analysis

The risk of falling is substantial among the elderly who have neurological disorders, and individuals with indications of nervous system deficit, dementia, or a past stroke are at the highest risk of falling. According to surveys conducted throughout the world [109], based on emotion analysis in older adults, even those with minor emotional disorders fall at least three times per year, which is 13.2% greater than other fall-related categories. Resilient fear of falling leads to health difficulties as well as cognitive deficits, causing anxiety and emotional dread in the elderly [110]. The emotion-based analysis can be further zoomed into 4 main categories namely: Stress and Depression, Emotional Intelligence (EI) and Adaptive Mechanism, fall-related apprehension, and Medical Assessment and Interviews, which discuss various research and real-world projects on elderly fall prevention. Figure 2.6 depicts the classification of analyses based on emotion monitoring in the elderly.

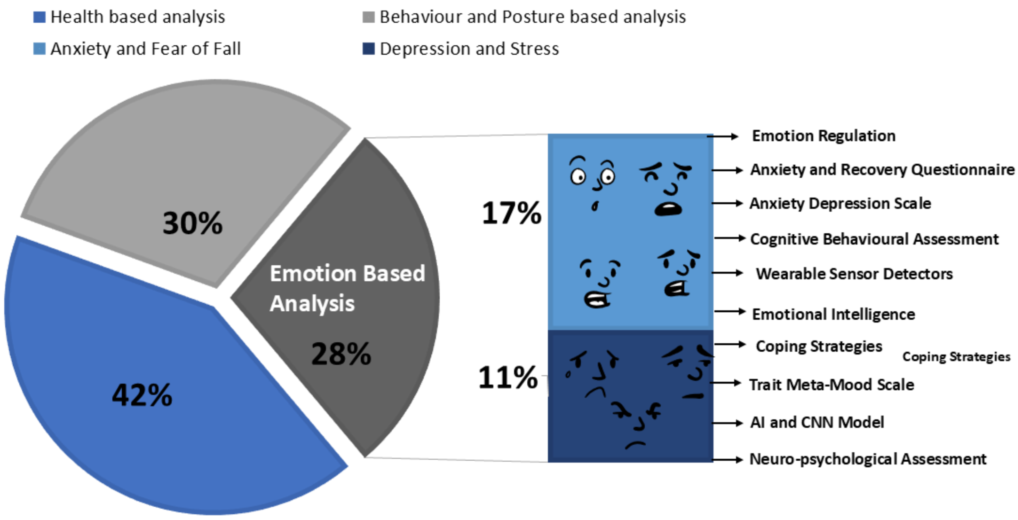


Figure 2.6: Emotion-Based Analysis on Elderly Fall Prevention.

2.6.1 Depression and Stress

Emotional Intelligence (EI) and Coping Strategies: A method indicated in [111] that could assist the elderly in overcoming their depressive state of mind through Emotional Intelligence, which is the ability to recognize, analyze, and transmit one's emotion with accuracy that is focused on the dimensions of attention, clarity, and repair. A meta-analysis of the relationship between depression and coping strategies was conducted in [112] based on previous depression disorder issues in older adults, and it was discovered that people with more depressive symptoms had more problem-oriented accidents (falls), while those who used coping strategies had fewer depressive symptoms. As a result, research suggests that coping methods can serve as a bridge between EI and depressed states. To assess EI and fall prevention techniques, 214 healthy volunteers (over 60 years old with no indication of cognitive impairment or dementia) were recruited, and the study protocols were implemented [113]. A Trait Meta-Mood Scale (TMMS) was used to measure EI in three significant aspects: recognition of emotion, emotional clarity, repair, and order of emotion, with a scale of 1 (strongly disagree) to 5 (strongly agree), followed by a 42-item coping strategies questionnaire, and finally the Beck Hopelessness Scales (BHS), which reflects negative expectations. Using statistical analysis, including structural equation modelling, the collected data was grouped into three major aspects, and the results reveal that EI offers protection against poor mental health through coping techniques, which may avoid falls in the elderly with a 90% accuracy.

Using ML and AI: AI, IoT, and Big data analytics were utilized by Researchers to develop an emotion-aware fall monitoring system [114] that recognizes older adults' emotions using IoT sensors, cameras, RFID, and RADAR sensors implanted in smart houses. Wearable sensors, such as wristbands, smart watches, and waistbands, which contain a pedometer, accelerometer, magnetometer, and gyroscope, were used to collect data on the elderly's mobility, while a camera captured their facial expressions. All of the information is collected in the AI-enabled emotion identification module, which distinguishes five geriatric facial expressions (angry, sad, fearful, joyful, and neutral), and the emotional categories are classified using a CNN model. The results of the emotional shifts were instantly communicated to family members or carers, prompting them to seek assistance and monitor the elderly's health status; the developed model predicted emotional facial expressions with 81% accuracy.

2.6.2 Anxiety and Fear of Falling

The main health issue that affects the elderly is fear of falling, which has negative repercussions such as decreased social involvement, functional decline, lower life standards, and anxiety [115]. According to research on elderly falls [116], approximately 15-55% of older adults limit their everyday activities due to their fear of falling. The relationship between fear of falling and a sudden fall is complex, and the majority of the elderly develop this anxiety after a fall. There are numerous explanations indicated in [117] for this fear of falling, with anxiety being one major factor.

Medical Assessment and Interviews: A SOC-ER (selection, optimization, and compensation with emotion regulation) structural analysis in [118] suggests that cognitive-behavioural therapy treatment that trains the elderly in new ways of analyzing a situation can lower anxiety, perhaps preventing more falls. In [119], a wearable device model for detecting anxiety was developed, which employs computing technologies to continuously monitor and detect anxious periods. The Spontaneous Blink Rate (SBR) and Heart Rate (HR) are tracked using Google Glass and the Zephyr H x M Bluetooth band. To detect anxiety, the acquired data is evaluated with a threshold-based algorithm. FaceIt, a multimodal system based on cognitive behavioural treatment, was developed in [120] and incorporates heart detection, video and audio capture, GPS tracking, and a pulse sensor to detect anxiety through elevated heart rates. Logs based on daily mood aberrations are kept for anxiety reduction therapy.

Using ML and AI: In [121], a cohort study was carried out with 500 elderly participants (aged 70-90 years), and a detailed screening process was performed, including medical assessment (face-to-face interview and full body check-up), physiological assessment (fall-related factors), neuropsychological assessment (attention and trial tests), and fall follow-ups (fall history). The obtained data was analyzed using logistic regression, and the classification and regression tree analysis predicted 40% physiological fall risk and 54% anxiety among participants. In [122], a research-based analysis accepted by the National Health Services (NHS) Research Ethics Committee conducted a community assessment with 117 elderly individuals (over 65 years). The study included four separate classifications: the Fall Efficacy Scale-International Standard (FES-I), a questionnaire based on fear of falling, difficulties with emotion regulation, and hospital and anxiety depression. The data collected and analyzed by the regression model revealed a convincing positive link between emotion control and fear of falling, with the system predicting an 89% correlation between the two. To avoid falls in the elderly, measures must be made that address both fall risk and physiological variables.

Discussion: Several studies, research, and surveys focus on health, behaviour, and posture-based geriatric analysis, but just a few include emotion monitoring. Preventing falls in the elderly is extremely difficult, particularly fall prevention using emotion monitoring, which is a rigorous research topic. There have been various analyses and programs conducted for emotion monitoring, but all they have provided are tips to the elderly on how to maintain their equilibrium when experiencing emotional fluctuations. AI-based emotion monitoring could be a useful option because it employs classifiers and continual training to predict and track the emotional state of the elderly in predicting and preventing future falls. Using Fuzzy Logic is a good option, and while it does not achieve the same level of accuracy as other methods, it can be improved through accurate data input, continuous training, and improvisation because Fuzzy Logic can categorize emotions from low to high levels.

2.7 Analysis of AI-Based Smart Devices

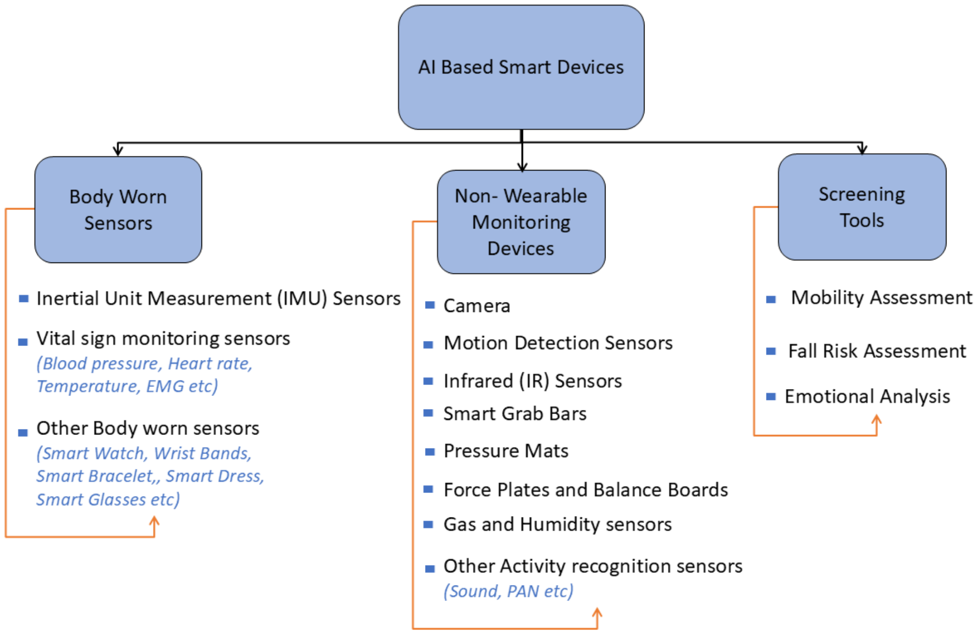


Figure 2.7: Classification of AI-Based Smart Devices.

In the domain of fall prediction and prevention, background studies reveal a consistent trend highlighting the pivotal role of smart devices in research, surveys, and practical applications. These devices are widely employed to collect data from older adults and to facilitate communication based on analytical outcomes for fall detection, prediction, and prevention. Their significance in healthcare, particularly in elderly fall-related contexts, is well recognized. Leveraging Machine Learning techniques, these smart devices enable IoT systems to learn from data, automate processes, and progressively enhance their performance over time. Figure 2.7 depicts three types of smart devices: body-worn sensors, non-wearable monitoring devices, and screening tools.

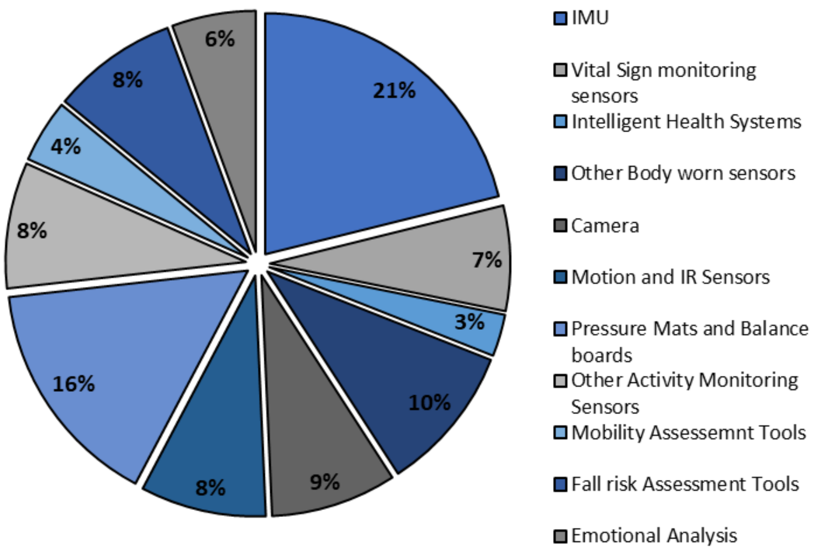


Figure 2.8: Cognitive Device Analytics.

Body-worn sensors are attached to specific areas of the human body, such as the chest, ears, hands, wrists, legs, and thighs, and the acquired data is conveyed. Numerous studies have found that smart gadgets equipped with body-worn sensors produce results comparable to medical devices. This category includes IMU sensors, vital sign monitoring sensors, and other wearable devices like smartwatches, wristbands, bracelets, smart eyewear, and smart apparel. The research cited in [8, 19, 42, 47-49, 63, 64, 68, 74, 84, 90, 107, 122, 123] uses IMU sensors for geriatric fall detection and prediction. IMU sensors are used in about 40% of the studies covered in this analysis for data collection and communication, with the majority of these studies achieving accuracy levels above 80%. Vital sign monitoring sensors, such as blood pressure, heart rate, temperature, and Electromyography (EMG), as detailed in [15, 18, 44, 70, 92], are used in both AI and non-AI fall detection and prevention studies. Interestingly, non-AI-based technologies outperform their AI counterparts in terms of accuracy. Research in [59, 70, 71, 84, 88, 96, 123] investigates the use of various body-worn sensors such as smartwatches, wristbands, and smart eyewear. These smart devices, which are renowned for their superior intelligence and ease of use, can react to situations by promptly warning and alerting the elderly when they identify abnormalities. The utilization of research focused on these smart devices is expanding, and it is expected to grow more in the future. However, a significant disadvantage of body-worn sensors is that they must be worn continuously by older people, thereby raising the risk of falls. Furthermore, concerns such as data disconnection when charging or inappropriate wearing present difficulties. These issues can be addressed by adopting non-wearable monitoring devices. Figure 2.8 depicts an overview of the cognitive device analytics data collected from the smart devices addressed in this literature review.

As discussed in [42, 68, 91, 93, 94, 97, 101, 105, 118, 122], camera systems, motion detectors, and infrared sensors can be positioned strategically to continually monitor the behaviour and gait patterns of the elderly. These devices collect large amounts of data, which can be retained for subsequent analysis and reference. Innovative technologies such as grasp bars, pressure mats, and force plates, as mentioned in [13, 23, 57, 65, 76, 106, 113, 116, 117, 119, 120, 122], allow sophisticated behaviour and gait monitoring by directly interacting with older adults during their daily activities. Some studies [16, 41, 46, 51, 52, 121] use gas, sound, and humidity sensors to investigate environmental factors that contribute to falls in older persons. While some of these systems are reasonably priced, others are less popular due to high costs and privacy concerns (particularly camera systems) [4]. More than two-thirds of falls among older adults are caused by posture, gait, or emotional states. Early detection of these factors can be accomplished using screening measures such as mobility evaluation, fall risk assessment, and emotional analysis, as mentioned in [32, 55, 77-81, 86, 104].

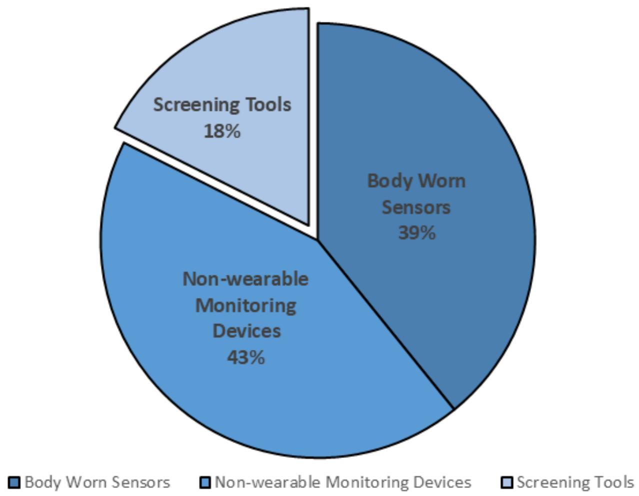


Figure 2.9: Smart Devices Utilization Metrics.

In-home monitoring applications use these screening measures as a foundation to analyze older adult’s physical and mental well-being. These technologies help to forecast future falls by assessing an aged person’s existing fall risk. Furthermore, these sophisticated tools are created as user-friendly apps that can be downloaded to smartphones, allowing older adults to selfassess their risk of falling. Based on the findings of the screening analysis, more sophisticated versions can even offer recommendations and guidance. Figure 2.9 shows an overview of the metrics for smart device utilization. Around 43% of research activity is based on non-wearable monitoring equipment for continuous data collection, with approximately 39% focussing on body-worn sensors for health monitoring. Posture and gait monitoring research employs screening tools (18%) for fall detection and prediction. Overall, these three types of AI-based smart devices are interconnected, and they play an important role in in-home monitoring systems and hospital settings for identifying fall hazards and predicting falls in older adults.

2.8 Summary of Reviewed Systems and Methodologies

The challenges, issues, and limitations of fall prevention are centered on the functions of deployment, adaptability, and profitability. Older Adults should learn to adapt to the developed models, and adequate flexibility must be implemented. Furthermore, it is unrealistic to expect older adults to always use smart devices to navigate the smart environment. It has been a critical issue in the data set to analyze the concerns before constructing the model. Deep Learning has improved significantly in terms of accuracy in domains such as behaviour, health, image identification, object detection, and other advanced technology. AI without human interaction is making headway in a variety of industries, although it remains under development for safety reasons. As AI learns from its surroundings and its behaviour through interaction with its environment, there are several factors to consider. When deploying aided robots for patient monitoring and fall prevention, judgment and identification based on these parameters combining AI and robotics may occasionally anticipate inaccurate results. In [124], an autonomous mobile assistant model was suggested that uses Deep Reinforcement Learning to interlink the nursing environment and patients, providing allocation, discharge summary, and fall monitoring; however, the model interrelated the details of inpatients and outpatients. Even though the model uses Deep Learning to identify its environment, it does not achieve a 100% recognition rate. However, after the risk extraction and reduction techniques are implemented, AI can be employed in any linked subject, including safety. Table 2.1 shows a comparison of health, behavior, posture, and emotion-based research analysis which was done using ML, AI and other methods based on similar elderly monitoring approaches.

Table 2. 1: Fall Prevention comparison using AI, ML, and other methods.

Category	**Fall Prevention with AI**			**Fall Prevention without AI**		
	Title	ML	Result (%)	Title	Technique	Result (%)
Health-based	Smart Home Technologies in Health	Neural networks	100	Health monitoring	Arduino UNO	90

Analysis	Monitoring [18]			System [52]		
	Fall Classification [125]	Logistic regression algorithm	99	Heart rate monitoring system [51]	Threshold based algorithms	97.6
	Pre-impact Fall prediction [50]	Deep Neural Net-Works	95	Fall Monitoring Using Eyeglasses [126]	Threshold based	95.44
	In-house monitoring system [48]	XGBoost-CNN	98	Fall Prevention Practices [58]	Exercise programs	70
	Fall Characteristics Monitoring System [37]	SVM Classifier	99.19	Fall Prevention survey [44]	Questionnaire	75
	Health Care Monitoring System [54]	Neural networks	98	Smart Healthcare Monitoring System [53]	ESP32 processor	95
	Health Care Analysis [56]	Fuzzy Logic	83	Pre-impact fall detection [45]	Threshold based Method	80
Behavior-based Analysis	Health and behavioral indicators in IoT! [72]	Decision Tree	99	In-home Health Monitoring System [23]	RFID	96.7
	Multi-agent system [74]	Fuzzy logic	64.07	Remote-behavioral Monitoring [77]	Sensor	83
	Recognition Motion Analysis [75]	ML	100	Human Activity Surveillance [79]	Built algorithm	68
	Face Tracking with Camera [65]	Linear model	74.7	A multi-agent care system [68]	Context-aware Agent	60
	Sleep Quality Monitoring [86]	Neural networks	94.2	Action recognition [69]	Euclidean sequencing	93.6
Emotion-based	AI Driven Fall Monitoring [114]	CNN algorithm	81	Emotional Intelligence [113]	EI and Coping Strategies	90

Analysis	Physiological risk of falling [121]	Regression Tree analysis	94	The Fear of Falling [115]	Questionnaire	95
	Fear of Falling [56]	Regression Model	88.9	Anxiety detection monitoring [119]	Heart rate	72
				FaceIt [120]	Cognitive Behavior Treatment	89
Posture-based Analysis	Differences in walking [95]	Deep Neural Net-Works	96.3	Tools for predicting future fall [106]	Fall risk test analysis	89.4
	Posture Recognition [96]	Fuzzy Logic	74.3	Fall risk prediction [102]	Wii Balance Board	84.9
	Anomaly Detection [98]	Support Vector Machine	92.7	Four-square step test [107]	Cross-Configuration	below 60
	Classification of ADLs [88]	KNN classifier	86			

2.9 Conclusion

Early fall prediction using AI technology paired with IoT can activate an on-time alert and alarm for emergency assistance, particularly for elderly people living alone. Monitoring the external and cognitive health of older adults might help the elderly and their families feel more comfortable. By analyzing data reports acquired from remote health centers using AI, older adults can gain confidence during difficult moments. More reliable and accurate predictions can be achieved with the use of temporal convolutional network models and Deep Learning models. As a result, AI-IoT-based monitoring can be viewed as a new age in the healthcare industry in terms of disease prediction, detection, and prevention, as well as the activation of emergency alarms, particularly for fall prediction in older adults. However, to create an intelligible and trustworthy AI system, additional effort and research must be conducted in real-time. The aforementioned aspects form the key components towards converging upon a novel Co-operative AI model for fall prediction in older adults using Fuzzy Logic and Deep Belief Networks. Upon merging these 2 AI models with a single Meta model the requirements for predicting and minimizing falls in older adults using predictive modelling can be achieved.

Chapter 3. Methodology Used

3.1 Introduction

Artificial Intelligence has emerged as a transformative technology capable of enhancing healthcare systems. Over the past few decades, AI and Machine Learning have notably contributed to improving the quality of life, particularly in healthcare applications. The tools and procedures used must be authentically congruent with the needs of the core research component concepts. As discussed at the end of Chapter 1, this research is motivated by two main goals. First the need for a Fall risk prediction system and second to reduce healthcare expenses. This research introduces a novel Co-operative AI Model for future fall prediction by leveraging both vital signs monitoring and Activities of Daily Living analysis. The proposed AI-based fall risk prediction system integrates multiple deep learning algorithms to provide an early warning of fall risk levels to the elderly, caregivers, or medical professionals.

The AI framework consists of three models: the first AI model (AI-1) utilizes Fuzzy Logic to analyze vital signs such as blood pressure, blood oxygen levels, and heart rate to predict fall risk levels such as *Normal, Low, Moderate, High, and Emergency* based on physiological abnormalities. This model was validated using data from the PhysioNet public repository [127] and compared to the Morse Falls Scale, a widely used clinical evaluation instrument, to ensure robustness and reliability [128]. A real time test using a smart app was also carried out using the AI-1 model. The second AI model (AI-2) employs Deep Belief Networks to monitor ADLs such as sitting, standing, walking, running, and jumping. The model detects deviations from normal movement patterns by leveraging the Long-term Movement Monitoring Dataset from PhysioNet, which contains 75 hours (3 days) of continuous motion data from 71 elderly participants [129]. Through Contrastive Divergence pre-training, neural network-based fine-tuning, and Adam Optimization, the model classifies fall risk levels into *Low, Moderate, and High*. Both AI-1 and AI-2 models will first independently assess fall risks with different factors and then work collaboratively by learning from each other to generate a promising result.

The first two models analyze health and behavioural patterns. In contrast, the final model integrates their outputs through interactive cross-learning forming a Co-operative meta-model that refines the final outcome to deliver a comprehensive prediction of future fall risks. By continuously learning over time, these models adapt to changes in health or behaviour, enabling timely risk identification. The final system classifies fall risks into three divisions: *Low, Moderate, and High.* The AI-based meta-model enhances the accuracy of prediction outcomes by validating results against the Morse Fall Scale. The proposed system achieves a good prediction accuracy thus demonstrating its reliability in identifying individuals at risk of future falls. This research contributes to advancing AI-driven healthcare solutions, offering a proactive and cost-effective approach to fall prediction in older adults. This chapter discusses the methodology used and in-depth evaluation of the model development process. The background of the research and the framework are also discussed. An overview of the existing simulation tools is offered after this chapter, along with a detailed synopsis of relevant research for generic AI simulation tools utilized in current works, and the reason for using visual studio code for this study is also indicated.

3.2 Methodology and Model Development Phase

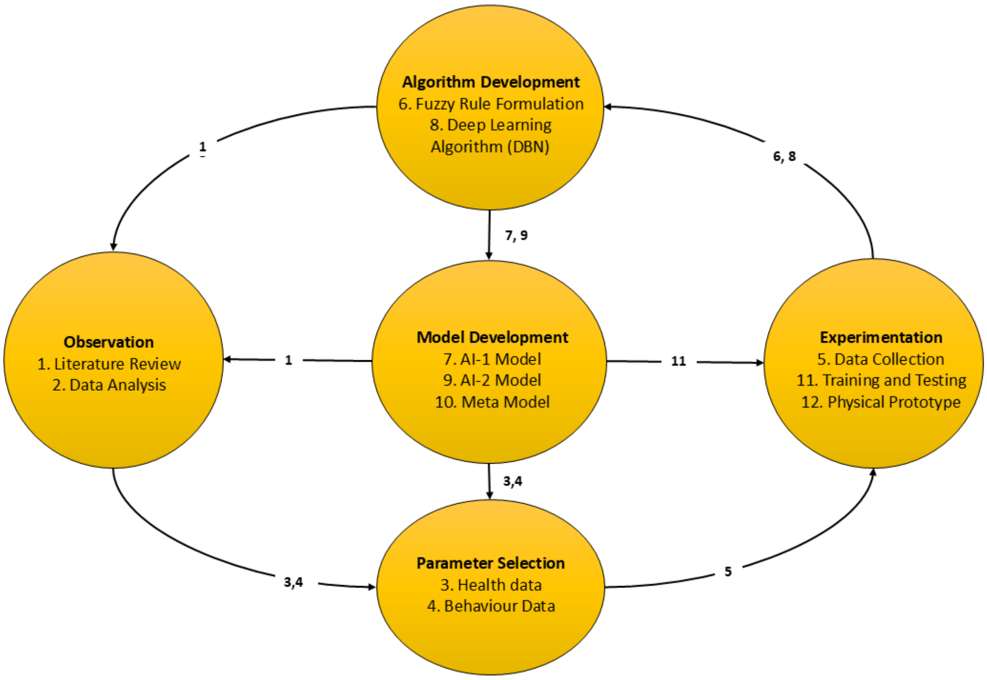


Figure 3.1: Workflow Process of Research Methodology.

In this research, a blend of qualitative and quantitative methods (mixed mode approach) is utilized for data collection and model development [130]. Two major parameters, such as health and behaviour, are used as key inputs for our model development. In the data collection process, the obtained health and behavioural parameters of the elderly are subjected to a trustworthy threshold. The health data relating to Blood Pressure, Heart rate, and Oxygen Saturation are co-related with the medical threshold values which cause a risk of fall or instability in the elderly. The health parameters are understood and the causes leading to falls are closely analyzed before formulating Fuzzy Logic. Similarly, the behaviour data relating to daily activities such as ADLs which are followed by older adults is analyzed. The behaviour parameters are understood and the causes leading to falls are closely analyzed before developing the DBN model. Both phases 1 and 2 of the AI model development process contain the following requirements: age, medical problems, and history of geriatric falls for reliable and accurate estimation of fall risks. The meta-model combines the outcomes of AI-1 and AI-2 and provides the final fall risk prediction outcome. Once the model is developed, the system interacts with the environment to send alerts to the elderly and their family based on the identified abnormality to predict future falls. The workflow process of the Research Methodology is shown in Figure 3.1. The fall risk prediction model is developed through a systematic, interrelated procedure.

- *Observation Phase:* Data analysis and literature study are carried out.
- *Parameter Selection Phase:* Parameters suitable for AI-1 and AI-2 models are determined based on health and behaviour.
- *Data Collection Phase:* Information is obtained from open sources.
- *Development Phase:* The AI-1 and AI-2 models are developed using fuzzy rules and the DBN algorithm.
- *Experiment Phase:* Training and testing are done on the developed models. A meta-model is developed, trained, and tested, followed by the creation of a physical prototype.

Although these phases appear to be independent, they are intrinsically interrelated and contribute to the overall development of the future fall risk prediction model in this research.

In Chapter 2, a literature analysis was undertaken based on the categories that increase the risk of falling in older adults and fall prediction methods were examined. Based on the study, two primary characteristics, health, and behaviour, are examined for the research since these two categories have a significant impact on generating a fall in older adults. The data assessment was done based on the 2 selected parameters,

- *Health Parameters:* Blood Pressure (BP), Heart Rate (HR), and Oxygen in Blood (SpO_2).
- *Behaviour Parameters:* Activity for Daily Living (Sitting, Standing, Walking, Running, and Jumping).

Data is collected for the selected values, and deep learning algorithms are developed. In Model Development, the AI-1 model employs Fuzzy Logic, the AI-2 model employs DBN, and the Meta-Model uses Random Forest to detect and classify abnormalities based on health and behavioural inputs. Following the successful development of the system, a training and validation process is performed to assess the accuracy of fall prediction using the physical prototype. The literature review analysis is also performed at each stage of the development process to ensure a thorough grasp and reliability of Fall Prediction. Figure 3.2 illustrates the context of this research and its applications. This research is carried out in three stages: *Data collection, Design and Development, Training, and Verification*.

Phase 1- Data Collection: The Health and Behaviour data of elderly individuals is collected from the public repository – PhysioNet [127].

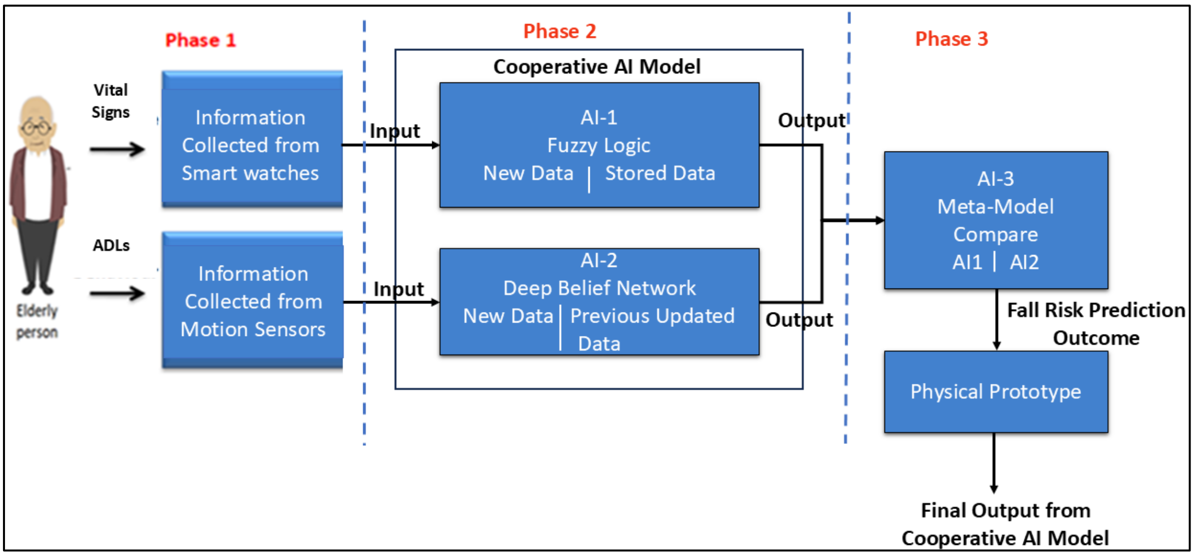


Figure 3.2: Context of Research.

Phase 2- Design and Development of AI model: The AI-1 and AI-2 models were developed using health and behaviour parameters obtained from the elderly (public database), and the results of the first model are compared to MFS, while the second model is compared to MFS and TUG. Fuzzy-based fall risk prediction algorithm is formulated for the first model, and a DBN-based fall risk prediction algorithm is formulated for the second model. Fuzzy logic provides significant advantages over other algorithmic methods, as it can combine ordinal, nominal, and continuous data into its rule-based framework while presenting the embedded information in patterns that are easier to interpret for clinical research. In New Zealand, the average fall rate among older adults has been steadily increasing each year, and emerging technologies such as AI and ML, particularly fuzzy logic and deep learning, offer great potential for earlier detection and prevention of falls. According to [131] Fuzzy logic is an algorithmic method that focuses on "degrees of truth" rather than the traditional binary "true or false" (1 or 0), enabling it to address problems by considering all available information. Based on these insights, fuzzy logic is a promising approach for enhancing the AI-1 model to predict and categorize fall risk. This study is also unique in that it exclusively uses vital signs to predict future falls in older adults.

Deep Belief Networks (DBNs) are models that learn features from data by stacking multiple layers of random variables. According to [132], they incorporate direct connections from upper layers to lower layers and link the top two layers in a manner that allows them to retain knowledge effectively. DBNs offer two main advantages: they can quickly learn relationships between layers and can infer hidden layer values from observable data in a single step. Learning occurs sequentially, one layer at a time, where the output of one layer serves as the training input for the next (unsupervised learning). This process can be further refined through supervised learning to improve accuracy. DBNs excel at handling complex datasets because they pre-train feature detectors using previously acquired information. In addition, they support transfer learning and can operate in both supervised and unsupervised settings, making them suitable for diverse tasks such as data analysis, image processing, and speech recognition. Overall, the distinctive structure and learning capabilities of DBNs make them a versatile and powerful predictive tool for a wide range of applications.

Phase 3- Training and verification: The two individual prediction outcomes are inputted to the meta-model where the results are compared, and the model is trained for future testing and accurate prediction. The outcomes of future fall alerts are obtained through the physical prototype which will be the future work in this study. Training is only done for the DBN model in Phase 2. Since the AI-1 model uses a set of fuzzy rules related to the health metrics the model is not trained. Therefore, through a fusion of an iterative model (AI-1) and a trained model (AI-2), whose outputs were aggregated into a meta-model utilized for estimating future fall risk, this thesis presents a novel approach termed as a "Novel Co-operative AI Model for Future Fall Prediction in the Elderly".

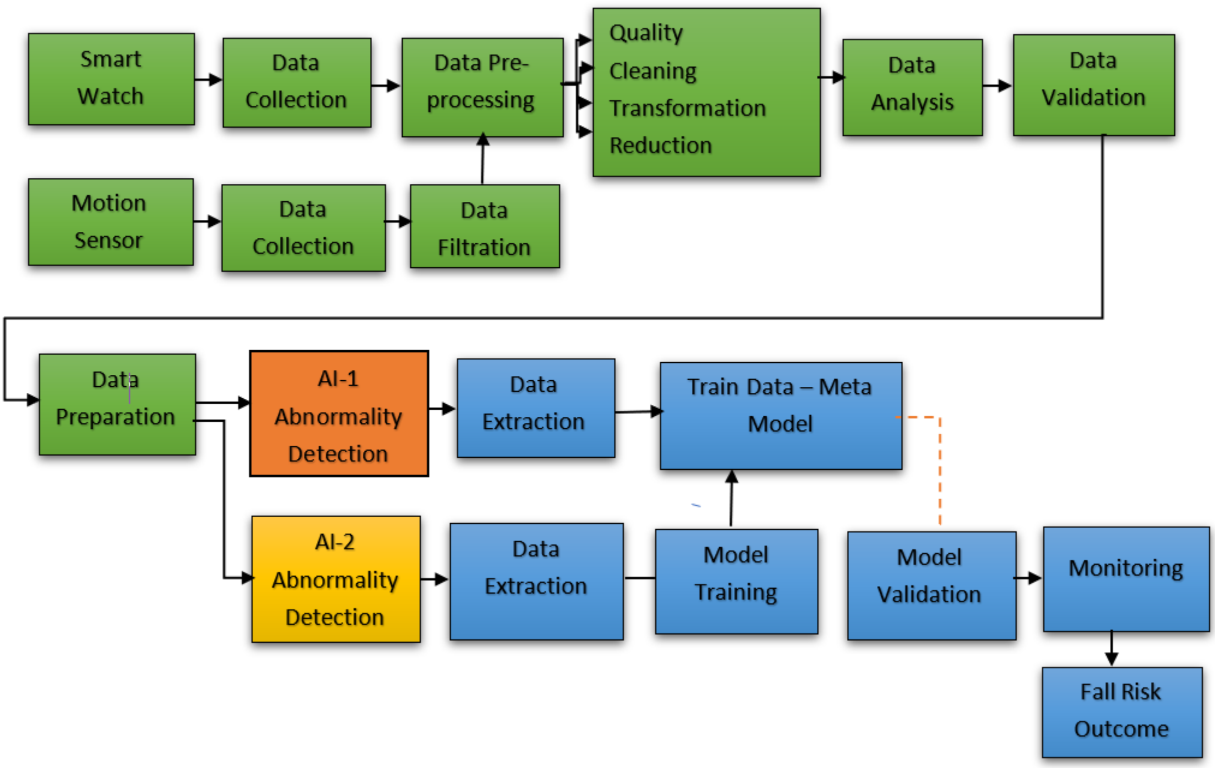


Figure 3.3: Framework of the Proposed Approach.

Figure 3.3 shows the architecture (Framework) for the research work that focuses on creating and evaluating data models for deep learning algorithms. The data is obtained from several parameters (Figure 3.2), and the collected data is filtered and pre-processed to eliminate extraneous data and keep only the relevant information. For example, when collecting data for health parameters using a public repository, the log will contain all of the information, such as Blood Pressure, Heart Rate (HR), O_2, age, gender, medical history, ECG, EMG, calories, and so on; however, to extract only the first three values from the database, the collected information is processed in data filtration. Pre-processing ensures that information is of high quality before it is processed by the following phase. The same procedure is used for data analysis and validation to ensure correctness. The obtained data module is then transformed to the appropriate format for data preparation and input into AI models 1 and 2. Fuzzy Logic is employed in the AI-1 model, whereas DBN is used in the AI-2 model, to categorize the severity of a fall based on the results acquired from health and behaviour data concerning time for accurate fall risk prediction. The extracted results from both models are inputted into the meta-model, which is then trained and validated again before the validation procedure, and the results are monitored to determine the fall risk outcome.

3.3 Simulation Tools for AI/ML Modelling and Development

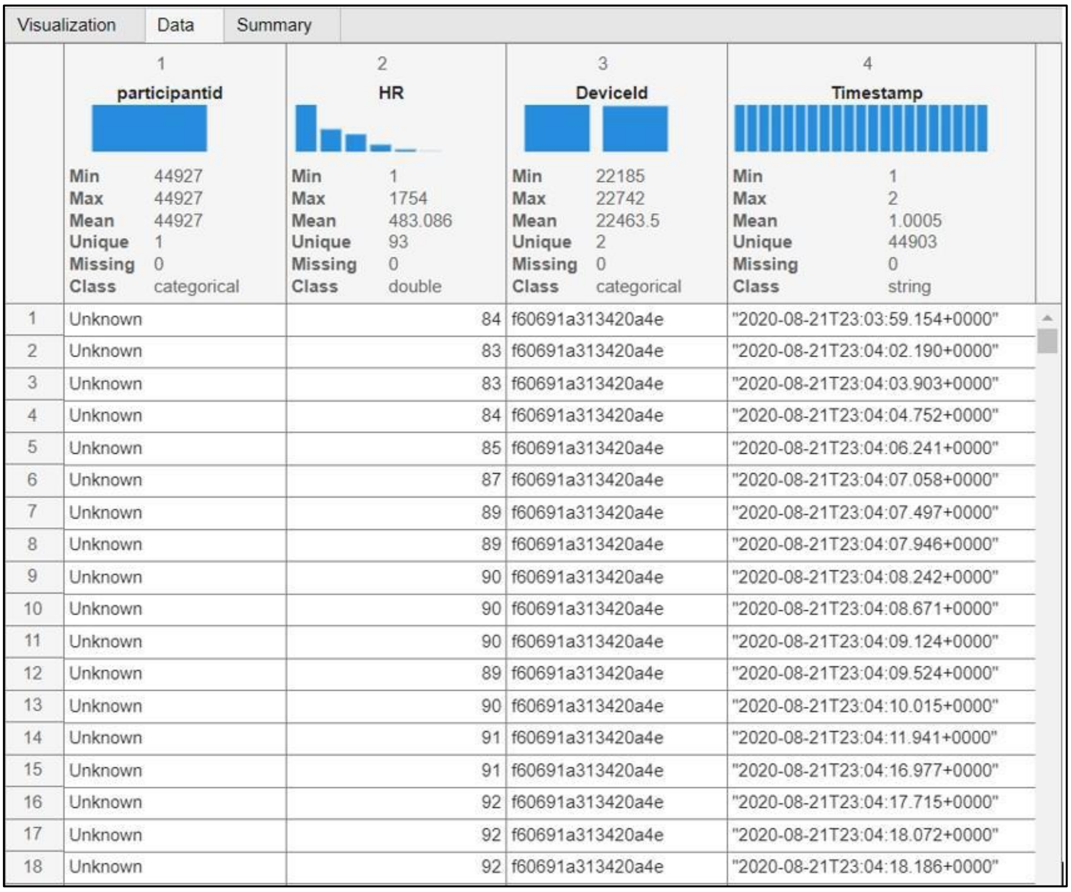
Artificial Intelligence transforms how healthcare models are designed and developed through programming platforms and simulation software. These technologies aid medical education, promote research, and enhance patient care. TensorFlow and PyTorch, AnyLogic, Matlab, Weka, Visual Studio code, Natural Language Processing (NLP) Tools, Robotic Process Automation (RPA), and Virtual Reality (VR) and Augmented Reality (AR) Platforms are some of the most popular AI programming and simulation tools available [133-135]. These tools and programs are used for advanced training, enhanced diagnostics, and increased operational productivity. However, this tool has exacerbated the challenges of data privacy, leading to costly implementation, and increased unemployment risks. A study in [136] used AnyLogic simulation to address space concerns at an elderly hospital, including overcrowding and poor patient experiences. AnyLogic was used to analyze patient flow, determine the optimal size for a waiting area as well as make recommendations for future space development. The advantage of AnyLogic is its capacity to predict the fairly complex dynamics of a hospital and attempt to deliver data-driven answers to the problem of inefficient use of available space. The requirement that the data be accurate and that the user must be at least slightly competent makes it difficult for individuals to use, which is a major drawback.

Similarly, research on combining RFID technology with AI in medical management was carried out in [137] which seeks to improve patient monitoring and asset tracking in healthcare institutions. This work uses the MATLAB simulation tool, and the integration provides benefits such as real-time data collection and increased operational efficiency. However, issues include making major investments in training. Researchers in [138] employ Artificial Neural Networks (ANN) to describe and forecast glaucoma disease progression to improve early detection and treatment options. Complex visual field data is analyzed over time utilizing simulation tools such as CNN and LSTM networks along with Pytorch. These techniques have the advantage of allowing us to assess both spatial qualities and changes over time in patient data to precisely estimate the disease's progression. However, these techniques rely on a large amount of high-quality image data as well as pre-trained convolutional neural networks, both of which are expensive and difficult to obtain and manage. Although each simulation program has pros and cons, MATLAB and Weka were first chosen for data cleaning and preliminary development based on the background analysis and methods presented.

Initially, 1446 samples of HR datasets were collected for a period of 3 days from an elderly through the Fitbit database [139]. These sample datasets were collected when the elderly were not performing any physical activity. The preliminary data cleaning and smoothing process was done using MATLAB R2022b. Figure 3.4 shows the HR details after the filtration process. The imported data is then cleaned and normalized for reliability. Figure 3.5 shows the data visualization graph when the normalized and smoothing data was obtained from the original input. To differentiate between the resting HR and HR when an older adult is performing a physical activity, 100 sample data sets were obtained, which had information about the Physical activity over a period of 3 months which is shown in Figure 3.6.

Figure 3.7 depicts the results of smoothed data from the original input data. These processed results are then exported and sent to the AI-1 model for the next process. Once after checking the reliability of the testing and training datasets, programming is done in a way that automatic filtration of data is processed in the database itself. Even though the initial data cleaning and normalization of the input data is straightforward using MATLAB, some issues occurred during this process. Firstly, every time the data pre-processing and normalization must be done manually (step by step), and MATLAB is very sensitive to large datasets. Secondly, upon using large datasets it takes a long time to provide the simulation results and most of all some inputs are accepted only when it is broken down into smaller bytes, which spoils the flow of the HR data as these inputs are continuous and breaking down will not provide accurate prediction results.

Next, Weka 3.8.6 was chosen to replace MATALB, and this time it was used for data pre-processing. Sample data models were taken from [140, 141] Fitabase public repository, that contains vital information about older adults performing regular activities. This is then tested using the Weka tool for data pre-processing. Figure 3.8 describes the Sample Data model obtained from FitaBase.



	1 participantid	2 HR	3 DeviceId	4 Timestamp
	Min 44927 Max 44927 Mean 44927 Unique 1 Missing 0 Class categorical	Min 1 Max 1754 Mean 483.086 Unique 93 Missing 0 Class double	Min 22185 Max 22742 Mean 22463.5 Unique 2 Missing 0 Class categorical	Min 1 Max 2 Mean 1.0005 Unique 44903 Missing 0 Class string
1	Unknown	84	f60691a313420a4e	"2020-08-21T23:03:59.154+0000"
2	Unknown	83	f60691a313420a4e	"2020-08-21T23:04:02.190+0000"
3	Unknown	83	f60691a313420a4e	"2020-08-21T23:04:03.903+0000"
4	Unknown	84	f60691a313420a4e	"2020-08-21T23:04:04.752+0000"
5	Unknown	85	f60691a313420a4e	"2020-08-21T23:04:06.241+0000"
6	Unknown	87	f60691a313420a4e	"2020-08-21T23:04:07.058+0000"
7	Unknown	89	f60691a313420a4e	"2020-08-21T23:04:07.497+0000"
8	Unknown	89	f60691a313420a4e	"2020-08-21T23:04:07.946+0000"
9	Unknown	90	f60691a313420a4e	"2020-08-21T23:04:08.242+0000"
10	Unknown	90	f60691a313420a4e	"2020-08-21T23:04:08.671+0000"
11	Unknown	90	f60691a313420a4e	"2020-08-21T23:04:09.124+0000"
12	Unknown	89	f60691a313420a4e	"2020-08-21T23:04:09.524+0000"
13	Unknown	90	f60691a313420a4e	"2020-08-21T23:04:10.015+0000"
14	Unknown	91	f60691a313420a4e	"2020-08-21T23:04:11.941+0000"
15	Unknown	91	f60691a313420a4e	"2020-08-21T23:04:16.977+0000"
16	Unknown	92	f60691a313420a4e	"2020-08-21T23:04:17.715+0000"
17	Unknown	92	f60691a313420a4e	"2020-08-21T23:04:18.072+0000"
18	Unknown	92	f60691a313420a4e	"2020-08-21T23:04:18.186+0000"

Figure 3.4: HR Sample Datasets.

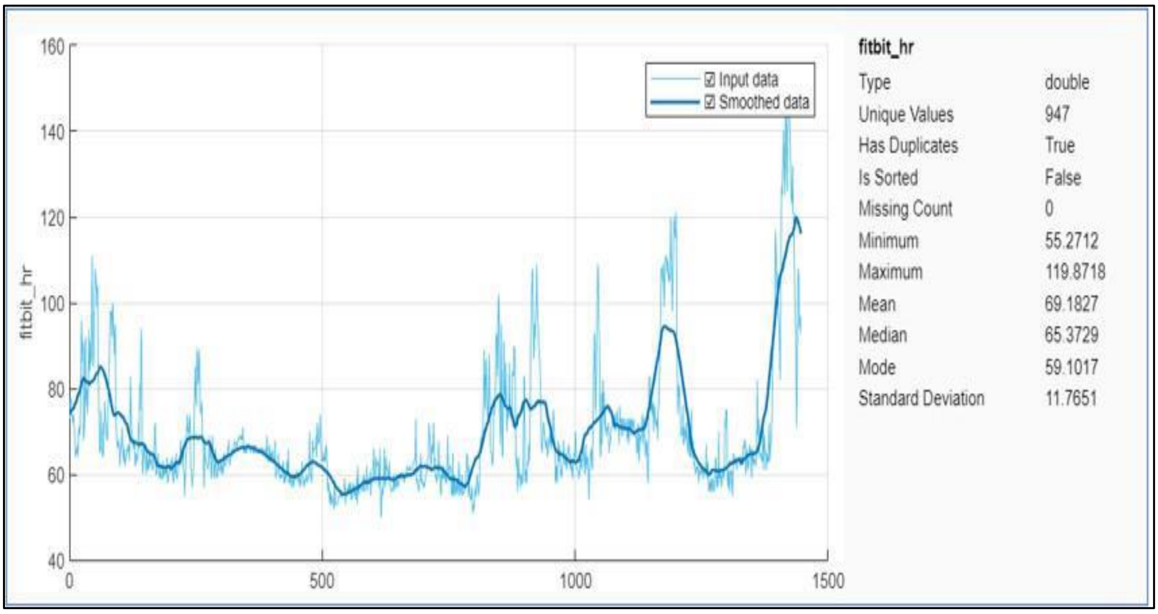
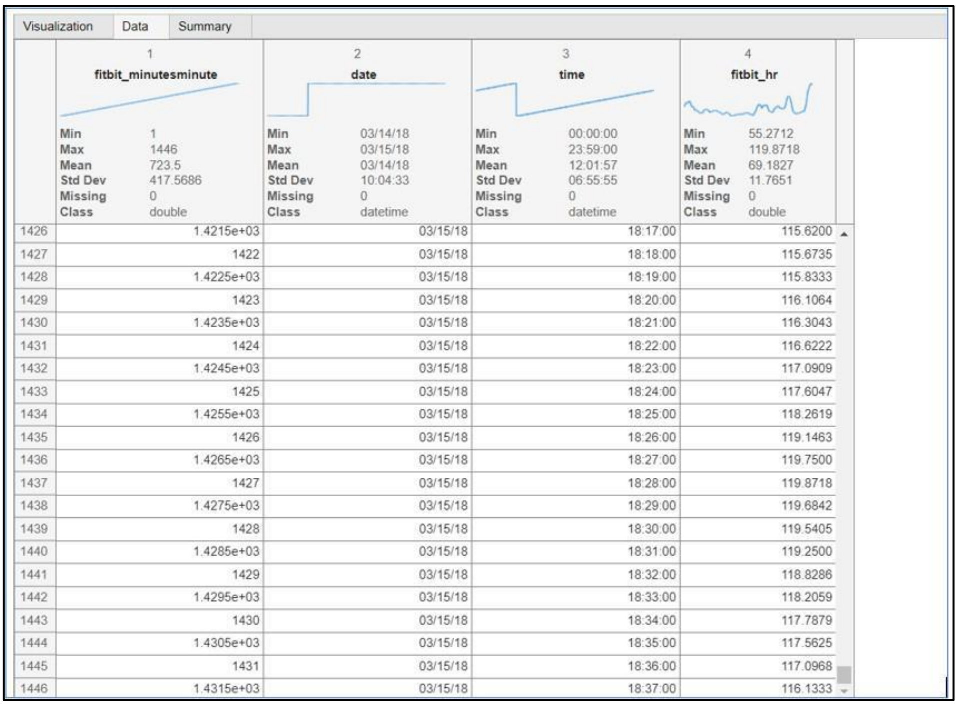


Figure 3.5: Data Visualization Results after the Smoothing Process.



Visualization | Data | Summary

	1 fitbit_minutesminute	2 date	3 time	4 fitbit_hr
	Min 1 Max 1446 Mean 723.5 Std Dev 417.5686 Missing 0 Class double	Min 03/14/18 Max 03/15/18 Mean 03/14/18 Std Dev 10:04:33 Missing 0 Class datetime	Min 00:00:00 Max 23:59:00 Mean 12:01:57 Std Dev 06:55:55 Missing 0 Class datetime	Min 55.2712 Max 119.8718 Mean 69.1827 Std Dev 11.7651 Missing 0 Class double
1426	1.4215e+03	03/15/18	18:17:00	115.6200
1427	1422	03/15/18	18:18:00	115.6735
1428	1.4225e+03	03/15/18	18:19:00	115.8333
1429	1423	03/15/18	18:20:00	116.1064
1430	1.4235e+03	03/15/18	18:21:00	116.3043
1431	1424	03/15/18	18:22:00	116.6222
1432	1.4245e+03	03/15/18	18:23:00	117.0909
1433	1425	03/15/18	18:24:00	117.6047
1434	1.4255e+03	03/15/18	18:25:00	118.2619
1435	1426	03/15/18	18:26:00	119.1463
1436	1.4265e+03	03/15/18	18:27:00	119.7500
1437	1427	03/15/18	18:28:00	119.8718
1438	1.4275e+03	03/15/18	18:29:00	119.6842
1439	1428	03/15/18	18:30:00	119.5405
1440	1.4285e+03	03/15/18	18:31:00	119.2500
1441	1429	03/15/18	18:32:00	118.8286
1442	1.4295e+03	03/15/18	18:33:00	118.2059
1443	1430	03/15/18	18:34:00	117.7879
1444	1.4305e+03	03/15/18	18:35:00	117.5625
1445	1431	03/15/18	18:36:00	117.0968
1446	1.4315e+03	03/15/18	18:37:00	116.1333

Figure 3.6: Physical Activity HR Datasets after Normalization.

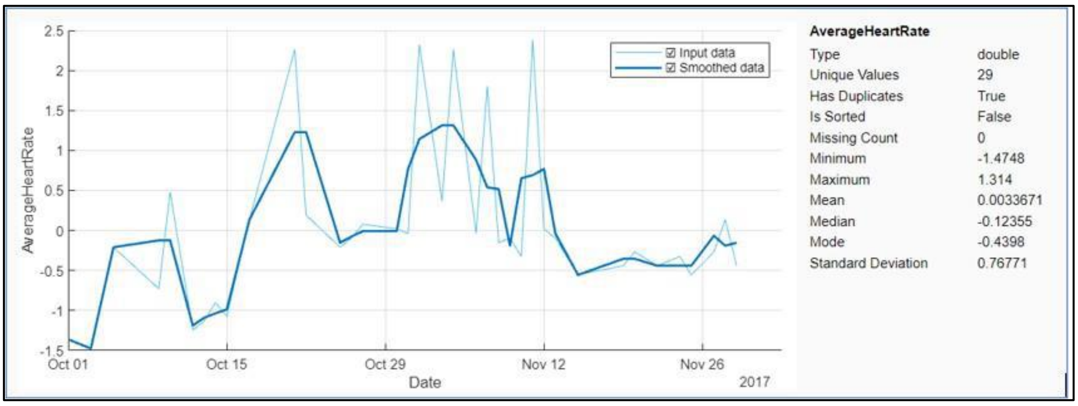


Figure 3.7: Data Visualization Results after Smoothing Physical Activity Datasets.

ActivityDate	RestingHeartRate	TotalSteps	SedentaryMinutes
10/01/2017	52	12578	611
10/02/2017	50	8352	711
10/03/2017	51	13299	635
10/04/2017	53	6344	816
10/05/2017	55	8347	789
10/06/2017	57	6876	781
10/07/2017	58	14591	713

Figure 3.8: Sample Data Model Obtained from FitaBase.

To pre-process this dataset, the Weka tool, a machine learning application was employed for data analysis. Figure 3.9 depicts the parameters and classifiers that can be used alone or in combination for pre-processing.

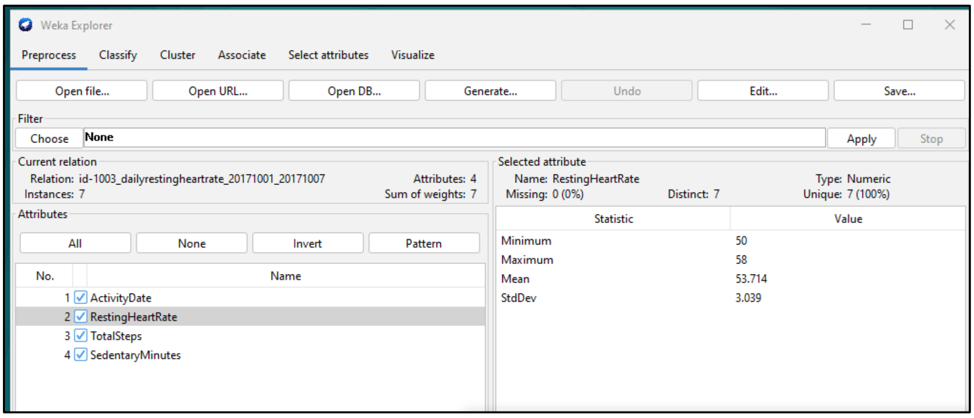


Figure 3.9: Parameter and Classifier Selection.

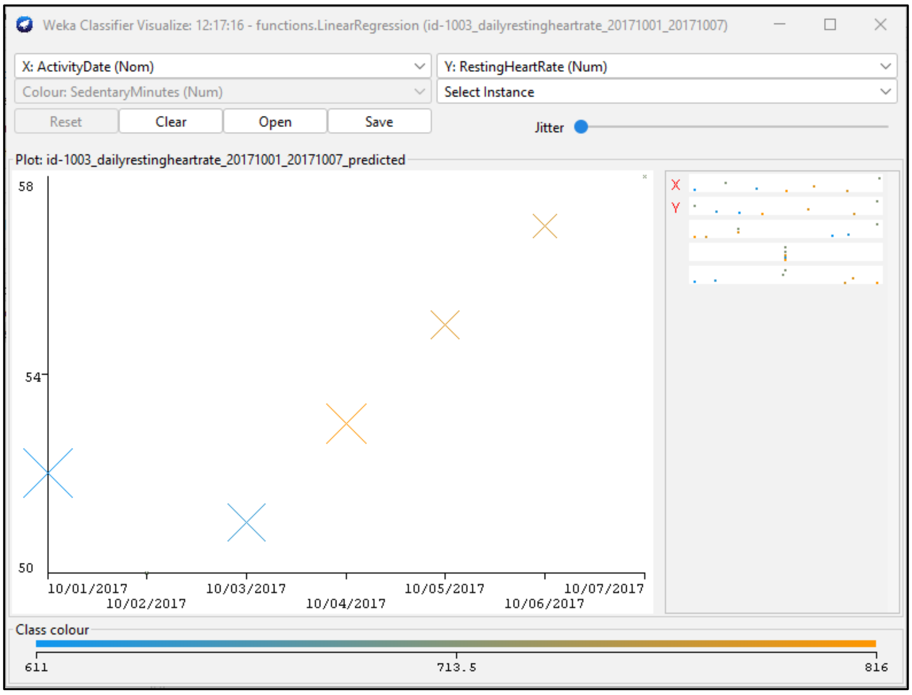


Figure 3.10: Comparison Analysis of HR and Normal Activity.

As illustrated in Figure 3.10, the findings were investigated by comparing resting HR data to normal daily activity data. Figures 3.11 and 3.12 show how the findings were classified into several categories based on the training outcomes. Despite its apparent simplicity, Weka is challenging to use properly since it requires a full understanding of the subcategories of model classification that are built into the simulation tool. When working with large datasets, Weka's restricted scalability due to its memory-intensive nature may result in performance issues. This is one of the primary downsides of using Weka. Furthermore, while it includes a variety of machine learning approaches, users with no prior data mining skills may find it difficult and time-consuming to refine and interpret the results.

```
Clusterer output

Number of iterations: 2
Within cluster sum of squared errors: 7.22573188890502

Initial starting points (random):

Cluster 0: 10/03/2017,51,13299,635
Cluster 1: 10/01/2017,52,12578,611

Missing values globally replaced with mean/mode

Final cluster centroids:
                                Cluster#
Attribute           Full Data          0          1
                        (7.0)      (3.0)      (4.0)
===================================================
ActivityDate       10/01/2017 10/02/2017 10/01/2017
RestingHeartRate      53.7143    51.3333       55.5
TotalSteps         10055.2857  9331.6667      10598
SedentaryMinutes     722.2857   720.6667      723.5



Time taken to build model (full training data) : 0 seconds

=== Model and evaluation on training set ===

Clustered Instances

0      3 ( 43%)
1      4 ( 57%)
```

Figure 3.11: Weka Classifier Training.

```
Classifier output
RandomTree
==========

TotalSteps < 8349.5
|   RestingHeartRate < 54 : 816 (1/0)
|   RestingHeartRate >= 54
|   |   ActivityDate = 10/01/2017 : 0 (0/0)
|   |   ActivityDate = 10/02/2017 : 0 (0/0)
|   |   ActivityDate = 10/03/2017 : 0 (0/0)
|   |   ActivityDate = 10/04/2017 : 0 (0/0)
|   |   ActivityDate = 10/05/2017 : 789 (1/0)
|   |   ActivityDate = 10/06/2017 : 781 (1/0)
|   |   ActivityDate = 10/07/2017 : 0 (0/0)
TotalSteps >= 8349.5
|   RestingHeartRate < 55
|   |   ActivityDate = 10/01/2017 : 611 (1/0)
|   |   ActivityDate = 10/02/2017 : 711 (1/0)
|   |   ActivityDate = 10/03/2017 : 635 (1/0)
|   |   ActivityDate = 10/04/2017 : 0 (0/0)
|   |   ActivityDate = 10/05/2017 : 0 (0/0)
|   |   ActivityDate = 10/06/2017 : 0 (0/0)
|   |   ActivityDate = 10/07/2017 : 0 (0/0)
|   RestingHeartRate >= 55 : 713 (1/0)

Size of the tree : 21

Time taken to build model: 0 seconds

=== Evaluation on training set ===

Time taken to test model on training data: 0 seconds

=== Summary ===
```

Figure 3.12: Final Classification Outcome.

3.4 Visual Studio-Based AI Simulation

Although specialized simulation software often serves a single domain, Visual Studio (VS) Code's adaptable environment enables developers to customize it to meet a variety of simulation requirements in diverse industries [142]. For example, extensions that enable Python and R can be used to set up Visual Studio Code for data analysis and modelling jobs in the healthcare industry [143]. This is particularly useful in healthcare research, as interdisciplinary teams routinely work on simulation models. The ability to monitor alterations and regulate code versions ensures consistent and accurate simulation results. VS Code has been utilized for a broader range of simulation-related advancements in the healthcare business. Researchers have employed Visual Studio Code for data science activities such as predictive modelling and patient data analysis. The editor's support for Jupyter Notebooks enables interactive data exploration and visualization, which are critical in medical research. It is an effective tool for simulation projects due to its adaptability and extensive extension marketplace, which allows users to customize their operations [144]. The retrieval of Vital Signs and Activities of Daily Living (ADLs) for the AI-1 and AI-2 models was done with the aid of Visual Studio Code. This simulation tool can fetch features efficiently and provide a step-by-step explanation of the simulation process. For instance, Figure 3.13 shows the simulation analysis of the AI-2 model, where each DBN layer was analyzed individually, and each step of the simulation process was explained. Also, epoch-wise analysis and the time taken by each process are well displayed in the VS Code terminal, a feature that is greatly missing in the WEKA tool.

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	16,512
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 32)	2,080
dense_3 (Dense)	(None, 1)	33

Total params: 26,881 (105.00 KB)
Trainable params: 26,881 (105.00 KB)
Non-trainable params: 0 (0.00 B)

Figure 3.13: Simulation Processes of AI-2 Model using Visual Studio Code.

Visual Studio Code is effective in providing a clean and well-structured output of results for each epoch used in the AI-2 model as time progresses. It is easy to understand how the model improves as it gets trained, thereby easy understanding of how improvements are achieved through iterations. Figure 3.14 shows this clearly through visualization of the training process, showing how each epoch enhances the accuracy and efficacy of the model. The VS Code terminal feature of tracking time per epoch also enhances usability, giving insight that is pivotal to optimizing the performance of the model.

The graphical depiction of Visual Studio Code is not only more stunning but also enhances readability with its simple and efficient visualization of data points. Despite its simplicity, it greatly facilitates data interpretation. Figure 3.15 illustrates the graphical analysis of the AI-2 model, illustrating the correlation between fallers and the history of falls using the Visual Studio Code simulation tool.

```
Epoch 1/10
746/746 - 2s - 3ms/step - accuracy: 4.1906e-05 - loss: -1.6352e+10
Epoch 2/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -4.6465e+11
Epoch 3/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -2.6746e+12
Epoch 4/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -8.2714e+12
Epoch 5/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -1.8797e+13
Epoch 6/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -3.5768e+13
Epoch 7/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -6.0640e+13
Epoch 8/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -9.5011e+13
Epoch 9/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -1.4051e+14
Epoch 10/10
746/746 - 1s - 1ms/step - accuracy: 4.1906e-05 - loss: -1.9881e+14
DBN1 (Low Risk) Training time: 10.70 seconds
Training DBN2 (Moderate Risk)...
```

Figure 3.14: Terminal Window Output of Visual Studio Code.

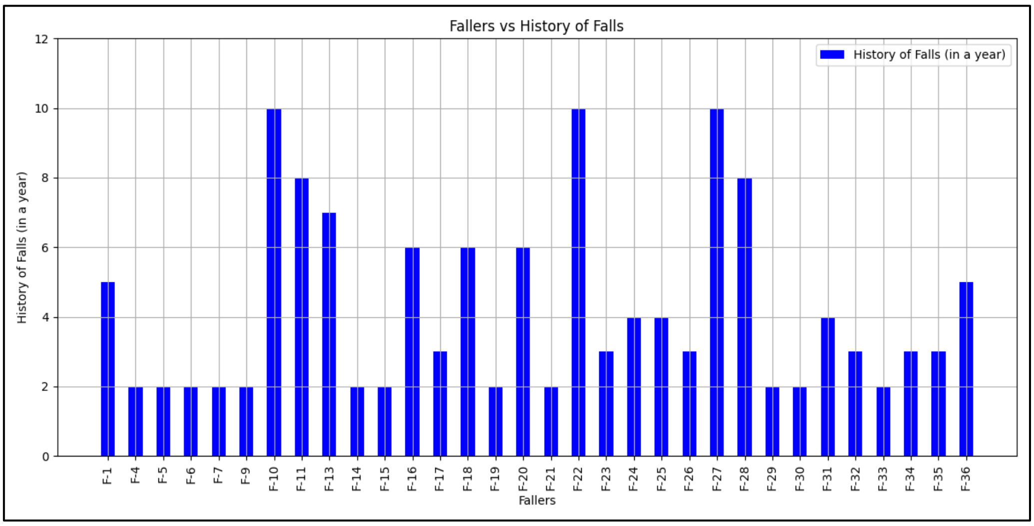


Figure 3.15: Graphical Analysis of Fallers using Visual Studio Code.

Because of all of these factors, as well as the successful implementation of the research findings by other researchers, visual studio code was chosen as a simulation tool for this study. The simulation findings using Visual Studio code are discussed in Chapter 4. For this research work, Windows 10 Enterprise, with its 3.00 GHz, 11th Gen Intel Core i7 processor, and 32 GB of internal RAM, is being used to run the simulation.

3.5 Conclusion

The developed AI prediction model is conceptualized in the context of Fuzzy Logic and DBN to create an adaptive system that can be dynamically regulated. This is ensured by conceptualizing data in the context of a virtualized software environment, where predictive models could be simulated and tested effectively with ease, optimizing them before physical implementation. The integration of these methods guarantees that the system is sensitive to changing input conditions, improving the accuracy and reliability of fall risk prediction.

This chapter provides a thorough explanation of the methodology and framework used in this research. One of the salient aspects of this research is the identification and ranking of appropriate simulation tools that facilitate model building, testing, and validation in a controlled virtual environment. Visual Studio Code, a widely used development environment, is utilized here. It provides key features like virtualization, scalability of the network model, and high reliability. These features make it a great source for AI-based simulations since they can be easily tested with different settings, algorithmic efficiency optimized, and model checked simultaneously. By utilizing these tools, this research ensures that the AI prediction models are thoroughly tested in a controlled virtual environment before use in physical space. Through this approach, the dependability, flexibility, and responsiveness of the fall risk prediction system are improved with assured effectiveness for real-world healthcare applications.

Chapter 4. Proposed AI-1 Model: Fuzzy-Based Fall Risk Prediction System

4.1 Introduction

The Fall Prediction methodology in this research can customize interventions based on individual needs, enabling timely preventive warnings before the elderly person experiences a fall. The focus of this chapter is to foresee a future fall in older adults by identifying the abnormalities upon monitoring the vital signs and notifying the risk of a fall earlier (the caregiver/concerned person) based on the Fuzzy risk level prediction analysis. This chapter introduces a fuzzy logic-based methodology for predicting potential falls in the elderly by monitoring their vital signs. It addresses a gap in the literature by focusing on fall prediction rather than just detection, specifically in the context of elderly monitoring. The fall prediction algorithm is versatile and can be adjusted to monitor various health indicators, facilitating the early identification of underlying health problems that may elevate the risk of falls. As part of this, vital signs such as blood pressure, heart rate, and blood oxygen levels serve as input parameters for the developed fall risk prediction model. The first model, AI-1 is focused on fall prediction among older adults through continuous tracking with the support of a pioneering Fall Prediction Algorithm aided by Fuzzy rules. The proposed prediction technique with the Fall prediction algorithm (FPA) uses the Fuzzy rule to learn and perform tasks. The model analyses the levels of fall risk into *Normal, Low, Moderate, High, and Emergency* and was validated across three different datasets in comparison to the Morse Falls Scale. This technology ensures early anticipation of falls among the elderly and possibly saves lives in crucial situations. Notably, it is also a novel contribution since it is the sole research that depends only on vital signs for forecasting likely falls in senior citizens. The chapter also summarizes the creation of the algorithm and vigorous testing using public datasets, validated against the Morse Falls Scale for accuracy as mentioned previously. This research aims to create a more precise fall risk prediction model and incorporate it into a physical prototype to receive timely notifications based on the predicted risk levels. The AI-1 model was evaluated in real-time using smart devices and obtained a successful prediction outcome which is also discussed at the end of this chapter. With these advancements in the proposed heterogeneous technology, the elderly's falls can be predicted earlier to save the lives of older adults.

4.2 Vital Signs Monitoring

The combination of fall risk factors and vital sign monitoring is critical for fall prediction. Vital signs are important indications of a person's overall health and current medical status. It is one of the most significant and sensitive parameters for healthy living that moves with an individual's lifestyle; therefore, it is vital to monitor them regularly, especially in older adults, as any imbalance in them may lead to a fall. It is logical that the more the frequency of vital sign measurements, the quicker clinical deterioration is noticed [145]. According to [146], the earliest evidence of potentially dangerous physiological changes or disruptions in the body can frequently be discovered in vital signs, which can also serve as the first indication that the disease has stabilized. The four most significant and conventional vital indicators are Blood Pressure (BP), temperature, pulse, and respiration rate. Recent additions include pain, threshold, and oxygen saturation measures [147]. Figure 4.1 describes the vital sign parameters.

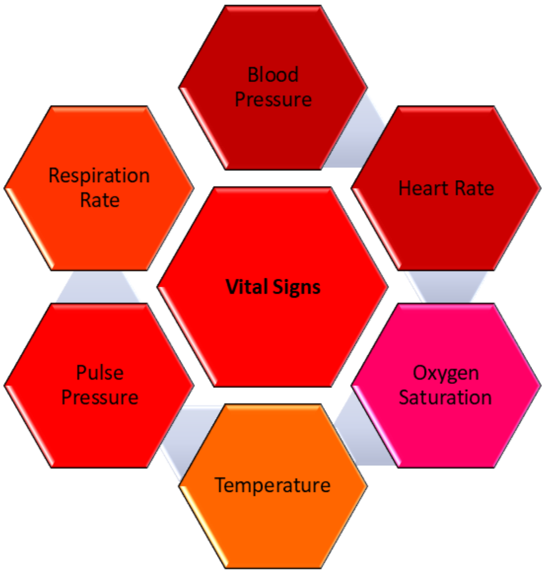


Figure 4.1: Vital Sign Parameters.

Some of the sensors used to measure Vital sign metrics are described as follows,

- **Heart Rate and Pulse Rate**
  Sensor: Photoplethysmography (PPG), Electrocardiogram (ECG) electrodes
  Uses: Measures heart rate, pulse patterns, and detects arrhythmias or cardiovascular abnormalities.
- **Blood Pressure**
  Sensor: Cuff-based pressure sensor (oscillometric method), Cuffless PPG + ECG-based sensors
  Uses: Monitors systolic and diastolic blood pressure for hypertension/hypotension detection.
- **Body Temperature**
  Sensor: Thermistors, Infrared (IR) sensors, Thermocouples
  Uses: Tracks core body temperature, detects fever, infection, or hypothermia.
- **Respiratory Rate**
  Sensor: Respiratory Inductance Plethysmography (RIP), Capnography (CO_2sensors), Accelerometers

Uses: Monitors breathing patterns, detects apnea, and evaluates respiratory health.

- **Oxygen Saturation (SpO_2)**

  Sensor: Pulse Oximeter (light absorption using PPG)

  Uses: Measures oxygen levels in the blood to monitor lung function, hypoxia, or during surgery.

According to research on elderly monitoring in [148], diseases can be predicted by tracking irregularities in vital indicators such as blood pressure, pulse pressure, heart rate, blood sugar, oxygen levels in the blood, BMI, and ADLs. Some important factors to examine include a person's history of falls, medical condition, social environment, and psychological state [149]. It is possible to anticipate future falls and reduce the possibility of falls if all these vital signs are regularly checked and compared to the individual's medical history. As a result, the first model in this research focuses on monitoring blood pressure, heart rate, and blood oxygen levels to anticipate, and predict a potential fall in older adults.

4.2.1 Blood Pressure

Blood pressure is the first indicator of health problems. This vital indicator is crucial to monitor because it can be either high or low, but it is abnormal when there is a slight health imbalance in the body. The definition of low or high blood pressure differs from person to person. Healthcare professionals have noted that a decline in systolic or diastolic blood pressure is common among the elderly. It is necessary to perform routine examinations to ascertain whether blood pressure is elevated. Age, body mass index (BMI), diastolic and systolic blood pressure are the input factors that define the blood pressure level's output characteristics [150]. Long-term research in [151] shows that blood pressure, both systolic and diastolic, falls with age; hence, systolic and diastolic blood pressure measurements can be utilized to identify more specific health problems. Table 4.1 describes the Standard Blood Pressure chart.

Table 4. 1: Blood Pressure Chart

BP (mmHg)	Normal	Low Risk	Moderate Risk	High Risk	Emergency
Normal BP	100/60-120/80	-	-	-	-
Low BP	-	90/60-70/40			
High BP	-	121/80-190/100			

Blood pressure levels can be used to calculate other significant pressure measurements, including pulse pressure and Mean Arterial Pressure (MAP). MAP is the median arterial pressure (including systole, and diastole) during a single cardiac cycle. Cardiac output and systemic vascular resistance both have an impact on MAP, and each is impacted by multiple factors [152].

The formula in (4.1) is used to determine the MAP.

$$MAP = DBP + 1/3(SBP - DBP) \text{ or } MAP = DBP + 1/3(PP) \quad (4.1)$$

Pulse Pressure (PP), Diastolic Blood Pressure (DBP), and Systolic Blood Pressure (SBP). This method is more suited for measuring MAP in most clinical situations since it allows for quick calculation when the blood pressure is known. The pulse pressure is calculated as the variation between the higher and lower blood pressure values. Pulse pressure tends to increase with age, and this number may indicate health problems before symptoms appear [153]. The formula (4.2) can be used to estimate the Pulse Pressure.

$$\text{Pulse Pressure} = \text{Systolic Blood Pressure} - \text{Diastolic Blood Pressure} \quad (4.2)$$

Typically, pulse pressure falls between 40 and 60 mmHg. If the pulse pressure exceeds 60 mmHg, it is referred to as "wide," and if it is less than 40 mmHg, it is referred to as "narrow," [154]. Both levels cause people to feel unstable or confused, which can cause falls, especially in older adults. This study will use pulse pressure as the key metric retrieved from BP to predict elderly falls in conjunction with other health data inputs.

4.2.2 Heart Rate

The heart plays a crucial role in the human body as it is the essential organ. The effective operation of the heart is undoubtedly important to an individual's life. A healthy adult's HR typically varies from 60 to 100 beats per minute (bpm). Maintaining a healthy heart rate is necessary for all physical activities [155]. A strong heartbeat ensures that nutrients and blood with high oxygen content are delivered to all parts of the human body while also eliminating waste products such as Co_2. Physically active individuals typically have lower heart rates (as low as 40), since their heart muscles are in good condition and need not have to work as hard to maintain a stable beat [156]. However, the underlying reasons for irregular heart rhythms must be investigated from time to time, particularly as people age. Heart rates are often lower in older adults. A formula for calculating a person's maximum heart rate HR_{max} is expressed in (4.3) as mentioned in [157],

$$HR_{max} = 220 - age\ (bpm) \quad (4.3)$$

For more accurate results the max. heart rate can also be calculated using (4.4) as follows [158],

$$HR_{max} = [207 - 0.7\ x\ Age](bpm) \quad (4.4)$$

Tables 4.2 and 4.3 below illustrate the resting, targeted, and maximum heart rates for older adults aged 60 and over. The ideal heart rate varies from 50% to 85% based on age and activity. A person's heart rate fluctuates between the target and maximum values while engaging in physical exercise. Upon considering these factors, HR is chosen as the second input parameter to the proposed AI-1 model.

Table 4. 2: Average Resting HR for Elderly above 60 years [159]

Age Range (years)	**Avg. resting heart rate (bpm)**
61 – 70	73.0
71 – 80	74.2
Above 80 years	78.1

Table 4. 3: Target and Max. HR from Age 60-100 [159]

Age (years)	**Target Heart Rate (50% - 85% bpm)**	**Avg. max. heart rate (bpm)**
60	80 to 136	160
70	75 to 128	150
80	70 to 119	140
90	65 to 111	130
100	60 to 102	120

4.2.3 Blood Oxygen Level (SpO_2)

Blood oxygen saturation, commonly known as blood oxygen level, is the quantity of oxygen in a person's blood. Most persons typically have an oxygen saturation level on a pulse oximeter that falls between 95% and 100%. The general oxygen calculation is presented in (4.5) as mentioned in [160],

$$\mathrm{Sp}O_2 = 100\ x\ \frac{C[HbO_2]}{C[HbO_2]+C[RHb]} \tag{4.5}$$

Where HbO_2 is oxygenated hemoglobin, RHb is deoxygenated hemoglobin, and C is its concentration level. The maximo SpO_2 algorithm, which is expressed in (4.6) as follows [160], is typically used for calibration when measuring the O_2 with a pulse oximeter.

$$\mathrm{Sp}O_2 = aR^2 + bR + c \tag{4.6}$$

where the following equation (4.7) determines R:

$$\mathrm{R} = \frac{{AC_{red}}/{DC_{red}}}{{AC_{ired}}/{DC_{ired}}} \tag{4.7}$$

and the calibration coefficients are a, b, and c. When oxygen saturations go below 92%, they are deemed to be too low and are usually classified as medical emergencies [161]. Shortness of breath, dizziness, and/or disorientation are all indications of low blood oxygen. An objectively higher blood pressure, quicker heart rate, or a subjective palpitation may be the result of the heart pumping harder and faster to spread more oxygen. Table 4.4 illustrates various levels of SpO_2 in elderly individuals [162]. Upon considering these factors, oxygen saturation is chosen as the third input parameter to the proposed AI-1 model.

Table 4. 4: Different Levels of SpO_2 in Older Adults

Age	SpO_2 level	Status
60 – 100	97 – 100	Normal
	95 – 96	Moderate
	90 – 94	High
	< 90	Emergency

Tables 4.1, 4.2, 4.3, and 4.4 clearly show that aberrant blood pressure, pulse pressure, heart rate, or blood oxygen levels might cause older adults to fall, or experience falls in the future. If all three levels are regularly tracked and monitored, the fall can be forecasted in advance. Many factors make it challenging to diagnose and treat older adults with aberrant health imbalances; in many cases, doctors find themselves having to make decisions only based on their intuition. To address this complexity, a fuzzy model was built that efficiently evaluates diverse elements.

4.3 Rationale behind Selected Vital Health Metrics

This section discusses the reasons for choosing the three health parameters for the development of the AI-1 model.

- *Blood Pressure:* The first indicator of an individual's health problem is their blood pressure. When there is a minor health imbalance in the human body, the most significant thing to observe is the blood pressure level, which will be either high, low, or abnormal.

- *Heart Rate:* When an imbalance in blood pressure is identified in older adults (due to cardiac problems, dizziness, dementia, fever, etc.), the heart rate falls from the normal range of 60 - 80 beats per minute to a high or below normal average.

- O_2 *in Blood:* Because of the change in heart rate, the O_2 level in blood falls below 95% of normal (95%-98% in older adults).

Table 4. 5: Vital Metrics for AI-1 Model

<table>
<tr><th colspan="2">BP (mmHg)</th><th>Normal</th><th>Low Risk</th><th>Moderate Risk</th><th colspan="2">High Risk</th><th>Emergency</th></tr>
<tr><td>Normal BP</td><td>SV/DV</td><td>100/60 – 120/80</td><td>-</td><td>-</td><td colspan="2">-</td><td>-</td></tr>
<tr><td>Low BP</td><td>SV/DV</td><td colspan="6">90/60 – 70/40</td></tr>
<tr><td>High BP</td><td>SV/DV</td><td colspan="6">121/80 – 190/100</td></tr>
<tr><td>PP</td><td>SV-DV</td><td>40 - 60</td><td colspan="5">< 40 and > 60</td></tr>
<tr><th colspan="2">HR (bpm)</th><th colspan="2">Normal</th><th>Moderate Risk</th><th colspan="2">High Risk (73% - 85% max HR)</th><th>Emergency
(93% max HR)</th></tr>
<tr><td rowspan="4">Age</td><td>60-70</td><td colspan="2">60-100</td><td>101-109</td><td colspan="2">110-139</td><td>>140, <60</td></tr>
<tr><td>71-80</td><td colspan="2">60-100</td><td>101-102</td><td colspan="2">103-129</td><td>>130, <60</td></tr>
<tr><td>81-90</td><td colspan="2">60-80</td><td>81-94</td><td colspan="2">95-119</td><td>>120, <60</td></tr>
<tr><td>91-100</td><td colspan="2">60-80</td><td>81-87</td><td colspan="2">88-109</td><td>>110, <60</td></tr>
<tr><th colspan="2">SpO_2 (%)</th><th colspan="2">Normal</th><th colspan="2">Moderate Risk</th><th>High Risk</th><th>Emergency</th></tr>
<tr><td>Age</td><td>60-100</td><td colspan="2">97-100</td><td colspan="2">95-96</td><td>90-94</td><td><90</td></tr>
</table>

Blood pressure and heart rate are not linked with one another, however, when an imbalance in BP is observed in older adults, the heart rate lowers from normal to an average high/low normal value.

- When BP is low → HR increases → O_2 increases (The HR increases to pump blood to bring back the body's condition to normal)

- When BP is high → HR decreases → O_2 decreases (The HR decreases, due to rapid heart pumping and it makes the heart muscles thicker which supplies less blood to the body). Table 4.5 illustrates the overall vital metrics chart used for this research.

4.4 Existing Works on AI and Fuzzy Logic

To assess the effectiveness of vital sign monitoring analysis, a background study was undertaken in two stages: AI and Fuzzy logic improvements in health care and their contribution to the prediction of falls and diseases. According to [131], fuzzy logic is an algorithmic approach that prioritizes "degrees of truth" over the standard "true or false" (1 or 0). Fuzzy logic aims to solve problems by considering all available information. Furthermore, fuzzy logic simplifies the handling of ambiguity. As a result, fuzzy systems appear to be critical for understandable artificial intelligence (XAI) [163]. Figure 4.2 describes the logical balance of Fuzzy Logic. Numerous smart technologies discussed in [164] have been improved to enhance healthcare, provide better facilities, reduce expenses, and achieve other goals. As AI advancements such as Deep Learning, Fuzzy Logic, Big Data (BD), and the Internet of Things become more widely used in numerous fields, advances in intelligent technology in healthcare become increasingly crucial in tracking people's health status. AI/ML has been established to be incredibly beneficial in disease detection and prediction. For example, it may take a long time to diagnose someone with coronary artery disease, but healthcare professionals can use machine learning techniques to gain relevant information about cardiac patients, allowing them to treat them more successfully [165].

A study [166] performed at the University Hospital Zurich, Switzerland employed force plate data and dual-task scenarios to predict the likelihood of numerous falls in a community-dwelling older adult. This study included 270 elderly people, both male and female, who tested their balance with and without vision. The assessment report was based on the elderly's previous history of falls, which determined whether they had fallen before or not. The force plates predicted several falls in both anteroposterior and medial-lateral directions. A reverse logistic regression technique was applied to predict multiple falls in both fallers and non-fallers.

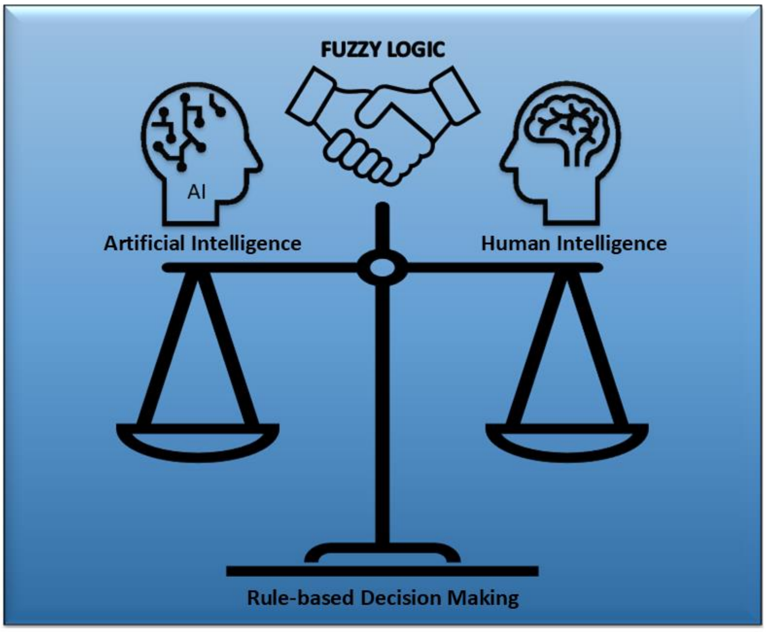


Figure 4.2: Logical Balance Structure of Fuzzy Logic.

Another study, published in [167], aimed to use machine learning algorithms and data from electronic health records to calculate the likelihood of a fall in residents of several senior care facilities. Information from 2785 senior citizens who lived in nursing homes with skilled staffing and senior residential communities, including independent and assisted living alternatives, across the United States was included. Three machine learning-based fall prediction systems were constructed, and analyses were performed to see how modifications to the input parameters, learning datasets, and prediction period affected their effectiveness. Vital signs such as blood pressure, heart rate, respiration rate, temperature, and standard risk indicators were combined as input characteristics to obtain greater prediction accuracy compared to either group of features operating independently. The Extreme Gradient Boosting model outperformed the other two machine learning prediction models, with a specificity of 84%.

The study published in [168] investigated the application of fuzzy logic to monitor vital indicators and detect irregular health circumstances. This study was categorized into two parts: first, to evaluate whether vital indicators can predict abnormal health conditions that have psychological consequences, and second, to identify whether a fuzzy rule system can provide decision assistance in predicting abnormalities based on an individual's health conditions. Fuzzy logic was used in this investigation because of its adaptability to relatively smooth variations in vital sign values. Vital sign observations and fuzzy rule-based techniques are used to determine the overall health condition and identify abnormalities. The Fuzzy Decision Support system was supplied with real-time data, and it was found that the prediction results provided in this experiment were 85% accurate. The use of vital signs for risk evaluation in home-based fall prevention and treatment was proposed in a study published in [169]. This study concentrated on older adults with Orthostatic Hypotension (OH) and Parkinson's disease. The age, medical status, and fall history of the elderly were initially collected. Then, using a smartwatch, the elderly's blood Pressure and Heart Rate Variability (HRV) were validated. These data are then used as input to the fuzzy model that was developed to quantify the immediate risk of falling. This study utilized fuzzy logic-based decision-making and predictive modelling. Using regression analysis, statistical modelling, and a fuzzy logic-based decision-making approach, the system accurately forecasted each participant's fall estimation rate.

Fuzzy logic offers advantages over other algorithmic approaches because it can integrate values from ordinal, nominal, and continuous datasets into its rules and record the information embedded with these rules in more understandable patterns for clinical research. The average fall rate among older adults in New Zealand is rising annually, and new technologies like AI and ML such as fuzzy logic and deep learning, will assist detect falls in people earlier. Many practical investigations have been carried out to predict heart illness [170], [171], [172], diagnose diabetes [173], [174], breast cancer in women [175], identify anomalies using heart rate and blood pressure [150], and predict falls in the elderly using fuzzy logic [176]. As a result of the above findings, fuzzy logic will be a good companion in the enhancement of the AI-1 model to predict and categorize the risk of falling. It is acknowledged that this study is unique in its approach as it solely employs vital signs to predict future falls in older adults.

4.5 Proposed Vital Sign-Based Fall Risk Prediction Model

To this effect, the proposed research combines a mixed-mode data collection strategy that includes surveys from health journals and interviews with two medical professionals who provided expert opinions to elaborate on a holistic view of predicting fall risk in older adults, Dr. A (MD), with Dr. B (MBBS), expressing that although vital metrics, such as blood pressure and heart rate variation, are not direct causes of falls, they represent physiological changes resulting in instability. These include the individual's lifestyle, intake of medications, or pre-existing medical conditions, which would affect their chances of falling. Dr. B explained that the presence of symptoms of advanced age, combined with a history of falls, would be predictors of future falls. Such symptoms as dizziness, fatigue, and shortness of breath are often signs of abnormal blood pressure levels that can cause instability. Moreover, vertigo or jitters from anxiety encourage hypotension or hypertension which scares an elderly individual from falling especially when they are alone. Dr. B also provided crucial insights regarding the benefit of wearable devices for monitoring vital signs. In a comparative analysis [177] with data obtained from a smartwatch, it is found that certain brands produced measurements of an 89% likeness to the assessment devices, which reaffirms the potential of these devices in reliable monitoring health conditions and the effectiveness of interfacing AI-generated wearable sensors into fall risk predictive modelling.

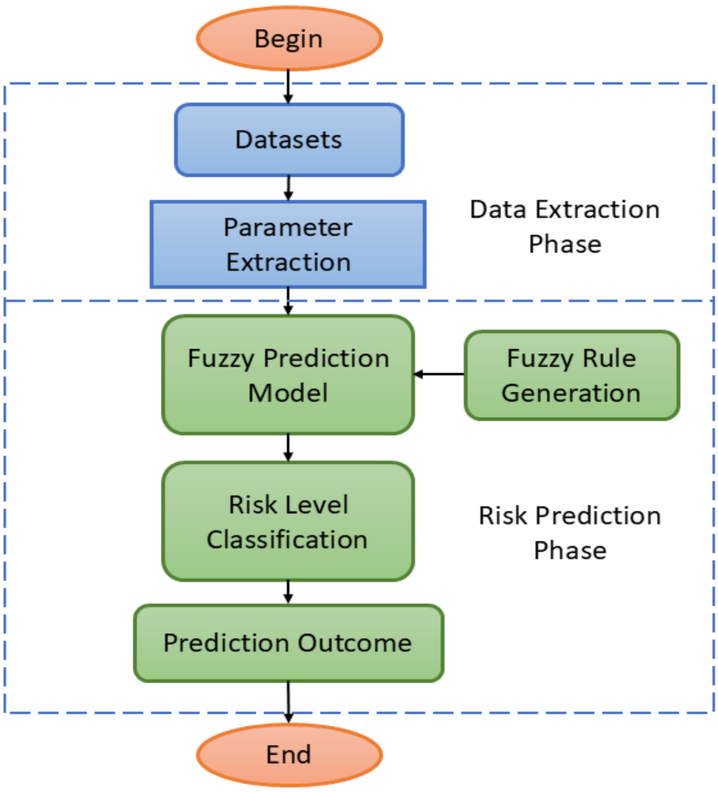


Figure 4.3: Vital Sign-Based Fall Risk Prediction Model.

This research is primarily on the prediction of future falls in the elderly through continuous monitoring of vital signs and AI analysis. To achieve this goal effectively, an efficient early recognition of physiological deficits is targeted through machine learning techniques, indicating moments of increased risk of future falls. This chapter presents the design of a Fall Prediction Algorithm constructed to function alongside the predictive model to provide fall risk assessment based on real-time health data. This prediction was found to correlate very strongly with other existing fall risk prediction frameworks, such as the MFS. The main target of this research is the geriatric population aged 60 years and over, who live independently and, therefore, are at risk of falling. Secondly, however, data from older adults residing in assisted living facilities could be considered, as their medical records and vital sign data are publicly available for researchers. These datasets are fed first for model training and validated subsequently with real-world cases. This study aims to show the need for instituted intervention strategies to prevent further declines in the growing population of the elderly. It is evident from the background research that the accuracy of fall prediction is increased when geriatric data, such as age and fall history, are merged with real-time and continuously varying vital sign metrics.

The AI-1 model categorizes the risk of falling using a Fuzzy rule-based prediction model and algorithm. Figure 4.3 depicts an overview of the suggested vital sign-based fall prediction model. Initially, data from the elderly participants in this study was gathered from open sources. Since the dependability of smartwatches and their data extraction functions takes some time, this will be investigated in future work. This chapter currently examines the level of prediction accuracy achieved by the developed model. The data obtained from the public repository is separated into fallers and non-fallers, and each type is sent independently to the fuzzy model. The Fuzzy Prediction Model gathers vital sign data such as blood pressure, pulse pressure, heart rate, and blood oxygen saturation. Using the membership function and fuzzy rules, the model classifies the risk of falling as *Normal, Low, Moderate, High, or Emergency*. This systematic method ensures an accurate and reliable fall risk assessment, allowing for more effective proactive intervention and increased predictive capability in fall prevention.

The blood pressure readings are categorized into three groups: standard (normal), reduced (low), and elevated (high). The low and high blood pressure levels are further categorized into high and low based on the risk levels. Systolic and diastolic pressure levels range from 100/60 to 120/80 on a normal blood pressure scale. In a similar manner, the range for Low BP is 90/60-70/40, whereas the range for High BP is 121/80-190/100 [178]. According to [179], the normal heart rate (HR) for senior people between the ages of 60 and 80 ranges from 60 to 100 bpm (beats per minute), whereas for people over the age of 80, the normal HR only varies between 60 and 80 bpm. The HR varies depending on the age of the elderly, as age advances, the HR drops. Similar findings in [180] show that older people between the ages of 60 and 100 have normal blood oxygen levels between 97% and 100%.

Fuzzy logic is a technique that provides various solutions to a question's uncertainty [181]. The Mamdani Fuzzy Inference System, a specialized fuzzy modelling approach, is used in the development of the AI-1 model to predict fall risk indicators in the elderly. Fuzzification, Inference, and Defuzzification are the three architectures or workflows employed in the approach [182]. Figure 4.4 depicts the architecture of the developed AI-1 fuzzy-based fall risk prediction model. The fuzzification approach is used to convert the clear data into membership grades. In this research, the blood pressure (mmHg), heart rate (bpm), and blood oxygen level are used as fuzzy input variables, which are determined using the fuzzification approach. This well-established fuzzy model transforms blood pressure directly into pulse pressure, which is subsequently fed into the fuzzification process. Each input parameter is assigned a membership value based on its risk prediction weight. The input values are then compared within the fuzzy inference system, which employs the generated fuzzy rules and membership function. The fuzzy sets are converted into crisp values during the defuzzification process, which will be explained in Section 4.7.

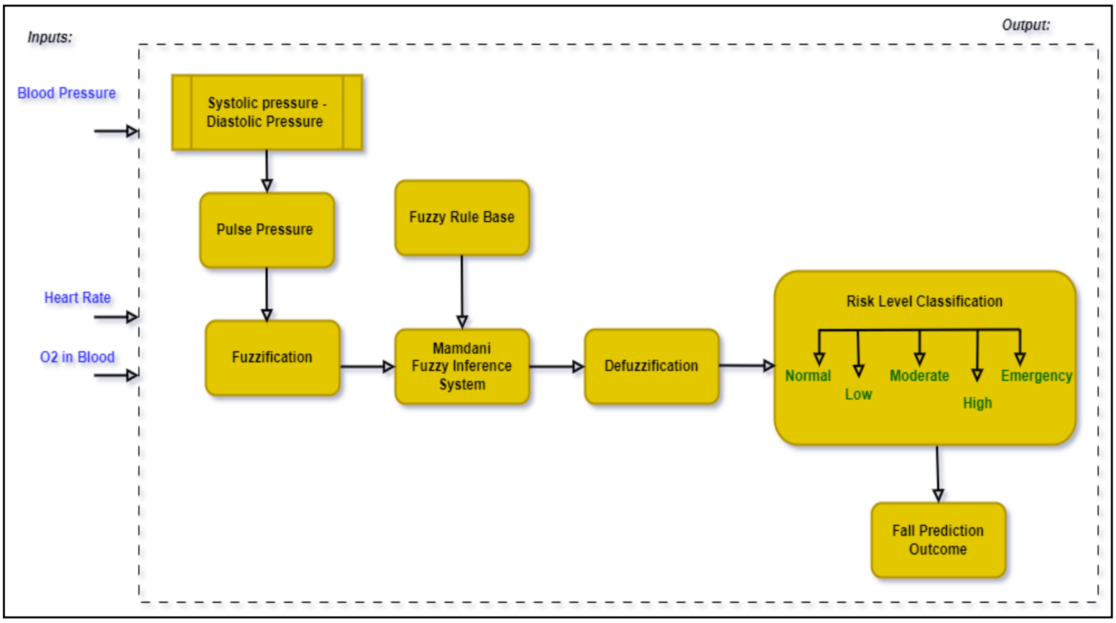


Figure 4.4: Architecture of AI-1 Fuzzy-Based Fall Risk Prediction Model.

This is the core design of the AI-1 model, and it does not require any training at this stage of the research. However, for future work, real-time vital sign data from older adults will be obtained, and training and testing will be required to validate the developed model.

4.6 Fuzzy-Based Rule Generation

Based on background analysis and expert advice, the vital sign patterns are thoroughly examined and devised 111 fuzzy rules for this research to determine the level of future fall risk in an elderly person, and the risk levels were classified as follows:

- *Normal:* no risk of fall.
- *Low:* may or unlikely to experience a fall.
- *Moderate:* risk of fall in future if this condition persists.
- *High:* high chances of falling and to seek medical help if necessary.
- *Emergency:* very high chances of fall (fall will occur in few seconds or minutes) - alert messages will be sent to the caregiver, family, and emergency services.

The Fall Prediction Algorithm is based on a set of vital sign data, as defined in Algorithm (FPA) - Pseudocode. The chosen datasets are based on age, fall history, and observed vital sign values. Several changes to the membership function and fuzzification techniques are offered to improve FPA prediction accuracy and it is one such approach that is used to simplify the input before fuzzification. The fuzzy rule is applied to each BP value's computed pulse pressure, which is calculated from the BP data.

Fall Prediction Algorithm (FPA): Pseudocode of the Proposed Model (Figure 4.4) [183]

Input: *Blood Pressure, Heart Rate and O_2 in Blood* - Datasets from public Repository.

Output*: Fall Prediction Outcome* - *Risk level classification*

1. Apply data sets for data extraction to the input datasets.
2. Feed the retrieved features to the fuzzy prediction model to train it and formulate rules for categorizing risk levels.

(a) ***Fuzzification:*** Transform crisp data into fuzzy data.

(b) ***Membership function:*** Formulate the membership function based on the parameter values (*Normal, Low, Moderate, High, and Emergency*)

Input function: 'trapmf'.

(c) ***Fuzzy Rule Generation:*** Formulate fuzzy rules from the fuzzy data.

Fuzzy rule: *Rule 1*: For **Normal** BP,

if PP is ***Normal***
and HR is ***Normal***
and O_2 is ***Normal***
then Risk Level is ***Normal*** (No risk of fall detected)

.
.
.
.

Rule 83: For High BP, (126-130/80-90)
if PP is ***High***
and HR is ***High*** (110-129 bpm)
and O_2 is ***Moderate*** (95%-96%)

then Risk Level is ***High*** (Will have a risk of falling in few days if this condition persists)

(d) ***Defuzzification:*** Transform the fuzzy rules into crisp rules.

3. Employ cross-validation on the model using the testing dataset with MFS. Evaluate the model's performance based on accuracy, specificity, and sensitivity metrics.
4. Perform evaluation results to validate the results.

When an emergency risk level is detected, alert warnings will be sent to the family and caregivers. Based on the identified threshold value and the level at which the older adult tends to feel unconscious, 111 fuzzy rules were developed to forecast future falls in the elderly. The sample test was created with Visual Studio code. The data inputs from the parameters BP, HR, and SpO_2 are chosen for the Fuzzification process, which uses a threshold-based membership function to classify the degree of risk. A Mamdani-type rule-based Fuzzy Logic technique is utilized to create the 111 health parameter rules, which use the functions *if, and, then* to compare the collected data inputs. The formulated Fuzzy rules are listed in Section A.1 of the Appendix for reference.

4.7 Membership Function and Rule Weighting

The fuzzy inference system receives crisp input which is converted using a fuzzy membership function. Furthermore, the fuzzy membership function accurately depicts the fuzziness of the data. The fuzzy set membership function defined on a disclosure space X is formally declared as μA: X → [0, 1], with each component of X translated to a numerical between 0 and 1. This value, also known as the degree of membership or the membership value, represents an element's level of membership in fuzzy set A. The fuzzy set A is derived from the universal set X. The primary input of the AI-1 model is the HR readings. Four membership functions were developed for this variable input. *Normal, Moderate, High, and Emergency* are the four categories of membership functions, in simple terms. These values are derived from Table 4.5. Since the heart rate values range from normal to emergency, the membership function has been assigned only for these specific parameters. For all other parameters listed below, the membership functions are categorized based on Table 4.5. The HR variable is estimated to be between 60 and 140 for older adults. From Table 4.5, the heart rate (HR) is categorized as follows: normal (60–100), moderate (101–109), high (110–139), and emergency (>140 or <60). Based on these ranges, the following equations were formulated to develop the membership function. Similarly, all other equations were derived using the corresponding parameter ranges. The same method is used for all of the other inputs in this research.

Figure 4.5 shows the HR membership function, which is shaped like a trapezium with modest shoulder curvature.

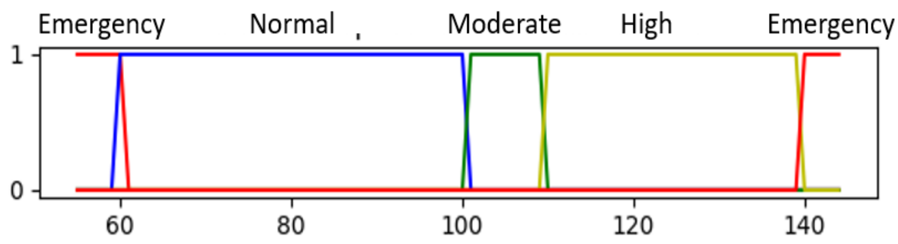


Figure 4.5: Membership Function for Heart Rate (bpm).

The membership function for HR is defined in (4.8), (4.9), (4.10), and (4.11) as follows:

1. Normal

$$\mu(x) = \begin{cases} 0 & ;\ x \leq 59 \\ \frac{x-59}{60-59} & ; 59 \leq x \leq 60 \\ 1 & ; 60 \leq x \leq 100 \\ \frac{101-x}{101-100} & ; 100 \leq x \leq 101 \\ 0 & ; x \geq 101 \end{cases} \tag{4.8}$$

2. Moderate

$$\mu(x) = \begin{cases} 0 & ;\ x \leq 100 \\ \frac{x-100}{101-100} & ; 100 \leq x \leq 101 \\ 1 & ; 101 \leq x \leq 109 \\ \frac{110-x}{110-109} & ; 109 \leq x \leq 110 \\ 0 & ; x \geq 110 \end{cases} \tag{4.9}$$

3. High

$$\mu(x) = \begin{cases} 0 & ;\ x \leq 109 \\ \frac{x-109}{110-109} & ; 109 \leq x \leq 110 \\ 1 & ; 110 \leq x \leq 139 \\ \frac{140-x}{140-139} & ; 139 \leq x \leq 140 \\ 0 & ; x \geq 140 \end{cases} \tag{4.10}$$

4. Emergency

$$\mu(x) = \begin{cases} 1 & ;\ x < 60\ and\ x > 140 \\ 0 & ;\ 60 \leq x \leq 139 \end{cases} \tag{4.11}$$

The Emergency membership function is activated when the SpO_2 value is less than 90%, the High membership function is activated when the SpO_2 value is between 90% and 94%, the Moderate membership function is stimulated when the SpO_2 value is between 95% and 96%, and the Normal membership function is activated when the SpO_2 value is between 97% and 100%. As seen in Figure 4.6, the SpO_2 membership function employs shoulder curves and a trapezium form. The membership function for SpO_2 is expressed in (4.12), (4.13), (4.14), and (4.15) as follows:

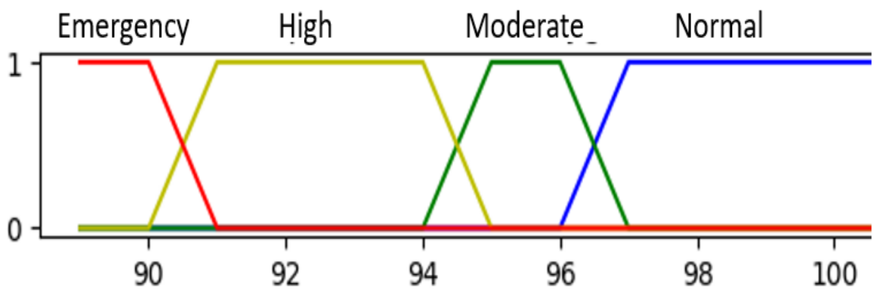


Figure 4.6: Membership Function SpO_2 Level in Blood (%).

1. Normal

$$\mu(x) = \begin{cases} 0 & ; x \leq 96 \\ \frac{x-96}{97-96} & ; 96 \leq x \leq 97 \\ 1 & ; 97 \leq x \leq 100 \\ 0 & ; x > 100 \end{cases} \tag{4.12}$$

2. Moderate

$$\mu(x) = \begin{cases} 0 & ; x \leq 94 \\ \frac{x-94}{95-94} & ; 94 \leq x \leq 95 \\ 1 & ; 95 \leq x \leq 96 \\ \frac{97-x}{97-96} & ; 96 \leq x \leq 97 \\ 0 & ; x > 97 \end{cases} \tag{4.13}$$

3. High

$$\mu(x) = \begin{cases} 0 & ; x < 90 \\ \frac{x-90}{91-90} & ; 90 \leq x \leq 91 \\ 1 & ; 91 \leq x \leq 94 \\ \frac{95-x}{95-94} & ; 94 \leq x \leq 95 \\ 0 & ; x > 95 \end{cases} \tag{4.14}$$

4. Emergency

$$\mu(x) = \begin{cases} 1 & ; x \leq 90 \\ \frac{91-x}{91-90} & ; 90 \leq x \leq 91 \\ 0 & ; x > 90 \end{cases} \tag{4.15}$$

Similarly, BP values are assigned a membership function that ranges from Normal to Emergency. As seen in Figure 4.7, the BP membership function employs a trapezium shape with mild shoulder curvature. Both Low Blood Pressure (LBP) and High Blood Pressure (HBP) are used to predict falls in the elderly. The membership function for HBP is expressed in (4.16), (4.17), (4.18), and (4.19), as follows:

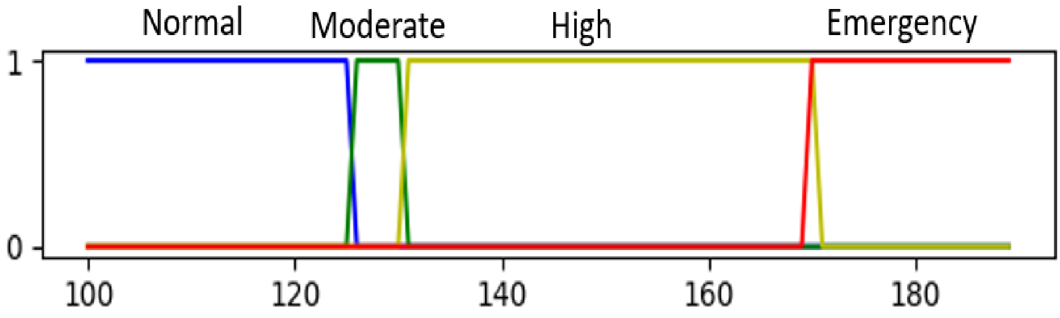


Figure 4.7: Membership Function for HBP (mmHg).

1. Normal

$$\mu(x) = \begin{cases} 1 & ; 100 \leq x \leq 125 \\ \frac{126-x}{126-125} & ; 125 \leq x \leq 126 \\ 0 & ; x \geq 126 \end{cases} \tag{4.16}$$

2. Moderate

$$\mu(x) = \begin{cases} 0 & ;\ x \leq 125 \\ \frac{x-125}{126-125} & ; 125 \leq x \leq 126 \\ 1 & ; 126 \leq x \leq 130 \\ \frac{131-x}{131-130} & ; 130 \leq x \leq 131 \\ 0 & ; x \geq 131 \end{cases} \tag{4.17}$$

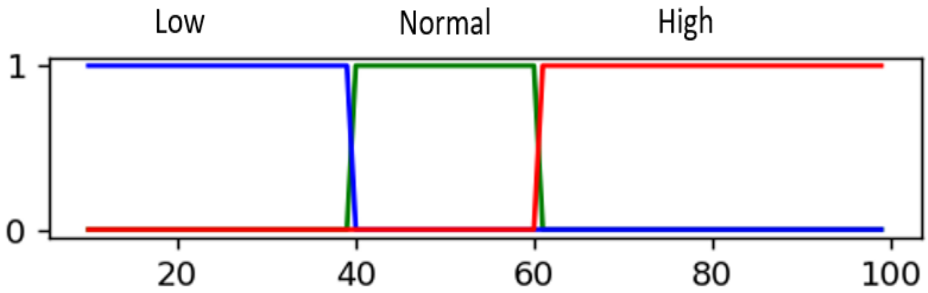
3. High

$$\mu(x) = \begin{cases} 0 & ;\ x \leq 130 \\ \frac{x-130}{131-130} & ; 130 \leq x \leq 131 \\ 1 & ; 131 \leq x \leq 170 \\ \frac{171-x}{171-170} & ; 170 \leq x \leq 171 \\ 0 & ; x \geq 171 \end{cases} \tag{4.18}$$

4. Emergency

$$\mu(x) = \begin{cases} 0 & ;\ x \leq 170 \\ 1 & ; x > 170 \end{cases} \tag{4.19}$$

The PP values are likewise assigned based on the membership function, which ranges from Normal to High. As illustrated in Figure 4.8, the PP membership function employs a trapezoidal shape, and the following is the formulation shown (4.20), (4.21), and (4.22) as follows:



:

Figure 4.8: Membership Function for PP (mmHg).

1. Normal

$$\mu(x) = \begin{cases} 0 & ;\ x < 40 \\ 1 & ;\ 40 \le x \le 60 \\ 0 & ;\ x > 60 \end{cases} \tag{4.20}$$

2. Low

$$\mu(x) = \begin{cases} 1 & ;\ x < 40 \\ 0 & ;\ otherwise \end{cases} \tag{4.21}$$

3. High

$$\mu(x) = \begin{cases} 1 & ;\ x > 60 \\ 0 & ;\ otherwise \end{cases} \tag{4.22}$$

Since a fuzzy system has a condition and a conclusion, its structure is comparable to that of an IF-THEN rule. The rule base contains a comprehensive fuzzy rule aimed at regulating the output variable [184]. Therefore, the most crucial phase in building a fuzzy-based fall prediction support system is rule formulation and weighting. The understanding of fuzzy rules is based on three sources: first the current works (such as surveys, publications, and medical journals); second the expert knowledge; and third the threshold parameter evaluation utilizing fuzzy analysis (section 4.2). The membership function (MF) ranges from MF: 0 → 1, and each risk level category is assigned a weight to the rules as shown below. *Normal - 0.2, Low - 0.4, Moderate - 0.6, High - 0.8, Emergency – 1.0*. Assuming BP value is 90/60, the systolic value (S_v) and diastolic value (D_v) are calculated as a difference to yield the PP value (S_v - D_v), which is 30. As a result, the developed prediction rules are: *"IF BP 90/60 and PP is less than 40, HR is 102, and O_2 is 95, THEN risk of fall is 0.6"*. Similarly, *"IF BP 120/80, PP 40, HR 90, and O_2 97, THEN the risk of fall is 0.2"*.

In order to produce fuzzy values from a collection of rules that contain numerical figures, the suggested automated method depends on the development of fuzzy modalities. The previous decision rules have IF and THEN sections, where the IF section gives the quantitative variable and the THEN section indicates the class label. The fuzzy membership function converts the quantitative variable provided in the IF section of the decision rules into a semiotic variable first, and the fuzzy rules' THEN section is comparable to the decision rules. For example, the generated Fuzzy rules will be, *"IF BP is HIGH, PP is LOW, HR is MODERATE, and O_2 is MODERATE, THEN the risk of fall is MODERATE"*. In a similar vein, all decision rules with numerical variables are handled and then uses a membership function to transform them into fuzzy rules. Figure 4.9 provides an example to illustrate how the fuzzy rule assessment works. Similarly, all decision rules are processed using numerical variables before being transformed into fuzzy rules using the membership function (FPA Algorithm). Defuzzification is then performed, and the various fall risk categories are generated. The results are validated by comparing the fuzzy model's prediction accuracy, sensitivity, and specificity to previous research.

Defuzzification: A fuzzy set (the combined fuzzy set output) is used as the input values for the defuzzification process to obtain a single integer. Following that, membership functions are used to map fuzzy sets to an exact output. The presented model employs a centroid defuzzification technique proposed in [176], which reduces the number of conclusions (μ_i) with various membership functions to a single-point output (X) which is mentioned in (4.23) as follows,

$$X^* = \frac{\sum \mu_i(X_i)X_i}{\sum \mu_i(X_i)} \tag{4.23}$$

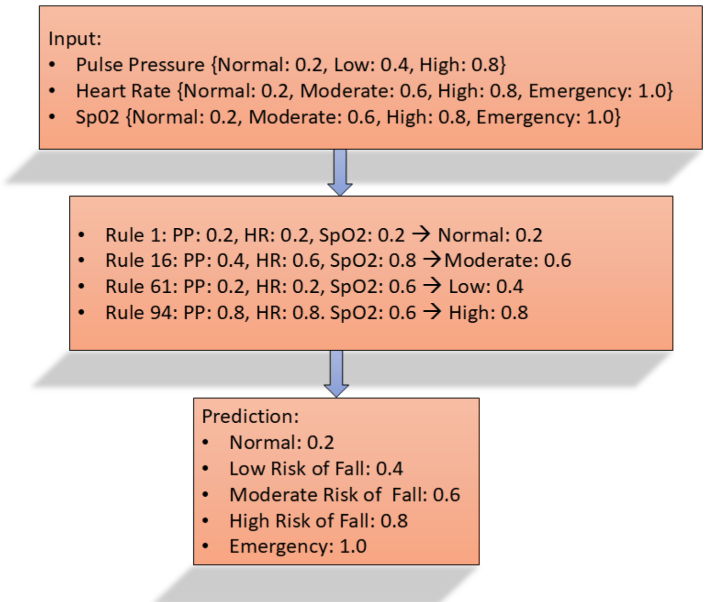


Figure 4.9: Fuzzy Rule Evaluation Metrics.

4.8 Evaluation of AI-1 Model

The validation of the proposed fuzzy logic model is presented in this section. It discusses the experimental risk prediction results from the Fall Prediction Support System. In this context, the suggested system's effectiveness is evaluated by comparing it to a Fuzzy Decision Support System and a Fall Prediction Assessment Tool. Visual Studio Code and Python ver.10.6 is used to implement the recommended technique. Windows 10 Enterprise, with its 3.00 GHz, 11th Gen Intel (R) Core (TM) i7 processor and 32 GB of internal RAM, is used to run the simulation.

4.8.1 Evaluation Metrics

According to the evaluation metrics outlined in [162], a test is considered sensitive when it accurately estimates the risk of falling. To calculate it, first, the proportion of true positives is determined. Specificity describes a test's capacity to anticipate a healthy outcome reliably. Calculating the percentage of true negatives at the normal level can help us estimate them. The ability of a test to accurately distinguish between risk and normal levels is an indicator of its accuracy. To determine a test's accuracy, the proportion of true positive and true negative results must be calculated in all investigated cases. The following can be stated mathematically using (4.24), (4.25), (4.26), and (4.27).

$$Sensitivity = \frac{TP}{TP+FN} \tag{4.24}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4.25}$$

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{4.26}$$

$$Predictability = \frac{TN}{TN+FP} \tag{4.27}$$

4.8.2 Data Collection – Vital Sign Data

The proposed model is tested with real-time data from a prior study and vital sign datasets supplied from the PhysioNet and Open-Source Files (OSF) repositories. These datasets have the following features:

- Age
- Sex
- Systolic Blood Pressure
- Diastolic Blood Pressure
- Heart Rate
- Oxygen Saturation (SpO_2)

Table 4. 6: Fall Risk Prediction Metrics

Prediction Class	Binary Classifier	Description
True Positive (TP)	1	when a risk of fall is identified
True Negative (TN)	0	when the participant has no risk of fall (normal/healthy)
False Positive (FP)	1	when a healthy older adult is notified of a risk of a fall (false alarm)
False Negative (FN)	0	when there is a risk of fall but notified as normal

The first dataset, obtained from the OSF repository [184], comprises mixed information about both fallers and non-fallers and the vital signs were recorded using a smartwatch. This is used to validate the developed fuzzy-based fall prediction model against the theoretical analysis. The second dataset (Source 1), acquired from an earlier study, contains information about an elderly person who is 85 years old, has been observed for two months, and has fallen more than twice a year [185]. The third dataset (Source 2) was obtained from PhysioNet, a source that provides vital sign data from patients aged 60 and up who are admitted to hospitals for health issues and general medical [186], and the final dataset (Source 3) is also obtained from PhysioNet [187] based on participants in the Early Prediction of Sepsis study. The MFS is then used to assess the findings' accuracy. The fall risk prediction approach uses the metrics from Table 4.6. with a binary classification system to predict fall risk. A true positive (TP) = 1, is recorded when a risk of a fall is identified, and a true negative (TN) = 0, when there is no risk of a fall identified which means the older adult is healthy and cannot predict any chance of future falls. Likewise, a false positive (FP) = 1, is indicated when the false alarm is activated which means a healthy older adult is notified of the future risk of fall, and a false negative (FN) = 1, is activated when an older adult is at a risk of fall but informed as healthy.

4.8.3 Morse Falls Scale (MFS)

MFS is probably the widely used tool in New Zealand healthcare system for assessing, and managing fall risks in patients, particularly the elderly. The MFS has been predominantly included in the criteria established by many healthcare organizations within hospitals and extended care facilities to identify patients at high risk of falls and take some measures for protection against falls. The Health Quality and Safety Commission in New Zealand noted the importance of developing individualized care plans that deal with the major fall risk factors identified by the MFS tool. Their recommendations advocate an in-depth assessment and tailored intervention to bring about a decrease in falls. A study in [188] investigated the MFS's prediction power for falls in older adults.

MFS-informed treatments resulted in a 30% reduction in fall incidence. A study in [189] created an AI-based model that combined MFS with live monitoring data to produce accurate predictions. Their model had an 18% improvement in prediction accuracy compared to MFS only. Research in [190] conducted a study comparing conventional MFS scoring to wearable sensor data in older adults. It was discovered that by combining these two, sensitivity in fall prediction could be increased by 22%. A tool in the assessment of fall risk, the Morse Fall Scale is widely used within hospitals, long-term care, and research. More recent works increasingly employ AI, wearable devices, and machine learning algorithms for improved predictive outcomes. Future technological advancements may look to real-time monitoring and AI notification to even better improve efforts at preventing falls.

Yet, it has been noticed that there is inconsistency in the use of the MFS across different healthcare settings. In summary, the MFS stands at the heart of New Zealand's approach to preventing patient falls, and there are attempts to recognize and address some of these system-wide challenges confronting the implementation of that scale. This was the primary reason for employing MFS in this research, and even more importantly, it matched the parameters and risk level predictions of the final risk results. MFS categorizes elderly fall risk levels as low (24), moderate (25-44), or high (45), while this research study elaborated in the thesis categorizes the final risk of falls as Low, Moderate, and High. Even though the scales are different, they correspond to similar risk indicators. Figure 4.10 depicts the MFS calculator.

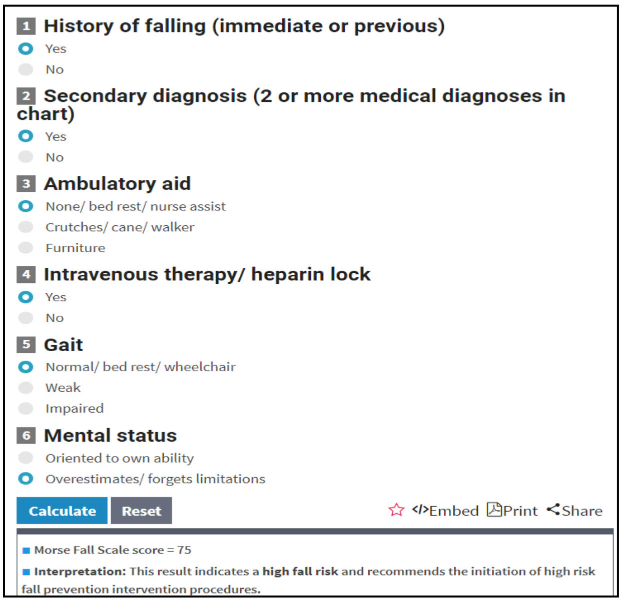


Figure 4.10: MFS Calculator.

4.8.4 Verification of the Developed AI-1 Model with Theoretical Analysis

From Section 4.8.2, the vital sign data of 50 participants (all over 60 years) was considered for this verification process. This test was conducted to verify the prediction accuracy of the developed fuzzy logic (VS code) simulation results with the theoretically formulated fuzzy rule. Initially, the coding was developed using VS Code utilizing all the 111 Fuzzy rules and the Fall prediction algorithm. The fall risk prediction model's output is divided into five risk categories: *Normal, Low, Moderate, High, and Emergency*. The scale for each prediction risk level is as follows: *Normal* (0-0.20), *Low* (0.21-0.40), *Moderate* (0.41-0.60), *High* (0.61-0.80), and *Emergency* (0.81-1.0). For every individual participant, the rule was calculated manually, and the prediction levels were identified which is the actual_risk (orange graph) as indicated in Figure 4.11. Then the entire data of all the 50 participants were simulated using the codes and the predicted_risk (blue graph from Figure 4.11) for each individual was analyzed. Finally, both the results were compared, and the comparison results are shown in Figure 4.11 which suggests the fuzzy-based fall risk prediction model which incorporates vital sign data of senior citizens (60 years and older) produced accurate predictions as expected.

With TP (21), TN (25), FN (4), and FP (0), the model achieved 92% accuracy, 100% specificity, 84% sensitivity, and 100% predictability. This test was conducted to determine the correctness of the suggested algorithm and fuzzy rule, as well as to incorporate them into the prediction model. Based on the results obtained, a few modifications were made in the code and in the fall prediction algorithm to enhance the accuracy of prediction. The main advantage of this prediction system is that it can accurately forecast the risk of falling in older adults simply by looking at their vital sign data, regardless of whether they have previously fallen or not. The emergency prediction is only activated when the elderly individual is about to fall in a matter of seconds or in a severe condition.

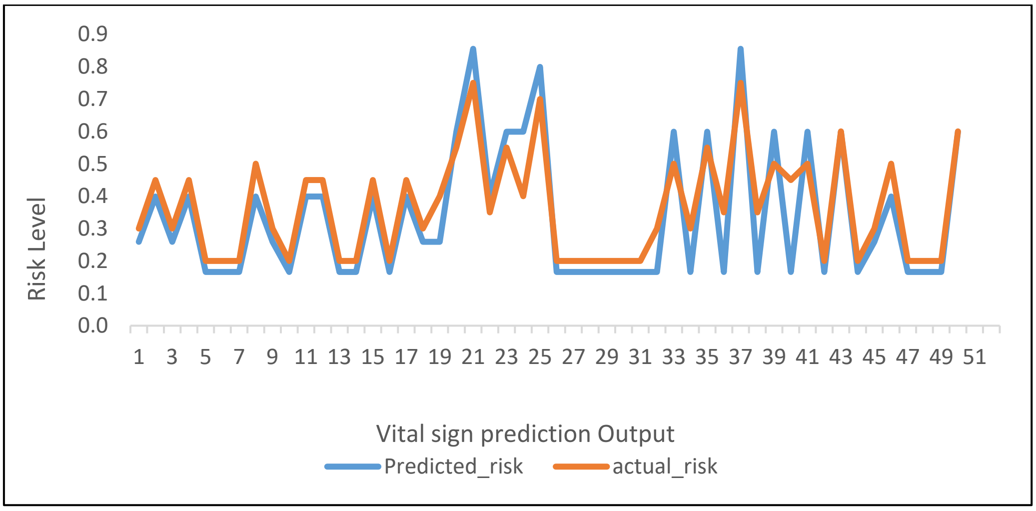


Figure 4.11: Fall Risk Prediction Evaluation Results.

4.8.5 Evaluation of the AI-1 Model with Data from a Public Repository and Existing Work

In this section, the developed and verified Fall Risk Prediction Model (AI-1 model) will be compared with data obtained from three distinct sources. The MFS is then used to evaluate the accuracy of the findings. Section 4.8.5.1 examines the validation of the proposed model using the evaluation results from a prior study [185], and section 4.8.5.2 analyses the model validation in conjunction with data collected from individuals admitted to the eICU and hospital for routine checkups [186]. Finally, section 4.8.5.3 discusses the accuracy assessment of the AI-1 model using the Sepsis research [187].

4.8.5.1 Source – 1 Validation: Datasets obtained from Elderly 85 years old with Multiple History of Falls [185]

In the second stage of evaluation, the prediction results were compared with an existing work that uses a similar approach. The data was collected from an elderly participant 85 years old who has been observed for two months and has fallen more than twice a year. Even though only a few information on older individuals was obtained from this existing research work, some important variables are taken into consideration, including blood pressure, heart rate, SpO_2, medication, history of falls, and breathing rate. Previous research solely relied on systolic blood pressure values for prediction analysis based on the acquired blood pressure readings. In contrast, this novel research approach incorporates both systolic and diastolic values to calculate pulse pressure, which is then internally integrated within the prediction model. This data was loaded into the developed fall prediction algorithm, which used this information and predicted a fall risk indication of "*High Fall Risk*" (Risk score – 71.7). The proposed system's results are then compared to those of the MFS risk assessment. The MFS ranges from (0-100), while this developed work scale is from (0-1). To match up with the MFS the scaling of the proposed model has been converted to 0-100 from 0-1, where Normal (0-20), Low (21-40), Moderate (41-60), High (61-80), and Emergency (80-100). Despite the variation in scaling between these two models, the risk indicators are the same. As a result, the risk assessment was conducted using MFS, and the anticipated MFS risk indication was "*High Fall Risk*" (Risk score 75). From the prediction comparison, this developed system has a predictive ability similar to MFS. The result of the simulation is illustrated in Figure 4.12, which demonstrates how the developed model predicts levels of fall risk from values in input datasets. The model translates the data input and allocates the risk levels based on it, enabling a structured calculation of fall probability. Figure 4.13 presents the predicted risk score generated by the model as 71.7, which represents the final prediction score. This outcome was independently verified through manual mathematical calculations, confirming that the model's computations were accurate. To further ensure the reliability of the developed model, an analysis was conducted in which the prediction results were individually cross-checked against the outcomes derived from the fuzzy rules. In addition, Figure 4.14 displays the outcome of using the Morse Fall Scale (MFS), a validated clinical assessment tool used to determine the risk of falling. The outcome of the MFS is a fall risk score of 75, which closely approximates the 71.7 predicted by the simulation with both the AI-1 model and MFS predicting a High Risk of Fall. This concordance between the output of the model developed and the validated clinical scoring system adds further support for the validity and accuracy of the proposed fall risk prediction model.

```
import numpy as np
import pandas as pd
import skfuzzy as fuzz
from skfuzzy import control as ctrl
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score

# Step 1: Load and preprocess your dataset
# Replace 'your_dataset.csv' with the path to your dataset file
dataset = pd.read_csv('realtimedata.csv')

# Perform data preprocessing here (e.g., cleaning, feature engineering)

# Define input variables (features) and output variable (fall risk)
# Example: Age, Gait Speed, and Fall Risk
pulse_pressure = ctrl.Antecedent(np.arange(0, 101, 1), 'pulse_pressure')
#heart_rate = ctrl.Antecedent(np.arange(50, 151, 1), 'heart_rate')
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL COMMENTS

```
Data Point 23: Predicted Fall Risk = 25.999999999999996
Data Point 24: Predicted Fall Risk = 25.999999999999996
Data Point 25: Predicted Fall Risk = 16.666666666666664
Data Point 26: Predicted Fall Risk = 16.666666666666664
Data Point 27: Predicted Fall Risk = 25.999999999999996
Data Point 28: Predicted Fall Risk = 25.999999999999996
Data Point 29: Predicted Fall Risk = 16.666666666666664
Data Point 30: Predicted Fall Risk = 16.666666666666664
Data Point 31: Predicted Fall Risk = 25.999999999999996
Data Point 32: Predicted Fall Risk = 25.999999999999996
Data Point 33: Predicted Fall Risk = 16.666666666666664
Data Point 34: Predicted Fall Risk = 25.999999999999996
```

Figure 4.12: Simulated Results from the Developed Model.

pulse_pre	heart_rat	spo2	risk level	predcitior	binary	actual	binary	
48	90	98	17	0.2	0	0.2	0	
37	92	97	17	0.2	0	0.2	0	
41	85	97	17	0.2	0	0.2	0	
44	90	97	17	0.2	0	0.2	0	
45	92	97	17	0.2	0	0.2	0	
32	94	98	17	0.2	0	0.2	0	
42	89	98	17	0.2	0	0.2	0	
35	95	99	17	0.2	0	0.2	0	
41	91	99	17	0.2	0	0.2	0	
36	100	97	17	0.2	0	0.2	0	
43	94	98	17	0.2	0	0.2	0	
40	78	95	26	0.3	0	0.2	0	
40	80	95	26	0.3	0	0.2	0	
45	82	98	17	0.2	0	0.2	0	
49	91	97	17	0.2	0	0.2	0	
70	93	97	40	0.4	1	0.4	1	TP
38	85	96	40	0.4	1	0.3	0	FP
33	82	97	17	0.2	0	0.2	0	
42	85	98	17	0.2	0	0.2	0	
36	85	95	40	0.4	1	0.3	0	FP
48	88	99	17	0.2	0	0.2	0	
51	85	99	17	0.2	0	0.2	0	
57	88	96	26	0.3	0	0.2	0	
40	88	96	26	0.3	0	0.2	0	
43	94	97	17	0.2	0	0.2	0	
44	65	97	17	0.2	0	0.2	0	
43	92	95	26	0.3	0	0.2	0	
41	82	96	26	0.3	0	0.2	0	
40	82	97	17	0.2	0	0.2	0	
41	85	97	17	0.2	0	0.2	0	
59	85	95	26	0.3	0	0.2	0	
41	85	96	26	0.3	0	0.2	0	
42	88	97	17	0.2	0	0.2	0	
41	85	96	26	0.3	0	0.2	0	
		MFS	717	71.7				

Figure 4.13: Predicted Risk Score from the Developed Model.

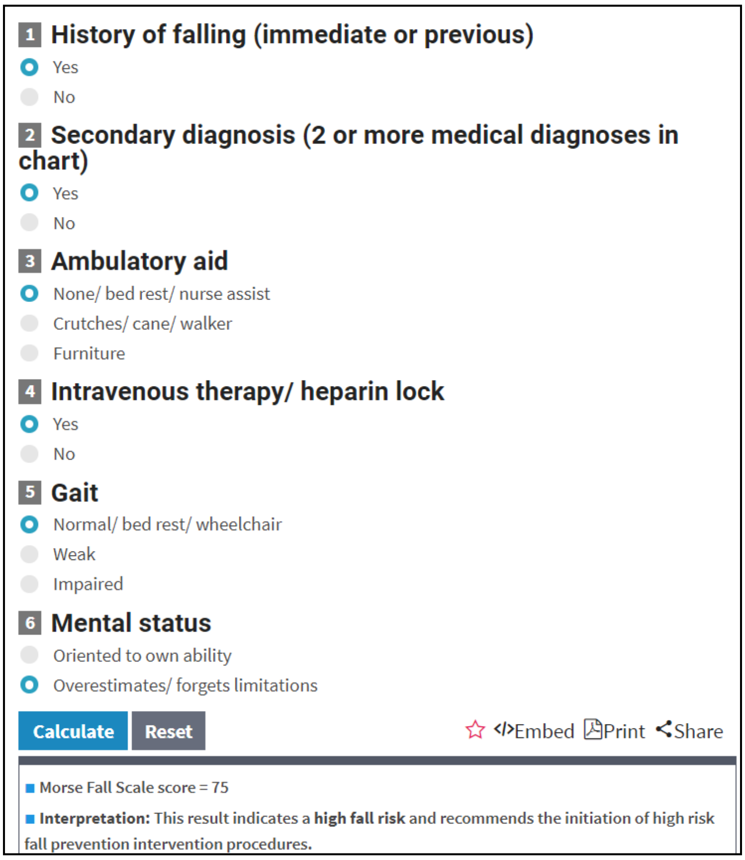


Figure 4.14: Results from MFS Assessment Tool.

4.8.5.2 Source – 2 Validation: Datasets obtained from PhysioNet based on an eICU Collaborative Research Database [186]

This results analysis makes use of vital sign data from 10 older adults. The vital sign data was collected during their stays at various hospitals in the United States between 2014 and 2015 [186]. Participant 1 (P1) has a history of coronary artery disease, while Participant 2 (P2) has had aortic valve replacement and is diabetic. Participant 3 (P3) was admitted for carotid surgery, and he has no previous health history, indicating that the patient is healthy based on the documents presented. Similarly, Participant 4 (P4) had a peptic ulcer (non-inflammatory illness) and was being treated for hypertension. Participants 5, 6, and 8 (P5), (P6), and (P8) were being treated for hypertension. Participants 7, 9, and 10 (P7), (P9), and (P10) have no previous health history. The obtained vital sign datasets of all 10 participants were loaded into the developed fall prediction model. The results obtained from fall prediction model show a "*High risk of fall*" (73%) for P1, for P2 "*High risk of fall"* (72%), for P3 "*Normal - no risk of fall"* (25%), for P4, P5, and P6 "*Low risk of fall*" (36%, 34%, and 47%), for P7 and P8 "*Normal - no risk of fall"* (16% and 11%), for P9 "*Moderate risk of fall*" (62%), and for P10 "*Normal*" (25%).

The acquired vital sign data was also analyzed with MFS, and the findings were compared to the developed model. The MFS results indicate a prediction risk indicator of "*High risk of fall*" for P1 and P2 (70%), "*Low risk of fall*" for P3 and P4 (20%), "*Moderate risk of fall*" for P5 and

P9 (35%), "*Low risk of fall*" for P6 (15%), "*Low risk of fall*" for P7, P8, and P10 (0%). The MFS scales from 0 to 100, including *low, moderate, and high fall risk* levels. Even though the risk level (%) fluctuates, the established model and MFS provide the same indication of fall risk prediction. To line up with the MFS, the scaling for the developed model has been converted to 0-100 to showcase the results, which has been discussed in Table 4.7 which provides a comparison result analysis of the generated model and the MFS utilizing data from Source 2.

Table 4. 7: Comparative Result Analysis using Source 2

		Proposed Model		**MFS**	
Participants	**Age**	**Predicted Risk Level**	**Predicted Fal Risk Indicator**	**Risk Level**	**Fall Risk Indicator**
P1	76	73	High	70	High
P2	67	72	High	70	High
P3	77	25	Normal	20	Low
P4	81	36	Low	20	Low
P5	84	34	Low	35	Moderate
P6	89	47	Low	15	Low
P7	68	16	Normal	0	Low
P8	74	11	Normal	0	Low
P9	89	62	Moderate	35	Moderate
P10	77	25	Normal	0	Low

4.8.5.3 Source – 3 Validation: Datasets obtained from PhysioNet based on Early Prediction of Sepsis Clinical Data [187]

The data gathered from this clinical investigation included information on participants of various ages. However, for this study, only the necessary data on individuals aged 60 or older who did not have Sepsis was retrieved and used for the outcome analysis. A total of 10 participant datasets (each participant with more than 500 vital sign information checked independently) that met these requirements were acquired from this database and used as input for the developed fall risk prediction model. It is clear from comparing this data with the MFS that the results produced by the model that was developed closely matched those of the MFS. Table 4.8 shows a comparison result analysis of the generated model and the MFS utilizing data from Source 3. It is evident from the result analysis that using data from three distinct sources and the prediction results the developed fall risk prediction algorithm produces precise predictions based on the vital signs metrics. Examining the results for each source reveals that there is only a slight divergence from the MFS. Both the proposed model and the MFS produce comparable fall risk indicators.

Table 4. 8: Comparative Result Analysis using Source 3

Participants	Age	Proposed Model		MFS	
		Predicted Risk Level	**Predicted Fal Risk Indicator**	**Risk Level**	**Fall Risk Indicator**
P1	83	57	Moderate	35	Moderate
P2	68	42	Low	10	Low
P3	70	40	Low	15	Low
P4	70	72	High	70	High
P5	75	22	Normal	0	Low
P6	62	22	Normal	0	Low
P7	88	22	Normal	15	Low
P8	77	37	Low	25	Moderate
P9	83	48	Low	15	Low
P10	81	20	Normal	15	Low

A total of 1159 vital sign data from 21 participants (Sources 1, 2, and 3) were used for simulation from the public repository, and the FPA approach was utilized to evaluate input data. In comparison to the Morse Falls Scale, the model produced TP (15), TN (5), FN (1), and FP (0), yielding an accuracy rate of 95.24%, specificity of 100%, sensitivity rate of 93.75%, and predictability of 100%. The emergency risk level indicator has not yet been tested using the current model. This can only be deduced during real-time testing, although real-time continuous data from elderly people may cause some alterations to the previously developed fuzzy rule. This will be considered for future work.

4.8.5.4 Initial Testing of the Developed Model- Smart Watch Integration Using Fuzzy Logic

A Tuya-enabled elderly smart watch (basic model with the health parameter) is used for this integration. Tuya is an AI and IoT platform service provider that offers cloud-based development and management platforms for programming, managing, and monitoring smart homes. Because this smartwatch contains a Tuya-controlled chip, it can be simply integrated with the Smartlife software. Initially, this research was funded by Callaghan Innovation from June 2022 – November 2023. During this period, the AI-1 model testing was carried out in Smartlife (IoT-based smart home company – Northshore, Auckland, NZ). The fuzzy rule and the fuzzy-based fall prediction algorithm were developed, and the model was integrated using the Smartlife app developed from Smartlife.

Model Specification: Figure 4.15

Type: Smart Watch

Model: KUMI KU3S
Technology: Bluetooth and Alexa control
Health Data Tracking: Yes
Battery Capacity: 175mAh (can use it in full operation mode for a week without charging)

Figure 4.15: Model of Tuya-Enabled Smartwatch.

The pairing is done through the Smartlife Air application platform where all the third-party devices are linked to the main cloud. Once after connecting the Smartwatch with the Smartlife Air app, the information from the watch is collected and recorded into the cloud. The Fuzzy Logic rule-based algorithm is now implemented so that from the received input (health data from Smartwatch) the AI-1 model compares Blood pressure, Heart Rate, Pulse Pressure, and SpO_2 with the Fuzzy Rule and it identifies the Risk of a fall if any abnormality is detected. For the initial testing and to understand the reliability of the Smartwatch, the logic is created manually in the app, and the Fuzzy Logic-rule algorithm is then utilized to automatically predict the risk of a fall and inform the outcome using the physical prototype. Additional testing features such as Watch status (Online/Offline), SpO_2 status (Low/Normal), and heart rate status (Low/Normal/High) are created in the Smartlife app. Figure 4.16 illustrates the integration of the Smartwatch with the Physical prototype.

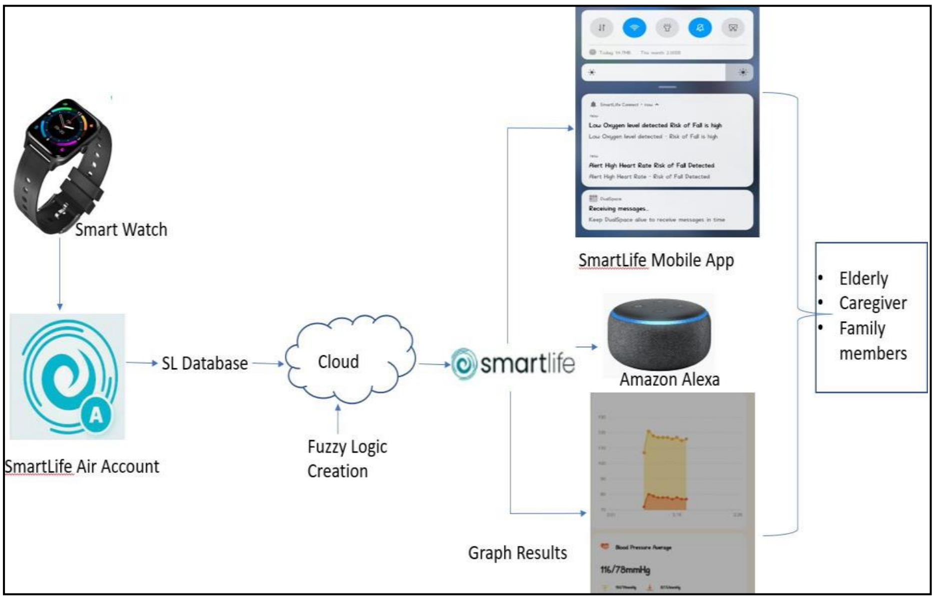


Figure 4.16: Smart Watch Integration Using Physical Prototype.

After the device connection and logic creation, an invitation will be sent to the Caregiver/ family members from the elderly participant's physical prototype, and upon accepting it, the family member/caregiver will get information about the health condition of the older adult. The data based on the health parameter will be compared with the logic, for example: if the measured Heart rate is High, then on comparing the value with the Fuzzy Logic rule, the alert message will be sent to the elderly and their direct links alerting them about the risk level and chances of falling. Figure 4.17 shows the results from the physical prototype. From the outcome received, a high heart rate and low oxygen level have been identified, hence the status is displayed as High risk of fall, and a notification will be sent to the older adults and their family members notifying the risk of fall. The final output will be obtained through the mobile app, Amazon Alexa. From the graphical representation, the status of fall risk will be sent to the linked contacts via notification/alert messages based on the severity of the identified abnormality.

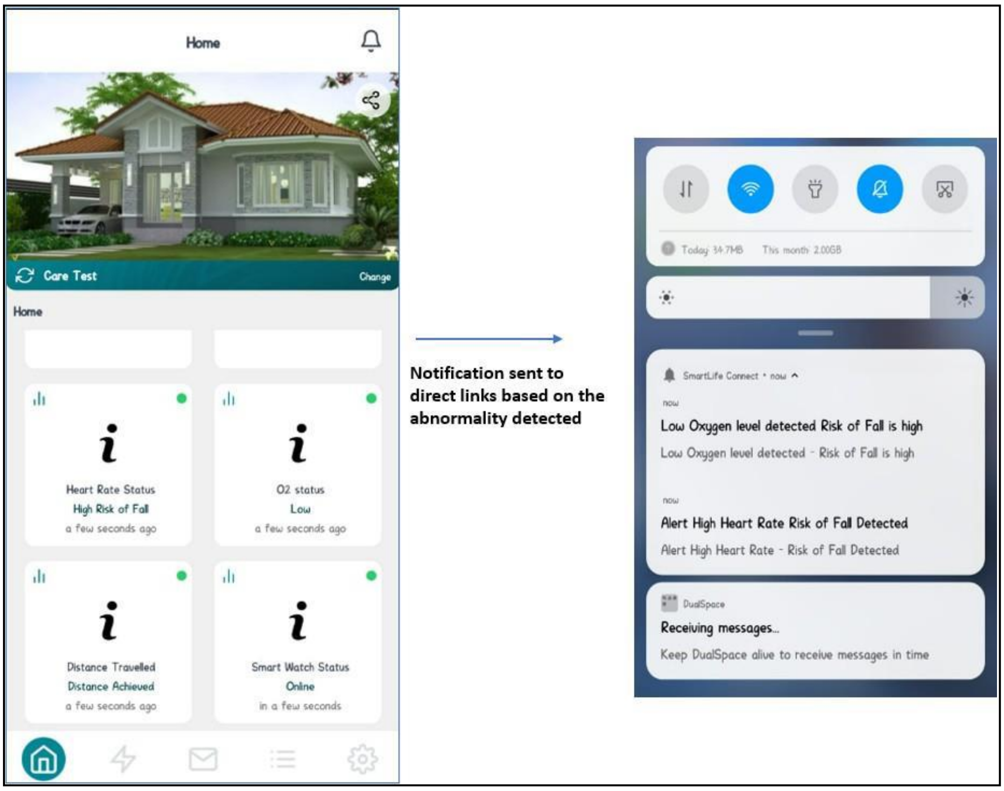


Figure 4.17: Risk Alert Notification through Physical Prototype.

This physical prototype offers several potential applications:

- **Life-Saving** – helps prevent falls and reduces the risk of injury.
- **Independent Living** – enables individuals to live confidently without constant reliance on others or fear of falling.

- **Early Disease Prediction –** supports proactive healthcare by facilitating early detection of health conditions and can be extended to broader healthcare monitoring services, particularly in elderly care.
- **Safety and Security** – ensures a safe, non-invasive system that alerts caregivers in case of emergencies or potential risks.
- **Smart Device Integration** – the concept can be further expanded to other health-related applications and integrated with smart healthcare technologies.

4.9 Conclusion

The aim of the proposed Fuzzy-Based Fall Risk Prediction Model (AI-1 model) is to predict older adults at risk of falls so that the economic and personal burden relating to injuries caused by falls can be minimized. This developed model would be a very good companion for older people, possibly those who live alone, as it educates them about falling risks and the prevention of any further falls. The model focuses on continuous monitoring of vital signs (blood pressure/ heart-rate/ blood oxygenation) for early detection of fall-related abnormalities. Integrating this model into smartwatches for real-time monitoring can alert the elderly and their caregiver in most cases, enhancing proactive fall prevention. This is demonstrated and proved in the above section. One of the advantages of the proposed model is the accuracy level of 95.24% accuracy with 100% specificity and 93.75% sensitivity with respect to the MFS using data from three sources. Further analysis based on behavior parameters will be carried out in the next chapter to derive conclusive predictive values of the model in terms of types of falls that can be avoided. The future goal of this work is to develop an overall fall risk monitoring system to predict a future fall in older adults involving real-time motion data integrated with vital sign monitoring. This is also discussed in the next coming chapters.

Chapter 5. Proposed AI-2 Model: Deep Belief Network-Based Fall Risk Prediction System

5.1 Introduction

The development of advanced monitoring techniques as well as the prediction and prevention of falls in the elderly population have been the primary focus of recent research. High-performance fall prediction requires a comprehensive understanding of key features such as gait measurements, balance, muscle strength, and environmental factors. According to studies in [191], 50%-80% of patients admitted to emergency departments for falls with injuries identify environmental home risks as the cause of their falls. Determining these indicators, along with the integration of wearable sensor data, medical history, and demographic data, can significantly improve predictive precision. This chapter provides an overview of the development of an intelligent fall risk prediction model that forecasts future falls among the elderly by continuously monitoring their ADLs and detecting abnormalities. To demonstrate the capabilities of deep learning to anticipate early fall risk, the model is built on a DBN and uses advanced AI techniques such as contrastive divergence for pre-training, backpropagation for fine-tuning, and the Adam Optimizer for minimizing loss. This could lead to more prompt treatment, lowering the frequency and severity of falls among the elderly. Evaluation of the developed model is achieved by assessing prediction outcomes with conventional fall prediction techniques and Ground Truth (GT). These findings demonstrate that contemporary deep learning technology can be effectively used to improve earlier fall risk prediction, hence minimizing the likelihood and severity of falls among the elderly. DBN's success exemplifies AI's transformative potential in elder care, enabling autonomy and optimizing quality of life. The extraordinarily high sensitivity and specificity rates represent significant advancements over prior falling prediction methodologies, with this technology providing a useful aid to fall prediction.

5.2 Behaviour-Based Monitoring

Behavioural monitoring, which uses sensors with artificial intelligence algorithms and wearable sensors, aims to detect health risks such as falls and declining cognitive capacity [192]. This gives the healthcare professionals information the knowledge of whether the medicine is being misused or is no longer effective by observing changes in behaviour, mood, and movement. The use of smart home technology and remote health monitoring supports the concept that assisted living facilities can enter real-time alerts and predictions. Studies in New Zealand [193], such as at AUT and the University of Otago, have looked into AI-based monitoring systems and smart home technologies, pushing for a method that might lead to independence and fall prediction.

Figure 5.1 shows the range of smart devices used for behaviour-based monitoring in older adults.

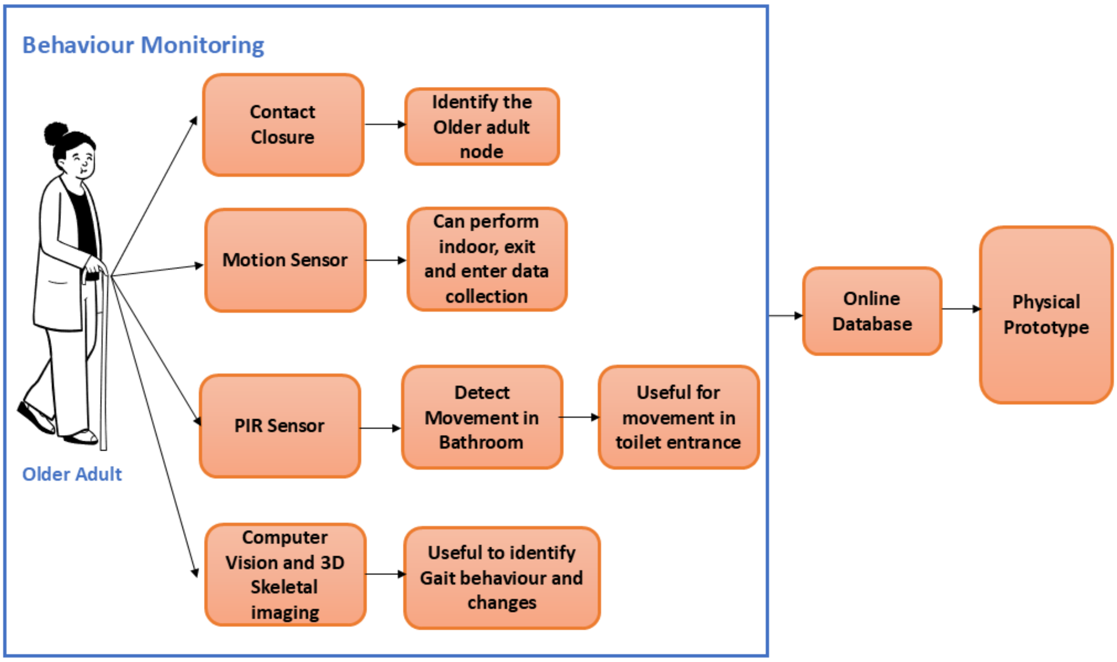


Figure 5.1: Behaviour-Based Monitoring Smart Devices.

Vision-based methods concentrate on depicting, segmenting, and recognizing human motions that include hand and body gestures as well as facial expressions. As a result, computer vision encompasses various techniques that act in both temporal and spatial realms. A study in [31] addresses the critical topic of forecasting falls, particularly flat falls, which can result in significant injury to the elderly. It describes a unique method for detecting gait patterns using computer vision and machine learning algorithms, to improve fall prediction accuracy. To highlight some of the numerous gait motions, 750 recorded clips of participants performing various activities such as walking and simulated falling are analyzed. Pose estimation and feature extraction algorithms are used to identify key spots on the human body in motion pictures and extract meaningful gait dynamics features such as stride, length, speed, and physical posture. Four machine learning algorithms such as CNN, SVM, KNN, and LSTM neural networks are utilized to automatically categorize three different gait patterns. The proposed strategy is 94.5% accurate in flat fall prediction and outperforms previous methods.

Similarly, a study in [34] suggested using deep learning to foresee falls among the elderly through a real-world dataset built by observing 50 individuals' walking patterns for 60 seconds at 50 frames per second. This dataset consists of recordings of individuals conducting various activities such as normal walking and simulated falls, and it is critical to the model's training for normal versus abnormal gait pattern distinction. Before analysis, data is pre-processed, including normalization and segmentation of gait cycles, to improve quality and ensure that it meets the requirements for deep learning models. For the model to learn efficiently from time-series data, the gait images are processed to extract features using CNNs, and the gait sequences and temporal correlations are learned using LSTM networks. The suggested Deep CNN (DCNN) model is compared to the standard CNN and ResNet50 models, and it is discovered that the DCNN has a high detection probability with a low number of false positives. In comparison to traditional models, the suggested DCNN has the greatest prediction rate of 98.64%.

In [194], a study was undertaken to enhance the accuracy of fall prediction systems by analyzing human bone critical points to predict falls in the elderly. Data was collected using motion capture techniques to obtain the skeleton critical points of various actions, such as walking and falling. The study makes use of the University of Montreal's publicly available Multiple Cameras Fall dataset, which contains 192 recordings of 24 different fall scenarios captured from various angles using eight cameras. The model identifies major skeletal locations, such as joints and limbs, that represent a person's posture and movement patterns. Transfer learning is subsequently applied to train a CNN on this database, resulting in a new fall prediction model. This approach is unique in that it uses bone maps created from photographs for fall prediction. The final experimental findings suggest that the new system has an accuracy rate of 91.7%.

A study published in [195] describes a cutting-edge strategy for detecting and forecasting falls using transfer learning and transformer models. The MPOSE dataset contains 15,429 samples from 100 people across 20 activities such as walking, jogging, and so on. Pre-trained CNNs, such as ResNet, are used to extract video frame information. These attributes are fed into a transformer model, which outperforms temporal sequence analysis using attention mechanisms to identify major frames concerning falls. Transfer learning, combined with transformers, is used to improve fall detection and prediction. The transformer model processes sequential video data, identifying frames with a higher fall risk to improve the system's prediction power. The model achieved 96.4% fall detection accuracy by combining transfer learning for feature learning and transformers for temporal analysis.

Gait has also been recognized as a primary indicator of falls and fall risk evaluation. Another method of evaluating an individual is to look at their gait symmetry and stability, which shows constancy of safe movement [165]. A study in [30] discusses using wearable technology to predict fall risks among older adults who live independently, emphasizing the growing problem of falls leading to serious outcomes such as fractures and hospitalization. The investigation included 171 individuals aged 56 to 90, with a mean age of 74.3 ± 7.6 years. All the participants walked ten meters while wearing wireless sensors on their chests. To build the model, 127 individuals' trunk movements were analyzed for fall risk, and to differentiate fallers from non-fallers the linear and nonlinear approaches were used. The wearable sensors continuously evaluated gait, balance, mobility, and other biomechanical factors without requiring intrusive procedures. Machine learning methods such as decision trees, SVM, and neural networks were used to classify the obtained data as low or high fall risk. The models were further evaluated against actual fall incidences collected during the study, with the neural network providing the highest accuracy (87%).

Similarly, a study in [196] focuses on explainable predictions and examines how gait analysis and geriatric evaluation can forecast fall risk in older adults. This simplifies physicians' and carer's comprehension of how personal characteristics relate to falling risks, allowing them to make more educated intervention options. The study integrates gait measurements with geriatric assessments, including physical, cognitive, and clinical aging. Standardized tests for geriatric assessment were utilized, including ADL, Instrumental ADL (IADL), Geriatric Depression Scale (GDS), Mini-Mental State Examination (MMSE), and Short Form Survey (SF12). TigerPlace, Columbia Aging-in-Place, recruited 92 participants to foresee 6-month fall risk utilizing geriatric examinations, spatiotemporal gait measurements, and previous falls. ADL, IADL, Functional Ambulatory Profile (FAP), Gait Speed, and Physical Component (PCS) were all more predictive of falls. Fall risk models can help physicians evaluate individual evaluations quickly and take early steps to reduce future falls. Explainability approaches such as SHAP (SHapley Additive Explanations) were used to identify the specific gait metrics or geriatric examination scores most responsible for the prediction of fall risk. Overall, the predictive machine learning frameworks for fall risk were at 85%, and the addition of explanations is critical since it allows for more focused strategies to reduce falls among older adults.

The study in [197] applies wearable sensors and deep learning models to predict falls more accurately. It focuses on the Sisfall dataset, which consists of data from 38 participants carrying out daily activities and 15 fall classes. Over 4500 experiments were captured by sensor accelerometers and gyroscopes. CNNs and LSTM networks were used to handle sensor data in time. A hybrid Convolutional Long Short-Term Memory (ConvLSTM) model was proposed by combining CNNs for spatial characteristics and LSTMs for temporal dependencies. The hybrid model improves early fall detection and reduces false alarms. Assessment based on different techniques and window lengths improved prediction accuracy to 90%. One-second advance fall prediction is the goal, which will allow elderly people to take precautions. This work offers an effective solution for instantaneous fall detection and prevention using wearable devices.

Another novel method introduced in [198] combines two algorithms: one estimating the probability of a fall from ADLs and the other classifying if the activity is a fall or not. In this model, three IMU sensors are utilized, mounted on the thoracic, hip, and knee joints, with quaternions as the orientation representation. It calculates joint angles from a T-pose skeleton as a reference coordinate. With the IMU that has real-time human movement data, the model was efficient with an average sensitivity of 70.4% for training 71.4% for testing, and a specificity of 75.3% on average for training and 75.5% for testing. The logistic regression model obtained 88% overall training accuracy and 87.75% overall testing accuracy. Based on Human Body Kinematics (HBK), this model can differentiate between non-falls and falls among the elderly.

Based on the comprehensive background analysis of behaviour monitoring, it is evident that wearable devices, combined with advanced AI and machine learning algorithms, can significantly enhance fall prediction strategies, enabling timely interventions to minimize incidents and enhance the quality of life for the elderly. However, monitoring through vision presents a computational challenge; even low-resolution video needs extensive data preparation due to the dense information it contains. More current video monitoring applications fail to leverage all available data in real-time, focusing only on specific elements. Although computer vision systems can identify objects in video footage, they struggle to process all aspects concurrently. Additionally, many fall prediction studies utilize CNN, DCNN, and SVM for prediction and classification, often relying on simulated data collected from actors or younger individuals and not from older adult's continuous monitoring data. Most research effectively uses daily activities, such as ADLs, as parameters for predicting fall risk through various methods, including HAR, wearable sensors, gait patterns, skeletal imaging, or assessment tools. This highlights the crucial role ADLs play in forecasting fall risks, particularly future falls.

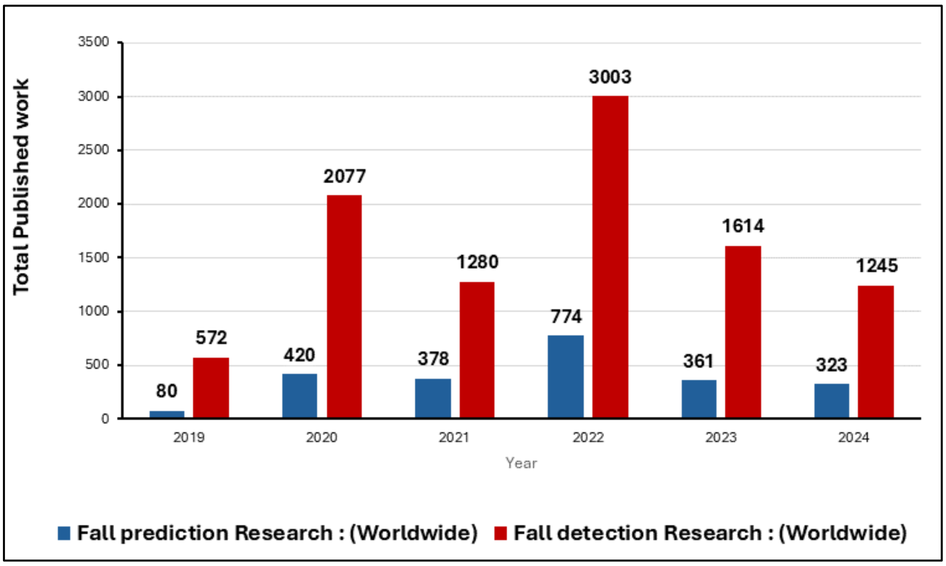


Figure 5.2: Worldwide Statistics of Fall Detection and Prediction Research:2020-2024.

Fall prediction and detection research have increased significantly in recent years, with most countries making efforts towards conducting this research, as discussed in [199]. Figure 5.2 depicts the world trend of fall detection and prediction research from 2020 to 2024, obtained from Google Trends. Even though most modern smartphones and intelligent systems nowadays feature AI-driven fall detection systems, there has been a substantial shift towards fall prediction. This area has been given significant research focus since 2020, bearing in mind that fall prediction before occurrence is more useful than fall detection after occurrence. Globally, and especially in countries like New Zealand, more and more research is being carried out to improve fall prediction methods among elderly people, as presented in [200]. In general, the trend is shifting towards prevention, with the presumption that prevention of falls is more beneficial than curing their aftermath.

5.3 Importance of ADLs

As previously stated in Chapter 2, Section 2.2, risk factors for falls can be classified as intrinsic or extrinsic. Age, gender, ethnicity, postmenopausal status, low BMI, cognitive and sensory impairment, musculoskeletal problems, balance issues, a history of falls, and the intake of certain medications are all intrinsic risk factors [201]. Sedentary lifestyles, malnutrition, slippery, uneven flooring, outdoor floor surfaces, poor lighting, ill-fitting footwear, and other external distractions are examples of extrinsic risk factors for falls [166]. These must be examined for, as they are typically environmental hazards. Multiple research listed in [202] focus on fall detection while doing ADLs such as walking, running, toileting, dressing, and showering. The ADLs are then divided into Basic ADLs (BADLs) and IADLs. BADLs include basic skills for meeting basic bodily demands such as personal hygiene, dressing, toileting, transferring, and feeding. IADLs are more complicated independent living skills, such as money and drug management, meal preparation, household cleaning, and laundry. A prospective observational study in [176] evaluated pre-admission and post-hospitalization ADL function and found that older adults are released with decreasing ADL performance from baseline. Another study in [203] is based on Japan's Ministry of Health, Labour, and Welfare (MHLW) and uses a public measure of ADL known as the bedriddenness rank, which is broadly used in Japan's long-term care insurance. This measure reflects how much a patient is immobilized during the day, such as in a bed, a chair, or at home, although no fall prediction model utilizing this rank has been demonstrated. According to studies, weakness of muscles, a history of falls, gait abnormality, and balance impairment are the best predictors of falls in older adults. Patients aged 65 and above should be examined for a history of falls as well as difficulties walking or balancing to identify those who are most at risk.

A person's independence and health can be evaluated through ADLs. Learning to perform one's own ADLs reveals a lot about a person's functional state, particularly in elderly people, where the limitations in ADLs typically point to underlying medical conditions, frailty, neurodegeneration, or need for surgery. In healthcare and long-term care settings, ADL performance is measured because it enables the planning of suitable interventions, the assessment of extended care services and protection coverage eligibility, and the identification of the need for support with caring. The inability to do ADLs is also linked to an increased risk of falls, hospitalization, and a general decline in health. Furthermore, the availability of modern technology, such as wearable sensors and artificial intelligence-based monitoring systems, enables real-time monitoring of ADL performance, enabling early diagnosis of functional deterioration and interventions. ADL independence is critical for older individuals' dignity, confidence, and quality of life; hence ADL evaluation has become a major component of geriatric care and policy formulation.

5.4 ADL Parameter Selection

Physical frailty, obesity, medical conditions, and the emotional impact of losing close family members like spouses, kin, or friends all contribute to older adults' decreased capacity to undertake personal ADL. When left ignored, this can lead to social isolation and a significant risk of falls [204]. The assessment of a participant's physical and health status is directly concerning the ability to perform his or her everyday activities, which are critical for maintaining daily routines and general well-being. In recent decades, numerous research has concentrated on continuous monitoring of ADLs among the elderly [205]. Monitoring ADL can dramatically improve care for older adults by boosting safety and quality of life while also allowing for early detection of critical events such as disease onset or falls, allowing for appropriate intervention. Long-term monitoring also provides valuable information to healthcare providers, allowing them to make data-driven decisions about the progression of health issues. Elderly people who struggle with fundamental ADLs such as meal preparation, eating, bathing, or ascending and descending stairs, or who do not adhere to their medications properly, are likely to have a significant decrease in their well-being and health condition, as well as a fall.

Figure 5.3: Behaviour Parameter Selection.

Based on the background research undertaken in [206] and [207] on monitoring abnormal behaviour patterns in the elderly, a solid understanding of the importance of ADLs in fall prediction is gained. As a result, this study focuses on five essential ADLs that help predict future falls in older adults.

- Sitting
- Standing
- Walking
- Running
- Jumping

Figure 5.3 depicts the behaviour parameters chosen for this proposed research. The essential functioning of older adults depends on all five ADLs. This chapter focuses on estimating the fall risk in older adults during their regular activities and workouts, which are directly related to their health parameters. Since behaviour patterns are influenced by health and vice versa, tracking these variables will provide useful information for the DBN model, which predicts fall risk. Activities such as sleeping and lying down are not included in this proposed work as they can result in fall detection scenarios that are outside the scope of this research. The long-term activity monitoring dataset, which includes recordings of older adults practicing ADLs, was collected from a public repository. The raw data is then converted into the appropriate ADLs using the ADL conversion technique described in Section A.2 of the Appendix. These ADLs are then utilized as input into the DBN model, which predicts the likelihood of future falls.

5.5 Deep Belief Networks (DBN)

DBNs are models that learn features from data by combining multiple layers of random variables. According to [132], they employ direct connections from the upper layers to the lower layers and link the top two layers in a way that helps them retain knowledge. Two main advantages of DBNs are their ability to quickly learn the relationships between layers and their ability to infer values in the hidden layers from observable data in a single step. Learning occurs one layer at a time, with the output of a single layer serving as training information for the next layer (unsupervised learning). This approach can be improved by fine-tuning the model for greater precision (Supervised Learning). DBNs are very successful at handling complex data because they pre-train feature detectors with acquired information [208]. Furthermore, DBNs enable transfer learning and may support both supervised and unsupervised learning methodologies, making them ideal for a collection of complicated tasks namely as data, picture, and speech recognition. Overall, DBNs' unique structure and learnability make them an adaptable predictive tool for a variety of applications. Figure 5.4 shows an outline of the DBN structure in AI.

A study published in [209] discusses the advancement of detection and classification of cardiac arrhythmia illnesses caused by breakdowns in electrical signal conduction within the heart. For efficient feature extraction of the ECG signal, they employ the unsupervised DBN and a straightforward logistic regression (LR) classifier. Measures like precision, recall, specificity, and the F1-score are used to compare the effectiveness of this parameter extraction with unenriched, plain data. The DBN-LR framework outperforms a 1D traditional approach by 5% and a non-feature extraction approach by 10%. This demonstrates DBN's effectiveness in enhancing data features to improve arrhythmia detection accuracy.

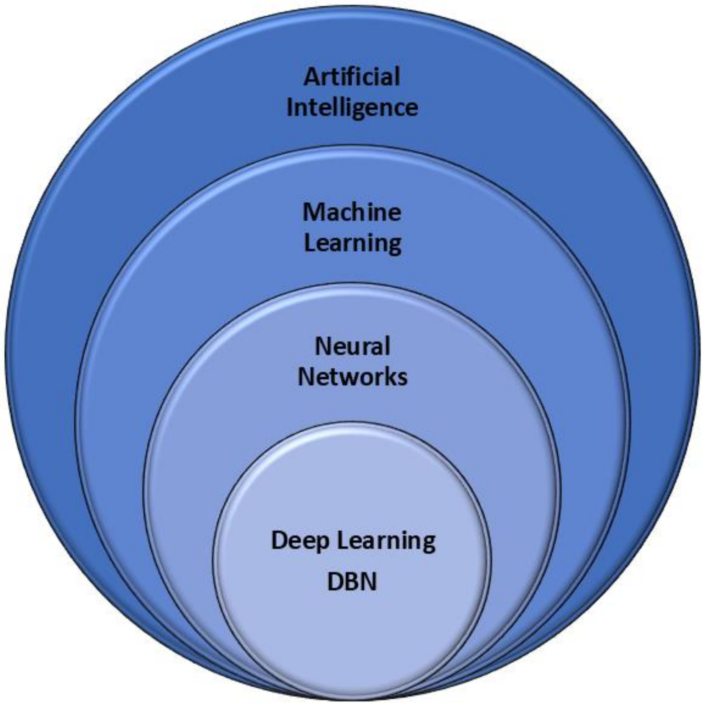


Figure 5.4: DBN Overview.

A new approach to cervical cancer screening based on a DBN model is presented in [210]. The study focuses on automating the diagnosis process by analyzing colposcopy images, which are required for the detection of pre-cancerous lesions. A multi-layer structure is used to extract valuable information from photos and categorize the stages of cervical cancer. As a result, DBN automatically learns the hierarchy of characteristics from colposcopy images, allowing the model to differentiate between normal and higher-than-normal tissues. When compared to traditional methodologies, the model performs significantly compared to the classification accuracy, sensitivity, and specificity. The proposed DBN-based technique shows promising findings, showing that it will be a useful tool for the early identification of cervical cancer, perhaps leading to better patient outcomes.

Another DBN model is used in [211] to provide a new, advanced technique for heart disease prediction. The DBN model structure combines the Ruzzo-Tompa method and a Stacked Genetic method to enhance the model's accuracy and efficiency. The study demonstrates the importance of appropriate feature selection and optimization for improving Bayesian Networks' prediction abilities. Using these strategies, the Optimally Configured and Improved Deep Belief Networks (OCI-DBN) model can detect patterns and correlations in data with improved accuracy when predicting the risk of heart disease. When compared to existing classical methods, it demonstrated enormous gains in predicting accuracy over OCI-DBN methodologies. Such approaches indicate that this method is a potential option for early diagnosis of heart disease, which can lead to earlier intervention and better patient management. As mentioned in the findings above, DBN outperforms other neural networks in terms of prediction accuracy.

Although extensive research has been conducted on falls, fall detection, and some aspects of fall prediction and prevention in the elderly, numerous challenges remain in the current fall analysis systems. One effective solution is to implement deep learning models capable of predicting the underlying conditions and contributing factors to various problems. In [212], an advanced prediction algorithm for the risk of Coronary Heart Disease (CHD) is presented, which responds to the global concern over mortality, which remains a serious problem despite advances in modern medicine. They developed an Optimized Deep Belief Network (Optimized-DBN) that was tuned with a genetic algorithm to give the ideal number of layers and nodes. An accuracy of 89% was recorded by this model, beating Framingham and standard DBN techniques. The results indicate that the optimized DBN gives a highly accurate and reliable prediction of the risk of CHD. Herein, the fuzzy deep belief network-based classifier called Deep Belief Networks-based Takagi-Sugeno-Kang Fuzzy Classifier (DBN-TSK-FC) is developed in [213], combining DBNs with a fuzzy system for predicting indoor user movements in assisted living environments. It uses Fuzzy C-Means clustering to create fuzzy rules and unsupervised DBN pretraining to build a neural representation. Merging these two approaches with machine learning eliminates the need for slow fine-tuning. Tests on the Movement using the Ambient Assisted Living - Received Signal Strength (AAL_RSS) dataset show that DBN-TSK-FC effectively predicts user movements, making it a promising tool for assisted-living applications.

An intelligent framework described in [214] was introduced to classify, detect, and notify elderly falls using a personal mobile phone to capture tri-axial acceleration. The system processes the data by extracting relevant features following preprocessing and time-stamping the test sets from a stationary window. A Deep Belief Network is employed to train and test the framework on two public datasets, which include nine fall classes and a single class of everyday activities. The simulation outcomes of the Temporal Fall (T-fall) and Mobile Fall detection (Mobi Fall) datasets reveal that the framework achieved a high precision of 97.56% with a sensitivity of 97.03% and specificity of 100% and surpassed nine other comparable studies. The results prove the effectiveness of the framework in identifying and preventing falls among elderly individuals. A comprehensive overview of fall prevention among elderly patients is provided in [67], which provides a detailed overview of various categories of falls among the elderly and available technologies used for the prediction and prevention of future falls. The findings indicate that a significant percentage of falls among individuals above 60 years of age is caused due to imbalances in ADL.

Monitoring these activities and predicting falls before they happen is highly likely to reduce the risk of injury and mortality. Thus, a clear need for a standardized fall prediction method in older adults is evident. For these reasons, this research involves integrating ADLs into DBN and to estimate the chance of future falls among older adults. This study focuses on quantifying ADLs and using DBN models to foresee future falls in the elderly, as stated in the following sections. As far as can be determined, this is the first model that employs a DBN to predict falls in older adults using only ADLs and medical history.

5.6 Proposed DBN-Based 3-Stage Fall Risk Prediction System

The current research aims to predict future falls in older adults and classify the fall risks as *Low, Moderate, or High*. The elderly and their family members will receive an alert concerning the possibility of a future fall, which will be discussed in detail in the thesis's future work section. Initially, data on older persons for this research was obtained from public repositories for model training and testing. The ADL conversion method outlined in Section A.2 of the Appendix is then used to transform the raw data into the relevant ADLs. The DBN model then uses these ADLs as input to forecast the probability of future falls. ADLs with a corresponding time for each participant serve as the input variables for the DBN model.

The approach considers five activities of daily living (ADLs) for elderly participants: sitting, standing, walking, running, and jumping. Each ADL is weighted according to its significance in fall prediction: sitting (0.2), standing (0.4), walking (0.6), running (0.8), and jumping (1.0). These weighted inputs are evaluated on each of the three DBN-based fall prediction models using the developed DBN-based Fall Risk Prediction Algorithm (DBN-FRPA). Pre-training of all DBN models is done using several Restricted Boltzmann Machine (RBM) architectures: DBN 1 → RBM 1-layer hidden nodes [128, 64, 32]; DBN 2 → RBM 2-layer hidden nodes [64, 32, 16] and DBN 3 → RBM 3-layer hidden nodes [32, 16, 8]. Figure 5.5 provides an overview of the proposed three-stage DBN-based fall risk prediction model. The input data is initially processed in DBN 1, where it is checked to determine whether it is in the *"Low Fall Risk"* category. If not, the data is passed on to DBN 2, which checks and assigns it to the *"Moderate Fall Risk"* category. If the data is not in the moderate-risk category, it is further processed by DBN 3, which assigns it to the *"High Fall Risk"* category. Each DBN receives its own transformed version of the input data from the respective RBM layers. The DBN-based Fall Risk Prediction Algorithm (DBN-FRPA) is designed using a combination of ADLs and is explained in Algorithm I (DBN-FRPA) – Pseudocode.

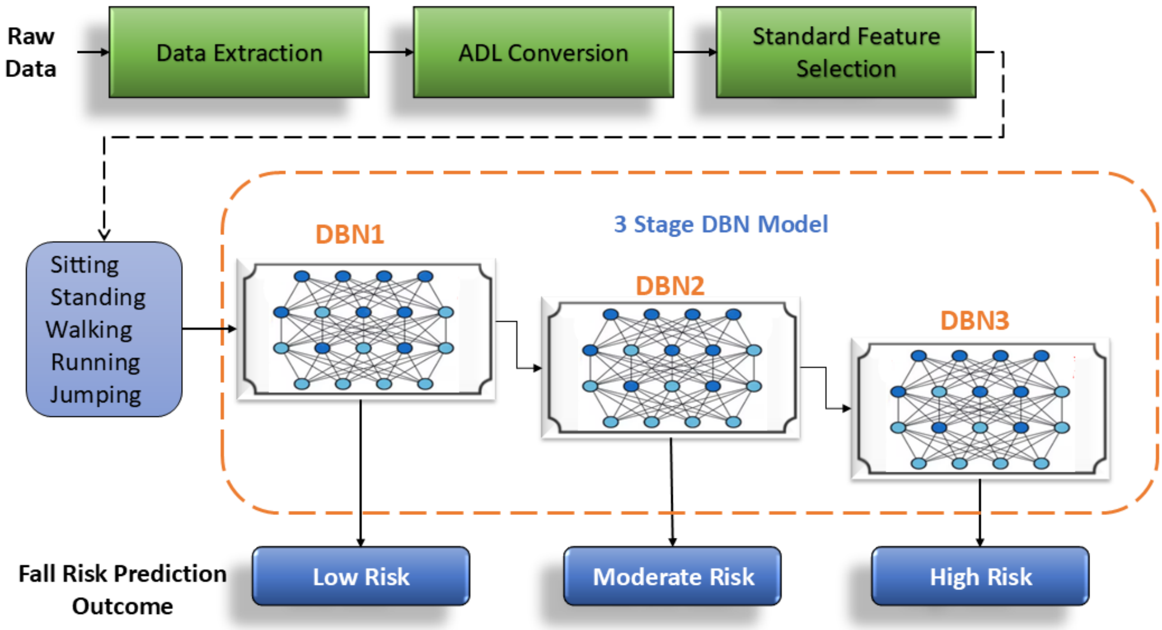


Figure 5.5: Architecture of the Developed 3-Stage DBN-Based Fall Risk Prediction System.

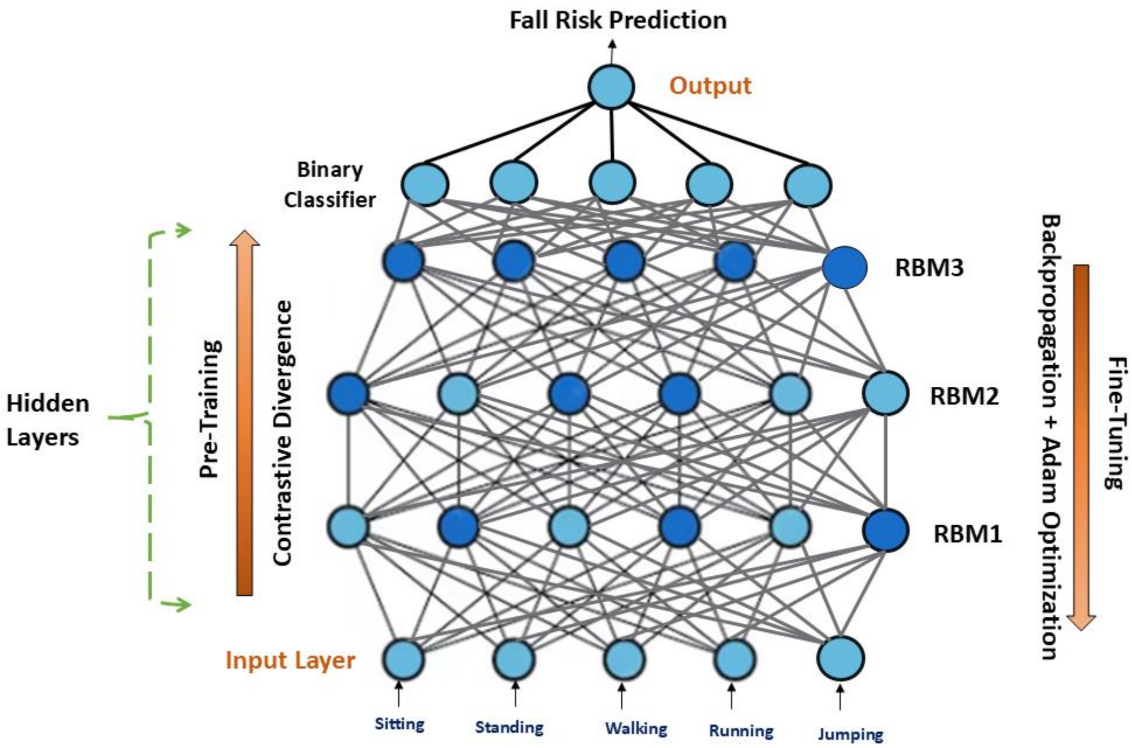


Figure 5.6: Network Structure of Proposed 3-Stage DBN-Based Fall Risk Prediction System.

To improve prediction accuracy, several enhancements are proposed for the unsupervised training models and fine-tuning procedures. The DBN models undergo pre-training using Contrastive Divergence in an unsupervised manner, starting from the bottom layer and progressing upwards. In the fine-tuning phase, a top-down approach is used, where backpropagation, optimized by the Adam optimizer, is employed to update the weights. A binary classifier is applied as the activation function. The model is trained using 80% of the data, with 20% reserved for testing. Using this developed DBN-based fall prediction model, the risk of future falls is effectively predicted. The Network structure of the proposed DBN model is depicted in Figure 5.6.

DBN-based Fall Risk Prediction Algorithm 1 (DBN-FRPA): Pseudocode of the Proposed Model (Figure 5.5)

Input: $X \rightarrow$ ADLs (Sitting, Standing, Walking, Running, Jumping)

$Y \rightarrow$ Fall risk level (Low, Moderate, High)

Output: $\hat{Y} \rightarrow$ Predicted fall risk levels

1. Data extraction from the input parameters
2. *Feature extraction* → Feature extracted data to the 3-stage DBN-based fall risk prediction model.

a) Data Normalization → min-max normalization to each feature X:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

b) Label Encoding: $Y \rightarrow$ target labels using label encoding

$$Y_{encoded} = Label\ Encoder\ (Y)$$

c) Data Splitting → Split the normalized data X′ and encoded labels $Y_{encoded}$ into training and test sets:

$$(X_{train}, X_{test}, Y_{train}, Y_{test}) = train\_test_{split}(X', Y_{encoded}, test_{size}, 0.2)$$

3. ***RBM Pre-Training for DBN Layers*:** Pre-train each layer using Restricted Boltzmann Machines (RBM) with contrastive divergence:

   Layer 1 (RBM1): X_{train_rbm1} = RBM1 (X_{train})

   Layer 2 (RBM2): X_{train_rbm2} = RBM2 (X_{train_rbm1})

   Layer 3 (RBM3): X_{train_rbm3} = RBM3 (X_{train_rbm2})

4. ***Define DBN Architecture*:** Initialize a DBN model with three layers corresponding to the pre-trained RBMs:

   DBN = Sequential ([dense (128), dense (64), dense (32), dense (1)])

   Optimizer = adam, loss = binary_crossentropy

5. ***Train DBN Models:*** Fine-tune DBN model using backpropagation on the labelled data. DBN.fit(X_{train_rbm}, Y_{train})
   - DBN1: Architecture → [128, 64, 32]
   - DBN2: Architecture → [64, 32, 16]
   - DBN3: Architecture → [32, 16, 8]

6. Transform the test data through the RBM layers:

   $\boldsymbol{X_{test\_rbm1}} = RBM1.transform(X_{test})$

   $\boldsymbol{X_{test\_rbm2}} = RBM2.transform(X_{test\_rbm1})$

   $\boldsymbol{X_{test\_rbm3}} = RBM3.transform(X_{test\_rbm2})$

7. Cross-validation using testing dataset → Determine the accuracy, specificity, and sensitivity of the model.

metrics= [122]

8. ***Result Evaluation*** → validate the findings and predict fall risk levels $\hat{Y}$

The workflow structure of the developed DBN model is shown in Figure 5.7.

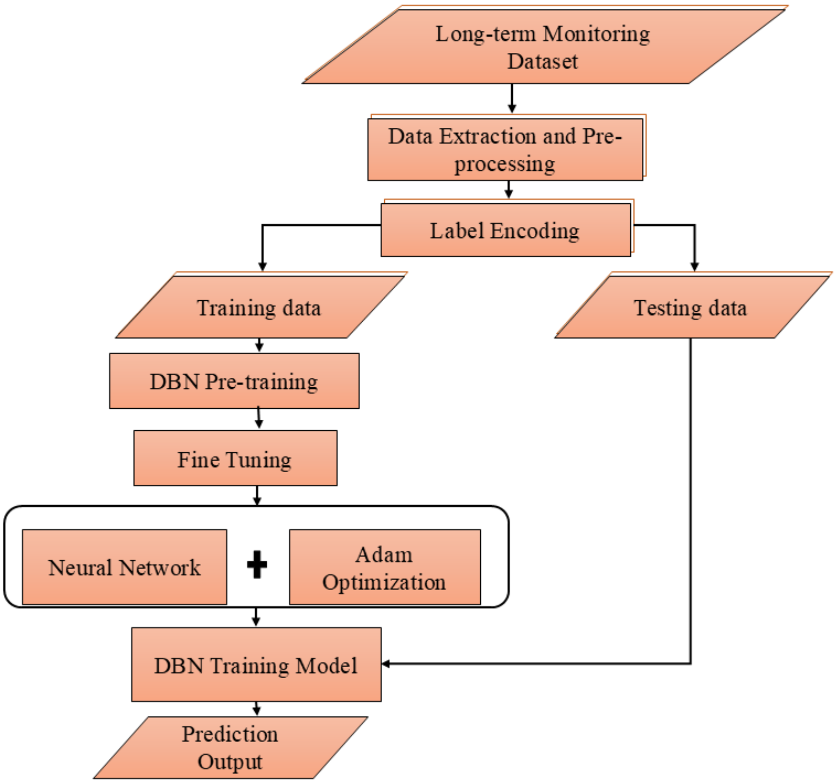


Figure 5.7: Workflow Structure of Developed DBN Model.

Unsupervised Pre-Training: Pre-training is one of the most important processes of machine learning, especially for deep learning and neural networks, whereby a model is pre-trained with a bigger dataset before fine-tuning on a limited, more focused task. Pre-training helps the model in its ability to learn representations effectively, primarily when the labelled data are limited. In deep learning, pre-training is extensively used in unsupervised learning to initialize the network's weights before fine-tuning the network with supervised learning [215]. One of the best examples mentioned in [216] based on DBNs, where a greedy layer-wise pre-training procedure is used to learn feature representations before performing supervised classification. Similarly, in natural language processing (NLP), BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) models are trained on extensive datasets of text data to learn language structures before they are fine-tuned for tasks like sentiment analysis, translation, or question answering [217]. Pre-training significantly reduces training time and generalization by allowing models to benefit from knowledge already learned before. It is especially helpful for deep architecture since training from scratch is computationally expensive and necessitates enormous amounts of labelled data.

The developed DBN model consists of three RBM layers, i.e., RBM_1, RBM_2, and RBM_3, with [128, 64, 32], [64, 32, 16], and [32, 16, 8] hidden units, respectively. The parameters were optimized through repeated trials and iterative training to ensure maximum accuracy. The RBM layers are trained by Contrastive Divergence (CD) one by one from the bottom layer to the top. CD is an efficient algorithm for training Restricted Boltzmann Machines (RBMs), which are the components of Deep Belief Networks (DBNs) [218]. It is an approximating method and is applied to estimate the gradient of the log-likelihood function through which the RBM learns the optimal weight distribution without running computationally costly computations. Each trained RBM layer acts as the input for the next layer, i.e., RBM_1, which is trained with the visible layer as input, serves as the visible layer for RBM_2 after training, and the same for RBM_3. This training is accomplished with the greedy layer-by-layer algorithm, as described in [43]. Each RBM is pretrained separately using contrastive divergence (CD) before fine-tuning the whole network. The network parameters were optimized using iterative training and several trials to achieve optimal classification accuracy. Greedy layer-wise training avoids stacking any RBM layers together until being pretrained separately. RBM_1 is the first hidden layer and pretrained on raw input data (visible layer). It gets trained using contrastive divergence (CD), an approximation of the gradient of the log-likelihood function in order to modify the weights. The trained RBM_1 computes the important features of input data. The output of RBM_1 is now taken as the new "input" of RBM_2 (i.e., the hidden layer of RBM_1 as the visible layer for RBM_2). RBM_2 takes the learned feature representation of RBM_1 as input and learns abstract higher-level features. CD is used once more to update the weights in RBM_2 in order to optimize feature learning. The output from trained RBM_2 is then accepted as input by RBM_3 for optimization. RBM_3 optimizes the features optimized by RBM_2, learning deeper patterns from data. Contrastive divergence is used once more to optimize the model. After the top layer has learned, the entire network has thus been pre-trained without supervision, each RBM capturing meaningful representations at different levels. The unsupervised learning technique permits each of the layers to learn from the input data efficiently with weight distribution according to fall risk analysis: Sitting - 0.2, Standing - 0.4, Walking - 0.6, Running - 0.8, Jumping – 1.0. Risk levels are divided according to related weights*: Low risk* – 0.3, *Moderate risk* - 0.6, and *High risk* - 0.9. The unsupervised layers provide feature extraction and pre-training so that each RBM layer can learn higher-order features of the data. The composition enables the DBN to uncover complex data features, where one RBM's output is the input for the next layer.

Backpropagation and Adam Optimizer-based Fine-Tuning: Fine-tuning is also a machine learning method in which pre-trained models are trained on a small, task-focused dataset. It aims to adapt the learned representation of the model to a new task while being able to make use of the knowledge it picked up during pre-training [219]. Fine-tuning is extremely prevalent in deep learning practice, particularly in transfer learning and neural networks, where pre-trained models are refined on large datasets are fine-tuned for specialized tasks such as sentiment analysis, image classification, medical diagnosis, or predictive analysis [215]. Fine-tuning involves training a part or the entire layers of the pre-trained model with a small learning rate to keep the features already learned earlier and learn the new data. Their method and success of better results are chiefly time-effective and allow re-training using limited labelled data. Backpropagation, also known as "backward propagation of errors," is a supervised learning approach for the training of artificial neural networks [220]. It minimizes the difference between deviated and actual outputs by modifying the neural network weights using the gradient descent optimization algorithm. Backpropagation enables deep networks to learn complex patterns and plays a significant role in building deep learning models namely convolutional and recurrent neural networks.

- **RBM_1 (First Hidden Layer - Low-Level Features)**
  Input: Raw data (Sitting, Standing, Walking, Running and Jumping).
  Output: Extracts low-level features from the input.

- **RBM_2 (Second Hidden Layer - Mid-Level Features)**
  Input: Features learned by RBM_1.
  Output: Recognizes higher-order relationships between features.

- **RBM_3 (Third Hidden Layer - High-Level Features)**
  Input: Features learned by RBM_2.
  Output: Finds complex patterns in the dataset.

After the RBM pre-training, the weights are fine-tuned by the supervised learning backpropagation method. The pre-trained DBNs are converted into fully connected feedforward neural networks with a specified architecture. This method adjusts the weights and biases of the network by the prediction errors. The network computes the difference between its prediction and the actual labels (y_train) using a binary cross-entropy loss function. Network parameters such as weights are optimized by optimization algorithms such as Adam Optimizer. Hence, after the Backpropagation of error, which is performed through the network, the weights are optimized to minimize the loss using an Adam optimizer. Fine-tuning is done for a fixed number of 10 epochs, and the weights are adjusted for each mini-batch of data. Finally, a binary classifier scales the output of all forecasted risk levels to correspond with the risk indicators: Low - 0.3, Moderate - 0.6, and High - 0.9.

5.7 Evaluation of the AI-2 Model

This section evaluates the effectiveness of the developed DBN-based fall risk prediction framework through experimental result analysis. The system's accuracy is initially evaluated by assessing it with the Ground Truth, which is calculated from a combination of the MFS and the TUG Test. Finally, the effectiveness of the developed model is evaluated with other similar existing literature in this field. The simulations were executed on Visual Studio Code on a Windows 10 Enterprise machine with an 11th Gen Intel Core i7 processor (3.00 GHz) and 32 GB RAM.

5.7.1 Evaluation Metrics

The developed model is assessed using real-time data from previous research obtained through PhysioNet. These datasets characteristics include,

1) Age
2) Sex
3) History of Falls.
4) ADL data

The fall risk prediction evaluation approach is carried out by utilizing the metrics from Table 5.1. Accuracy, Sensitivity, and Specificity are the measurements associated with TP, TN, FP, and FN.

Table 5. 1: Evaluation Metrics

Prediction Class	Binary Classifier	Description
True Positive (TP)	1	when a risk of fall is identified
True Negative (TN)	0	when the participant has a Low risk of fall
False Positive (FP)	1	When a healthy older adult is notified of the risk of a fall (false alarm)
False Negative (FN)	0	when there is a risk of fall but notified as normal

5.7.2 Data Collection – ADL Data

The model is trained on ADL datasets from older adults aged 65 to 87 who were recruited from PhysioNet's Long-term Monitoring Database [221]. To evaluate gait, stability, and fall risk, 71 older adults residing in the community participated in a 3-day 3D accelerometer recording which constantly captured their daily activities for 75 hours. However, only 66 participants' recordings are present in the repository. In this thesis (in this proposed AI research), data from 50 subjects with 65–75 hours of recordings were used for training, whereas data from 12 subjects were used for testing. Data from four subjects are excluded since their records are less than 30 hours. Every participant dataset is split into two groups: Fallers (Fx), who experienced more than two falls in a single year, and non-fallers, often known as the Control Group (Cx), who experienced either no falls or less than two falls annually. The recordings of the participants used for this research are formulated in Table 5.2.

Table 5. 2: Description of Participants' Recordings – PhysioNet

Data Analysis	**Participant count**
Total elderly participant data as mentioned in PhysioNet	71
Total records found	66
Usable participants dataset for research	62
Data with missed recordings that are not usable	4
Total Training Data used	50 (Fx-21, Cx-29)
Total Testing Data used	12 (Fx-7, Cx-5)

Data Preprocessing: The unprocessed data from the 3D accelerometer is divided into six signal categories: vertical (v)_acceleration, medio-lateral (ml)_acceleration, antero-posterior (ap)_acceleration, yaw_velocity, pitch_velocity, and roll_velocity.

- *ap_acceleration:* X-axis – Measures side-to-side movement (lateral shifts).
- *ml_acceleration:* Y-axis – Measures forward and backward movement (Walking, Running).
- *v_acceleration:* Z-axis – Measures vertical movement (up and down → Sitting, Standing, Jumping).
- *roll_velocity:* X-axis – Longitudinal axis measures tilting/rotation of object front and back.
- *pitch_velocity:* Y-axis – Lateral axis measures tilting/rotation of object side-to-side.
- *yaw_velocity:* Z-axis – Vertical axis measures tilting/rotation.

The clock frequency is set to 100 ticks per second, with one tick representing one sample from each of the six types of signals received along the timeline. Figure 5.8 depicts the raw signals recorded using the 3D accelerometer from Participant ‘C2’. The dense overlapping peaks in the figure suggest a period of rapid motion or activity (possibly walking or transition phases such as sit-to-stand). The grid background provides scale for both time (x-axis) and intensity (y-axis).

Each signal must be filtered and pre-processed to remove noise before feature extraction for fall prediction.

The signal shows the graphical plots for all 6 metrics with respect to time and this can be further simplified into numerical values as shown in Figure 5.9.

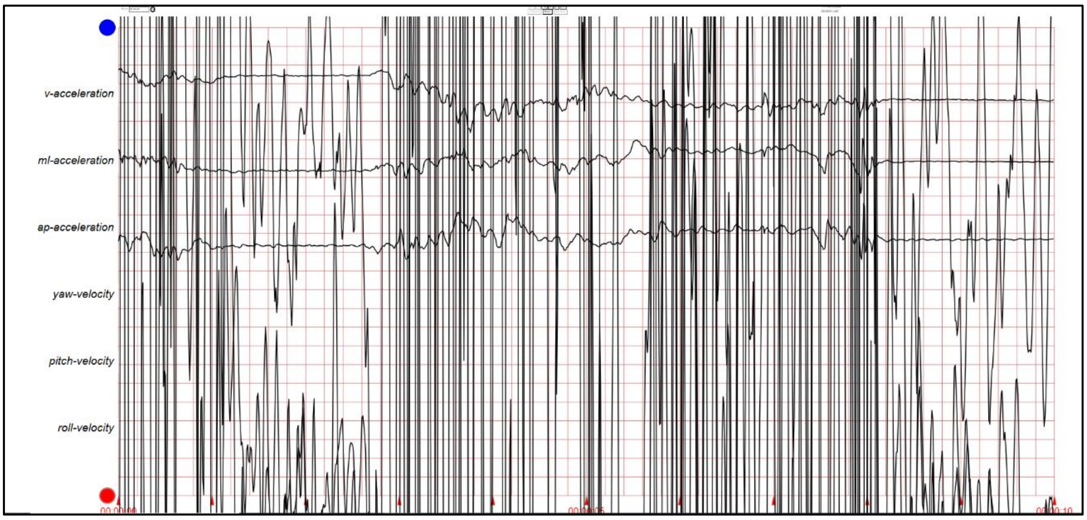


Figure 5.8: Raw Accelerometer Signal obtained from PhysioNet.

Signals

Time (elapsed)	v-acceleration *(g)*	ml-acceleration *(g)*	ap-acceleration *(g)*	yaw-velocity *(degrees/s)*	pitch-velocity *(degrees/s)*	roll-velocity *(degrees/s)*
01:00:00.000	0.243	-0.083	-0.997	-0.231	-5.490	0.869
01:00:00.010	0.243	-0.083	-0.994	-0.259	-5.376	0.857
01:00:00.020	0.243	-0.083	-0.994	-0.217	-5.204	0.893
01:00:00.030	0.243	-0.083	-0.997	-0.182	-5.250	0.857
01:00:00.040	0.243	-0.083	-0.997	-0.224	-5.456	0.809
01:00:00.050	0.243	-0.083	-0.994	-0.259	-5.353	0.916
01:00:00.060	0.243	-0.083	-0.994	-0.259	-5.124	0.809
01:00:00.070	0.243	-0.083	-0.994	-0.189	-5.273	0.893
01:00:00.080	0.243	-0.083	-0.994	-0.189	-5.433	0.821
01:00:00.090	0.243	-0.083	-0.994	-0.294	-5.353	0.904
01:00:00.100	0.243	-0.083	-0.994	-0.245	-5.204	0.845
01:00:00.110	0.243	-0.083	-0.994	-0.196	-5.227	0.964

Figure 5.9: 3D Accelerometer Numerical Signal Values.

The graphical representation of the six signals is displayed in Figure 5.10 obtained from Participant ‘C2’. All six signals have been derived using the numerical information provided by PhysioNet similar to Figure 5.9, so that the similarity and relation of each signal to the others may be identified and represented. Visual Studio Code is used to translate and transform raw accelerometer data into matching ADLs using threshold-based methods. Each participant's dataset in this proposed research has over 10,000 records from the 3D accelerometer sensor. Data conversion is carried out following the procedure given in [222], which specifies how to identify ADLs from raw recordings. These research-specific ADLs, namely sitting, standing, walking, running, and jumping, were then employed to train and test the built DBN model. Fallers and non-fallers data were gathered for every 10-minute interval (10 minutes x 60 minutes each hour x 75 hours over three days) and then converted into comparable ADLs. This pre-processed data serves as the input for the developed AI-2 model.

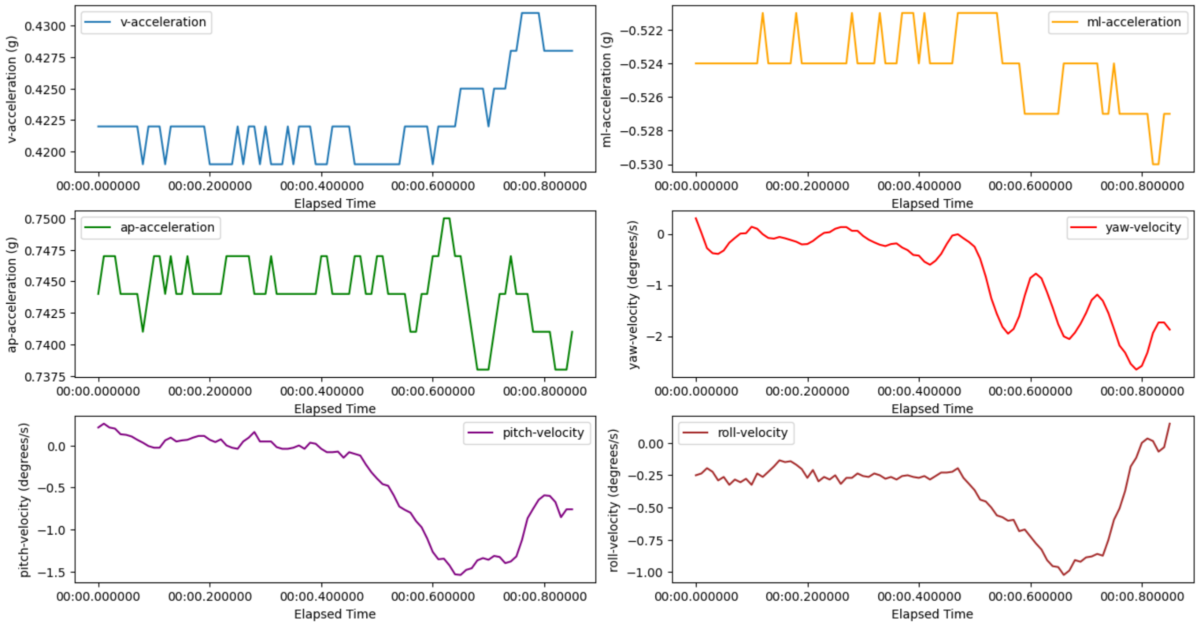


Figure 5.10: Six Signal Categories of the Accelerometer Data Obtained from Participant C2.

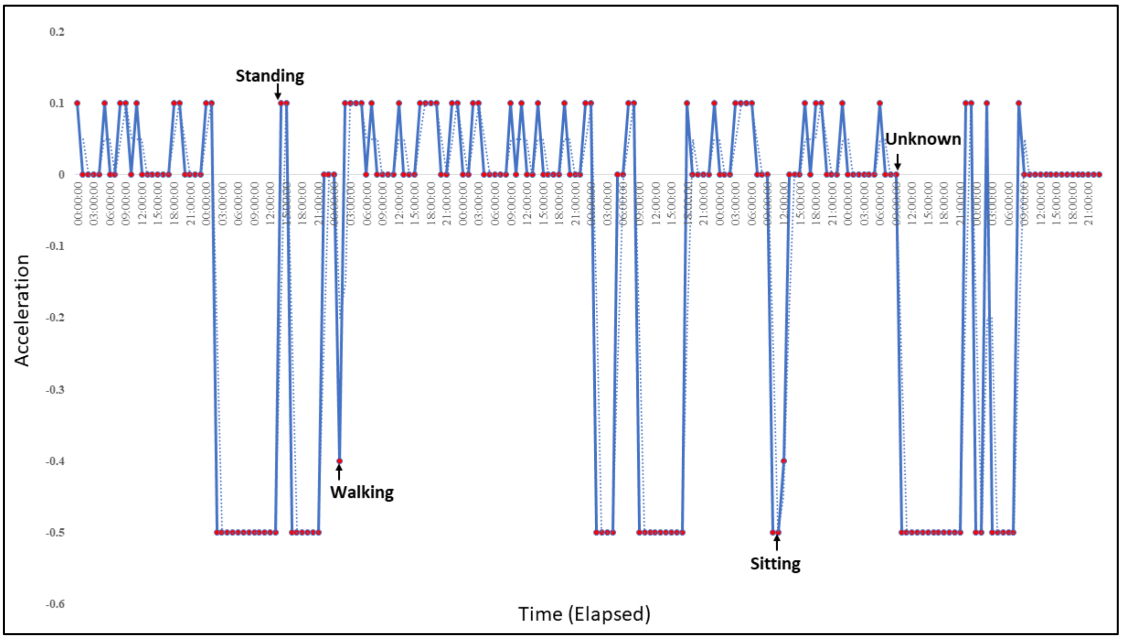


Figure 5.11: 3D Accelerometer Data of Participant C2.

Figure 5.11 displays the 3D accelerometer data obtained from participant 'C2' recordings. The recorded acceleration data was extracted for every 10-minute interval, with ADLs identified for every second. Labels marked as "Unknown" are generated when elderly individuals are performing tasks such as lying down or using stairs (both up and down). Because these actions are unrelated to the proposed work, they are classified as Unknown, which falls under the threshold of 0. In this similar manner, the raw data is converted to the corresponding ADLs. This processed data subsequently serves as input for the developed model. The input file fed into the DBN model includes historical fall data and ADLs (sitting, standing, walking, running, and jumping) with respect to time for each participant. An explanation of the ADL conversion algorithm is given in Section A.2 of the Appendix section.

5.7.3 Evaluation of the AI-2 Model with Data from Public Repository and Existing Work

In this section, the developed DBN-based Fall risk prediction model (AI-2 model) is evaluated against data from a public repository. Section 5.7.3.1 investigates the validation of the proposed model utilizing a dataset from a long-term monitoring database [221]. The developed model's outputs are compared to the Ground Truth, which is formulated by comparing MFS and TUG, and then utilized to assess the accuracy of the findings. Finally, section 5.7.3.2 examines the model's correctness compared to existing research works.

5.7.3.1 Verification of Proposed AI-2 Model with Ground Truth

As explained above, the records of real-time activity monitoring were collected from the PhysioNet long-term monitoring database. The sample data table is provided in Section A.3 of the Appendix. The subjects were under observation for three days to analyze their gait, stability, and falling risk. During these three days, they also conducted a series of assessment tests, including the Berg Balance Scale (BBS), FSST, TUG, MMSE, and the Activities-Specific Balance Confidence Scale (ABC). Of these, it was discovered that the TUG test results are highly consistent with the predictions of the developed fall risk model. The TUG test is a straightforward screening measure for assessing mobility and fall risk. It involves timing an individual to stand up from a chair, walk 3 meters, turn around, walk back, and sit down. Fall risk is classified as *Low, Moderate, or High* based on the time taken to conduct the test. Due to the overlap of risk grades, the TUG is chosen as the main measure for obtaining GT. The MFS was also used because it is a validated tool to forecast future falls in older adults. A study cited in [183] details how MFS has been used for fall risk assessment, categorizing fall risks into low, moderate, and high, which aligns with the proposed model's outcomes. Hence, the MFS is selected as the second metric for deriving GT.

To generate GT, we compared the risk levels from both TUG and MFS as shown in Table 5.3. If both TUG and MFS indicate a *low* risk, GT was labeled as *low*. This method was applied consistently: when both indicated *moderate* risk, GT was *moderate*, and similarly for *high* risk. In cases where one test suggested *low* risk and the other *moderate*, GT was labeled as *moderate*. If one test suggested *moderate* risk and the other *high*, GT was labeled as *high*, prioritizing the higher risk level to improve prediction accuracy. In cases where one test indicated *low* risk and the other *high*, the GT was assigned a *moderate* risk level to reflect an average risk. This comparison-based methodology was used to formulate GT for all participants. Table 5.3 shows the method used for integrating TUG and MFS for GT Formation in Fall Risk Prediction.

Table 5. 3: TUG and MFS for GT Formation in Fall Risk Prediction

Risk Assessment 1 (Tug or MFS)	**Risk Assessment 2 (MFS or TUG)**	**GT Prediction**
Low	Low	Low
Moderate	Moderate	Moderate
High	High	High
Low	Moderate	Moderate
Moderate	High	High
Low	High	Moderate

Table 5. 4: Comparative Result Analysis using GT

Participant	**Age**	**Monitoring period**	**Risk Level**	
			GT	**DBN**
			Indicator	**Indicator**
C18	84	70	Moderate	Moderate
C22	66	71.48	Low	Low
C30	82	43	Low	Low
C36	80	72.53	Moderate	Moderate
C37	77	71.25	Low	Low
F1	79	68.1	Moderate	Moderate
F8	74	71.01	Moderate	Moderate
F9	70	24.56	Moderate	Moderate

F10	75	69.48	Moderate	Low
F21	80	67.5	Moderate	Moderate
F26	73	69.5	Moderate	Moderate
F27	82	69.05	Moderate	Moderate

To evaluate the performance of the developed DBN-based fall risk prediction model, data recordings from 12 participants, each with more than 67 hours of continuous monitoring (241200 data recordings/participants), including 5 non-fallers (Cx) and 7 fallers (Fx), were utilized. Participants C18 and C36, who were 84 and 80 years old, respectively, experienced one fall in the previous 12 months. The remaining non-fallers, C2, C30, and C37, were in good health and had no falls during the period. F1 had five falls in the past year, while F9 and F21 each had two. Participants F8 and F29 reported three falls, whereas F10 and F27 reported ten falls in the past 12 months. The ADL data from all 12 participants were used as input to test the developed model, and the outcomes were compared to the generated GT. Table 5.4 depicts the results of comparing the developed DBN-based fall risk prediction model to the Ground Truth. More details of GT indicators for each participant are provided in Section B.1 of the Appendix.

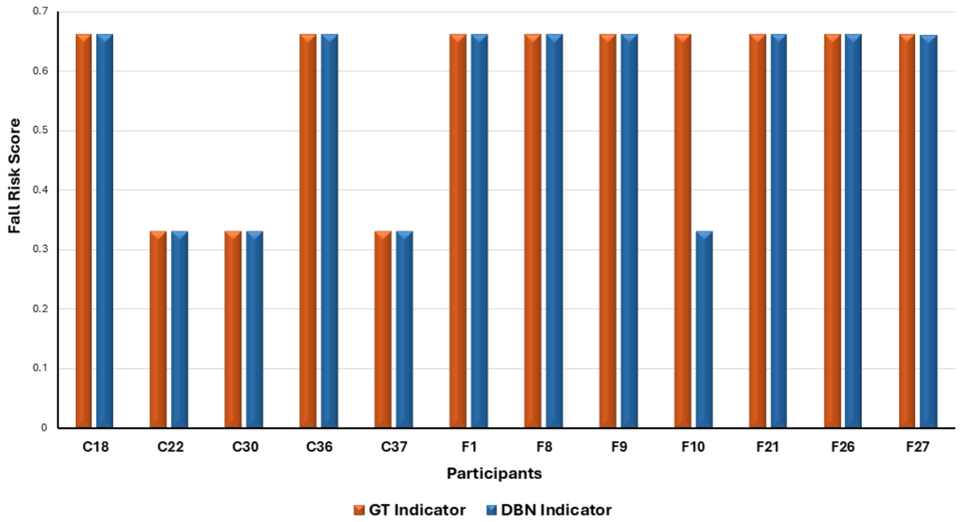


Figure 5.12: DBN-Based Fall Risk Prediction Evaluation Results.

The outcome of the developed DBN model indicates a "*Low fall risk*" for participants C22, C30, C37, and F10, whereas a "*Moderate fall risk*" is uncovered for C18, C36, F1, F8, F9, F21, F26, and F27. Of particular interest, no subject is found to have a "*High fall risk*". The GT output is of "*Low fall risk*" for C22, C30, and C37, and "*Moderate fall risk*" for C18, C36, F1, F8, F9, F21, F26, and F27, and no "*High fall risk*" was observed. This agreement between the developed DBN model's prediction and the GT output demonstrates that the model accurately predicts the majority of non-fallers. However, for participant F10, the DBN model predicts a "*Low fall risk*", while the GT categorizes them as "*Moderate fall risk*", this is likely due to their history of falls within the past year. Figure 5.12 displays the simulation results comparing the DBN model to the GT. For the result analysis, we added weights to the risk prediction outcomes with *Low risk* → 0.33, *Moderate risk* → 0.66, and *High risk* → 0.99.

The model achieved 9 true positives (TP), 2 true negatives (TN), 1 false negative (FN), and 0 false positives (FP), leading to an accuracy of 91.67%, sensitivity of 90.00%, and specificity of 100% when compared to the GT. Table 5.5 shows the confusion matrix layout of the predicted outcome where 1→ (Positive) indicates the positive category, or the event occurrence, and 0 → (Negative) indicates the negative category or the event non-occurrence.

Table 5. 5: Confusion Matrix Layout

Actual/Predicted	**1**	**0**
1	9 (TP)	1 (FN)
0	0 (FP)	2 (TN)

5.7.3.2 Accuracy Comparison of the Developed Model with Existing Works

The findings are compared with 6 highly related fall prediction studies to the proposed research. Notably, no study applies only ADL with DBN for predicting fall risk, which is a testament to the novelty of the proposed approach. Figure 5.13 provides information on the accuracy comparison between different Fall Risk Prediction Models. In [223], a fall risk model was developed from both clinical and robotic predictors. It covered 100 community-living older adults (65 and older), who were assessed for one year with real-time data collected through a robotic platform. The model used 20 robotic parameters and 8 clinical variables and had an increased fall risk prediction accuracy of 81%. Similarly, research conducted in [224] discusses machine learning applications in the prediction of the risks of falls among hospitalized elderly patients in Taiwan. The present research combines Electronic Health Records (EHR) and Comprehensive Geriatric Assessments (CGA) to develop a real-time fall risk prediction model using hospital data. The study employed XGBoost algorithm and attained an accuracy level of 73.2%.

A fall risk prediction model based on primary care EHR data for older adults was developed and internally validated in [225]. The study aims to improve fall prediction by utilizing both structured data and free-text documentation in EHRs. The study comprised 36,470 individuals aged 65 and older, involving real-time data taken from primary care EHRs. The model was 70% accurate and was built using Bootstrap-enhanced penalized logistic regression. The research in [226] attempts to develop a short-time prediction tool to find dementia patients who are at high risk of falling. Movement is continuously tracked over a week, and the collected data is used to forecast falls in 30 days. The Random Forest model and other categorization models were utilized, resulting in a prediction accuracy of 82%.

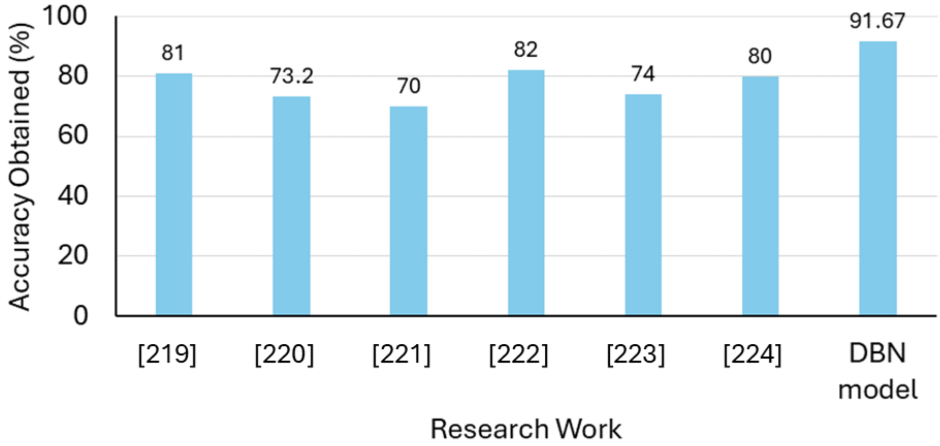


Figure 5.13: Accuracy Comparison between Different Fall Risk Prediction Models.

Similarly, the study in [227] focuses on identifying gait patterns that predict falls in Parkinson's disease individuals aged 60 to 80. Machine learning approaches, notably gait feature extraction, are used in conjunction with classification algorithms like Random Forest and Support Vector Machines. The model was found to have approximately 85% precision in identifying high-risk individuals, indicating potential clinical applicability in recognizing high-risk people. Similarly, in [228], various machine learning models based on spatiotemporal gait metrics were compared for predicting falls in older individuals, particularly those with osteoporosis. The study concludes that the Dynamic Bayesian Network supports expert knowledge in forecasting the probability of falling with 80% accuracy over 12 months. Compared to all other current studies, the developed DBN-based fall risk prediction model explained in the thesis is the only one that uses only five ADLs as relevant parameters to forecast eventual fall risk among senior citizens, with a higher accuracy of 91.67%. Table 5.6 provides a detailed overview of the comparisons between the existing work and the proposed research. The model performs well, but if timely fall risk warnings are ever to be a reality, more testing using real-time data is required. One of the model's limitations is that it only used four of the five specified ADLs to predict fall risk, even when the monitoring time was 75 hours, and the dataset size was large enough. The model's accuracy was less than 95%. Although the use of five ADLs was proposed as inputs, data for only four from the long-term monitoring database were obtained and did not use jumping activities for training and assessment. It is predicted that the inclusion of all five ADLs, including jumping, into future datasets will dramatically affect prediction accuracy, which might be larger than or less than 90%. Despite these constraints, consistent results are produced by the model when tested against genuine GT data.

Table 5. 6: Comparative Result Analysis with the Existing Work

Research Work	Purpose of Study	Participant Age (years)	Monitoring Period	Parameters used for predicting Fall Risk	AI/ML technique used	Accuracy Obtained (%)
[223]	Developing a fall risk prediction model that integrates both clinical and robotic parameters.	≥ 65	1 year	8 clinical assessments and 20 Robotic parameters including ADL	cross-validation method	81
[224]	Utilizing artificial intelligence to foresee fall risks in hospitalized elderly patients.	≥ 65	1 year	Vital signs, visual ability, hearing ability, previous medication, and ADLs	XGBoost	73.2
[225]	Developing a fall prediction model for community-dwelling elderly people using HER data.	≥ 65	1 year	Age, sex, history of falls, 2 medications, and 5 medical conditions	Bootstrap-enhanced penalized logistic regression	70
[226]	To predict short-term fall risk in older adults with dementia at high risk for falls.	Over 60 years with Dementia	More than 2 weeks	Age, sex, history of falls, dementia records, and other medical conditions	Random Forest	82
[227]	To develop a fall risk prediction model for individuals with Parkinson's disease using real-world gait data from inertial sensors.	60-84	2 weeks	ADL	Random Forest	74
[228]	To examine the effectiveness of various machine learning	≥68	12 months	Spatiotemporal gait parameters and prospective registration of falls	Dynamic Bayesian Networks	80

	models based on spatiotemporal gait parameters in predicting falls among elderly individuals with osteoporosis.					
Proposed DBN-based Fall Risk Prediction Model	To predict future falls in older adults	≥60	75 hours	ADL	DBN	91.67

5.8 Conclusion

The proposed DBN-based Fall Risk Prediction Model aims to identify senior citizens at risk of falls by continuously monitoring physical activities, with particular emphasis on ADLs. This model only uses behavioural data to forecast future falls and has outstanding predictive accuracy. The DBN model uses a layer-wise, unsupervised pretraining process with three RBM layers such that each layer progressively refines extracted features. The greedy layer-wise training algorithm ensures that each RBM is sequentially trained with contrastive divergence, and the final model is fine-tuned using supervised learning. The system appropriately classifies levels of fall risk based on activity-based weight distribution for an interpretable and robust fall risk predictive model. Fine-tuning is the most critical phase of DBN training that embodies the unsupervised RBM layers in an entire predictive model. The DBN is able to predict the levels of fall risk accurately with backpropagation and Adam optimizer. The developed AI-2 model's evaluation shows an accuracy of about 91.67%, a specificity 100%, and a sensitivity 90.00%. This developed model will be combined with the AI-1 model and Meta-model to produce the final fall risk prediction outcome. Furthermore, the prediction results are evaluated from various algorithms and transfer learning models, as well as tested in real-time scenarios which will be elaborated in the future work segment of this thesis.

Chapter 6. Novel Co-operative AI-Based Fall Risk Prediction Model

6.1 Introduction

The conventional assessment for fall risk has traditionally hinged on functional testing and clinical opinion that, while helpful, lack predictive capacity and necessitate subsequent testing. ML and AI for fall prediction have emerged with unprecedented potential to computerize risk assessment processes and aid early intervention programs. For example, the research study presented in [229] The Irish Longitudinal Study on Ageing (TILDA) dataset demonstrated that AI models can predict simple and complex falls with good accuracy. However, there are issues in making the results more generalizable, especially for complex fall events that are tied to severe health conditions. Further, Parkison Disease research [230] has ascertained that disease-specific and functional measurements are the key risk predictors for falls, highlighting general evaluation strategies involving clinical assessments along with artificial intelligence-based methodologies. Even though all these strides have been taken, current models usually lack the applicability required for real-world problems, so there is a need to create stronger predictive models.

Hence the developed research model presented in this thesis introduces a novel Co-operative AI model that can foresee future falls in the elderly with higher accuracy and validity. It is acknowledged that the present study is the first scientific investigation to specifically use two different AI models of different dimensions embedded with the Meta model to forecast the probability of future falls among older adults. This developed model is first calibrated with data downloaded from public repositories. In the following phase (future work), after validation, real-time information from older adults will be incorporated. Utilizing multi-modal datasets like physiological, behavioural, and functional assessments, the model aims to bypass the limitations of traditional classifiers and improve fall risk stratification. The strategy built has initially been validated through public datasets to ensure stability before incorporating real-time information in future stages. The proposed AI-driven solution can potentially enable early interventions, decrease the likelihood of fall injuries, and enable independent living for the elderly. As newer AI and ML technologies advance, they offer a robust platform to enhance fall forecasting to achieve enhanced healthcare outcomes. This is showcased at the close of this chapter in the GT, MFS, and Comparator validation of the Co-operative AI-based fall risk prediction model.

6.2 Comparator Analysis

To integrate two AI models, the initial intuition was to use comparators. In developing the third model, a series of comparators were utilized to effectively combine the results from the AI-1 model (Fuzzy-based Fall Risk Prediction model), and the AI-2 model (DBN-based Fall Risk

Prediction model), ultimately resulting in an improved prediction of future fall risk among older adults. Several systematic comparison methods were investigated for this goal, such as the Weighted Average Method [231], Rule-based Fusion Method [232], Decision Tree Approach [233], and Ensemble Learning [234]. Figure 6.1 depicts the comparator analysis.

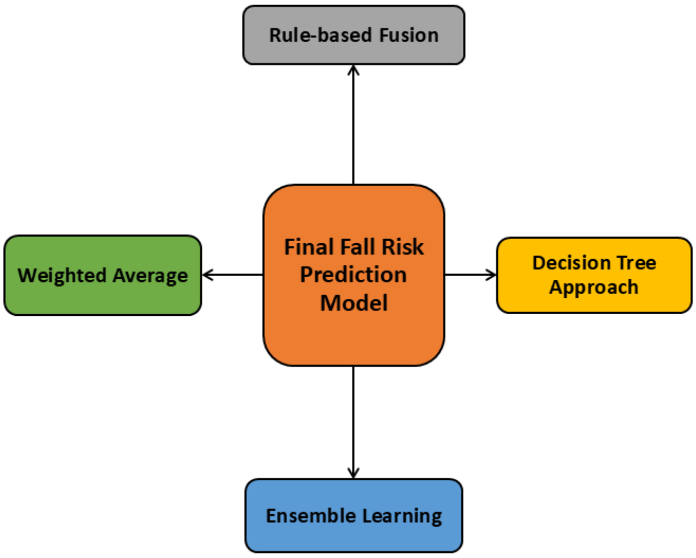


Figure 6.1: Comparator Analysis.

6.2.1 Weighted Average or Score Fusion

In this comparison approach, the outputs of both models are normalized to a shared numerical range, and weighted averaging is employed to aggregate the results, as presented in (6.1).

$$\text{Final prediction} = \frac{AI_1 + AI_2}{2} \qquad (6.1)$$

AI-1 weight allocations are as follows: *Normal* → 0.2, *Low* → 0.4, *Moderate* → 0.6, *High* → 0.8, and *Emergency* → 1.0. AI-2 corresponding weights are: *Low* → 0.33, *Moderate* → 0.66, and *High* → 0.99. Table 6.1 shows the weight assignment for AI-1 and AI-2 models. The overall fall risk score is estimated based on the average of AI-1 and AI-2 scores. The global weight distribution utilized to compute the final fall risk prediction result is illustrated in Table 6.2, derived from the score fusion measures. For example, if AI-1 predicts a result of *0.4 (Low risk of fall)* and AI-2 predicts a result of *0.66 (Moderate risk of fall),* then the ultimate comparator result would be (0.4 + 0.66)/2 = *0.53, a "Moderate fall risk"*. Although such a method is straightforward, it does not depict the complexity of fall risk estimation. Weighing and averaging scores in such a manner may be too simplistic and fail to provide a real representation of actual risk. Since this method is not good enough to capture the reasonableness of the resulting prediction based on two well-established models, the next comparator (Rule-based Fusion Method) is investigated.

Table 6. 1: Weight Assignment for AI-1 and AI-2 Models

<table>
<tr><th>AI-1</th><th>Score</th><th>AI-2</th><th>Score</th></tr>
<tr><td>Normal</td><td>0.2</td><td rowspan="2">Low</td><td rowspan="2">0.33</td></tr>
<tr><td>Low</td><td>0.4</td></tr>
<tr><td>Moderate</td><td>0.6</td><td>Moderate</td><td>0.66</td></tr>
<tr><td>High</td><td>0.8</td><td rowspan="2">High</td><td rowspan="2">0.99</td></tr>
<tr><td>Emergency</td><td>1.0</td></tr>
</table>

Table 6. 2: Score Fusion Metrics

Comparator	Score
Low	0.0 – 0.40
Moderate	0.41 – 0.80
High	0.81 – 1.00

6.2.2 Rule-Based Fusion Method

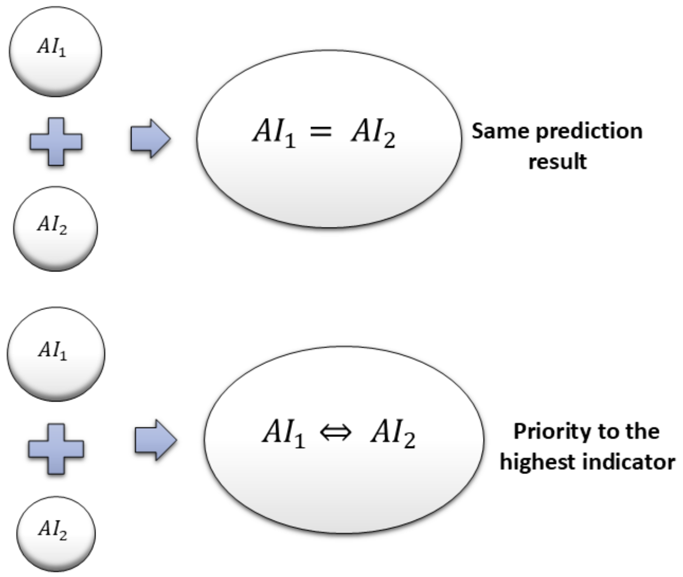


Figure 6.2: Final Predictions Derived from the Rule-Based Fusion Method.

In this approach, individual or threshold rules are applied to combine AI-1 and AI-2 prediction indicators. A majority voting approach is employed when both AI-1 and AI-2 predict the same category, and it is chosen as the final output. Priority-based rules are also stored to give preference to higher-level predictions over others. For example, if AI-1 shows "*Emergency*," and AI-2 refers to a "*High risk of fall*," the final inference will always be "*Emergency*," regardless of what the second model reports. Likewise, if AI-1 shows a "*Moderate risk of fall*," and AI-2 suggests a "*High risk of fall*," the final inference will accordingly be "*High risk of fall*," as this constitutes the greater risk factor. Figure 6.2 presents the final predictions derived from this rule-based method. Whereas this method successfully orders instances by severity, it is possible that it fails to represent all situations correctly and might result in false alarms. Acknowledging these shortcomings, another approach based on decision tree comparator is investigated.

6.2.3 Decision-Tree Approach

In this approach, the final fall risk estimation is done based on a structured decision tree using the outputs of AI-1 and AI-2 logically to reach an informed decision. The biggest difference between this approach and the rule-based method is that the decision tree is hierarchical rather than employing static priority-based rules. Table 6.3 provides the prediction of the Decision tree approach. For both Rule-based and Decision-tree approaches, the analysis is purely done using the prediction indicators (risk levels), and no weights are assigned to the fall risk levels.

Table 6. 3: Decision Tree Approach Predictions

AI-1	AI-2	Final Prediction (Decision Tree)
Low	Low	Low
Moderate	High	High
Emergency	Any	Emergency
Moderate	High	Moderate-High (Weighted Decision)
Low	Moderate	Low-Moderate (Adjusted Based on condition)

"*Moderate-High*" or "*Low-Moderate*" may be an adaptive choice here instead of a rigid hierarchy. The tree can also incorporate weight updates with real-world information. Both methods integrate AI-1 and AI-2 predictions, but the decision tree method gives a more formalized and adaptable classification instead of strict rule-based priority choices. It is more adaptable and reduces misclassification from predetermined rules. Even though the model produces good prediction compared to the above two methods it is still not convincing to use this analysis as the comparator cannot learn from the past and present predictions. Hence, the next learning model which is Ensemble Learning is investigated.

6.2.4 Ensemble Learning

Ensemble learning is an effective method that integrates multiple models to improve prediction accuracy [235]. Based on the background study conducted in [236-238] using ensemble learning, it is evident that this method suits the requirement for infusing the 2 AI models and produce a good prediction outcome through continuous learning. Hence, in this research work Ensemble learning based Meta model is used for the final fall risk evaluation analysis. In this thesis, a meta-classifier is utilized that takes AI-1 and AI-2 predictions as input features, evaluates the predictions, and produces one final future fall risk prediction outcome. In contrast to conventional fusion techniques based on rule-based or weighted averaging techniques, ensemble learning adapts to the final prediction using training data dynamically. The techniques, such as weighted averaging, rule-based systems, and decision-tree techniques, incorporated inherent inflexibility and assumptions that restricted their flexibility. Those methods did not assist in improving their forecasting ability during the specified timeframe, mainly because they had no training data.

The meta-model strategy enables the system to learn from past data and update its decision model, as opposed to rigid rule-based systems. This characteristic allows the classifier to improve its generalization ability, making its predictions more consistent and reducing the possibility of false positives. Instead of directly weighing or averaging AI-1 and AI-2 predictions, this method obtains helpful patterns and relationships between their predictions. The meta-classifier will consider previous cases derived from these AI models to function adaptively in selecting the optimum weighting for each provided AI model. The Random Forest algorithm was chosen as the primary training procedure for meta-classifiers due to its established efficiency and reliability in predictive analytics [239]. Some of its main strengths are:

- It would show non-linear messy correlations that may exist between the AI-1 and AI-2 output and thus possibly boost predictive accuracy.
- Unlike logistic regression, which assumes linearity, Random Forest has the capability of handling detailed decision boundaries [240].
- It builds many decision trees and averages the result, thereby cleaning up overfitting.

This makes the model generalizable to other datasets. As AI-1 and AI-2 are both capable of generating different risk scores or classes, the Random Forest algorithm automatically determines the input features that contribute significantly to the final prediction. It was chosen as the meta-model due to its robustness, interpretability, and ability to handle heterogeneous input features effectively. Unlike deep reinforcement learning (DRL), which requires large amounts of training data, careful tuning of reward functions, and extensive computational resources, RF can efficiently learn from smaller datasets and provide reliable predictions with minimal parameter tuning [241]. Additionally, RF naturally handles feature interactions and reduces the risk of overfitting through its ensemble structure, making it suitable for fall-risk prediction where input features may vary in type and scale. Moreover, the interpretability of RF outputs, such as feature importance scores, allows for better understanding and trust in the model's decision-making process, which is critical in healthcare applications. Overall, RF offers a balance between accuracy, computational efficiency, and interpretability, whereas DRL would introduce unnecessary complexity without clear advantages for this specific task. Figure 6.3

shows the model of Ensemble learning. This reduces the need for hand-built features and improves efficiency therein.

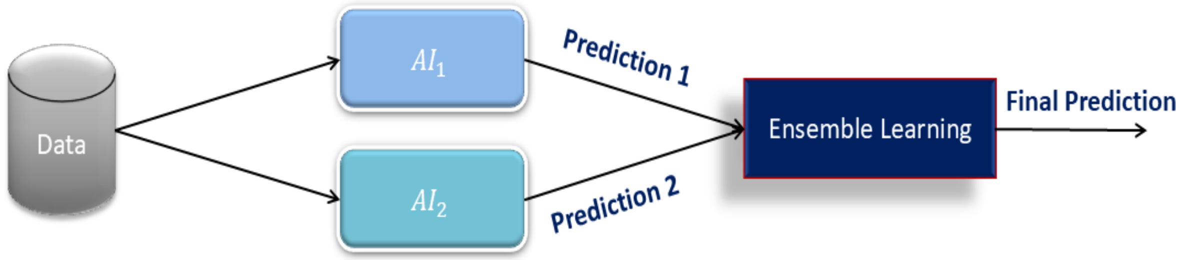


Figure 6.3: Model of Ensemble Learning.

Table 6.4 gives a brief description of the weight given to each risk grade used by AI-1 and AI-2 models. The On-Learning Random Forest meta-classifier will create a data-driven and adaptive older adult fall risk prediction system that is superior to existing fusion methods. The system applies the principle of ensemble learning to deliver a more accurate, interpretable, and scalable older adult fall risk prediction framework.

Table 6. 4: Weights assigned to each risk level of AI-1 and AI-2 Models

AI-1	**Score**	**AI-2**	**Score**
Normal	0.2	Low	0.3
Low	0.4		
Moderate	0.6	Moderate	0.6
High	0.8	High	0.9
Emergency	1.0		

6.3 Novel Co-operative AI-based Fall Risk Prediction Model Architecture Overview

This research aims to forecast the future risk of falls in the elderly by fusing two significant markers of health: vital signs and ADLs using a Co-operative AI-based methodology for fall risk prediction. The model seeks to maximize predictive accuracy by incorporating a series of artificial intelligence techniques, thereby facilitating timely and accurate estimation of fall risk in close alignment with the MFS, to achieve a very high concordance rate of about 90%. The design consists of two independent AI models, one evaluating vital signs and the other evaluating ADLs which are then fused into a meta-model via ensemble learning to enhance the overall prediction outcome. The first AI model (AI-1) evaluates vital sign patterns using Fuzzy Logic, whereby 111 pre-established fuzzy rules are used to classify fall risk into five categories: *Normal (No risk), Low, Moderate, High, and Emergency.* In the event of no abnormality detected, the model predicts Normal, which indicates no risk of fall, whereas abnormalities detected are graded according to severity. The second AI model (AI-2) uses DBN to analyze ADL patterns and predict fall risk based on learned history and categorizes the risk of falls as *Low, Moderate, or High*. The ADLs provide important information about mobility, balance, and patterns of movement that allow the AI-2 model to identify individuals with impaired movement and an elevated risk for falls. Following the predictions by these two models, their output is fed into the Meta-Model, which is one decision-making system, that refines the final prediction.

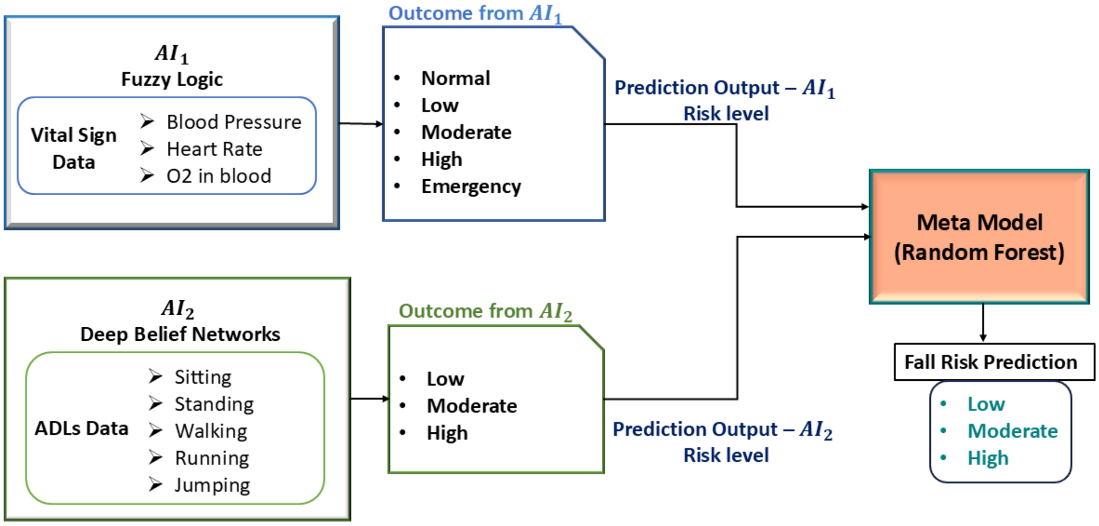


Figure 6.4: Architecture of an AI-based Co-operative Meta-Model for Fall Risk Prediction.

The DBN-based AI-2 model is closely related to the fuzzy logic-based AI-1 model, as both aim to address the challenge of fall risk prediction in older adults but from different methodological perspectives. The fuzzy logic model provides an interpretable, rule-based framework that captures the uncertainty and variability in vital signs by categorizing them into normal, low, moderate, high, and emergency risk levels. This approach ensures transparency and clinical interpretability, reflecting expert-defined decision-making processes. Building upon this, the DBN extends the analysis by adopting a data-driven approach, where hierarchical feature representations are automatically learned from the input data. Unlike fuzzy logic, which relies on pre-defined membership functions and rules, the DBN captures complex nonlinear relationships and hidden dependencies, thereby enhancing predictive performance and generalization. The integration of these two approaches demonstrates a complementary relationship: while the fuzzy model establishes a foundational and interpretable baseline, the DBN leverages deep learning to improve accuracy and robustness. Together, they highlight the balance between interpretability and predictive power, underscoring the importance of combining expert knowledge with advanced machine learning techniques in fall risk prediction. This relationship strengthens the overall contribution of the research by demonstrating that hybrid and complementary models can provide more reliable and effective healthcare decision support systems. Figure 6.4 depicts the architecture model of the developed AI-based Co-operative Meta-Model for Fall Risk Prediction.

Initially in developing the third model, different types of comparators were planned to be used. These comparators intend to combine the results of AI-1 and AI-2 to produce the future fall risk prediction outcome in the elderly as mentioned in section 6.2. Some systematic kinds of comparisons were analyzed such as Weighted Average or Score Fusion, Rule-Based Fusion Method, and Decision Tree-based Approach. Due to the significant weaknesses that were revealed in the previously outlined fusion models, particularly their poor capability in making predictions on the training data, an alternative approach was investigated that uses both the training and validation datasets. The meta-model-based fall risk prediction system is a composite model that trains a meta-model classifier that uses the output of AI-1 and AI-2 as input features and is utilized to generate a consistent prediction. The Co-operative Meta model Fall Risk prediction Algorithm based on the final fall risk prediction is formulated by integrating the output of both AI-1 and AI-2 models which is explained in section 6.4.

The meta-model determines ultimate risk levels based on the integrated inputs of AI-1 and AI-2, thus reducing intrinsic errors in individual models and enhancing the trustworthiness of predictions. For instance, if AI-1 predicts a "*Moderate fall risk*" and AI-2 predicts a "*High fall risk*", the meta-model uses these inputs and calculates the final fall risk outcome based on learned models and training data. This combination-based approach is superior to traditional rule-based models in that it continues to learn from previous predictions and adapts based on new data, thereby increasing its flexibility and credibility. One of the significant benefits of this technique is that it is very accurate, making it possible to be integrated into real-time health monitoring systems. The integration of Fuzzy Logic (AI-1) and Deep Belief Networks (AI-2) within the meta-model enables intelligent and holistic assessment of the risk of falls by using both physiological markers (vital signs) and behavioural markers (ADLs). The proposed model can be implemented within wearable healthcare technology and home automation systems to allow real-time tracking and immediate fall risk alerts to caregivers and health professionals (*early tests of the AI-1 model have been conducted and discussed in Chapter 4*). The interactive architecture of the system, whereby each AI model enhances the decision-making ability of the meta-model, forms a predictive mechanism that is highly adaptive and specific, learning from new data. The enabling of the meta-model with the ability to compare and harmonize predictions made by AI makes the meta-model a good predictive tool for predicting fall risk among the elderly. As a result, early interventions can significantly reduce the incidence of injuries and the related healthcare costs resulting from falls. This thesis illustrates that AI-powered Co-operative models are the key to developing predictive healthcare solutions, delivering a scalable and intelligent method for elderly fall risk prediction. Section 6.5 presents the performance analysis, confirming the effectiveness of this proposed AI-based Co-operative fall risk prediction model.

The framework in Figure 6.4 can be extended by incorporating additional features, such as image data, to further enhance prediction accuracy. For example, force-plate time series data captures biomechanical signals [100] but image data from video or depth cameras can provide complementary information on posture, movement patterns, and environmental context. By integrating such multimodal inputs, AI-1 and AI-2 could be augmented with a third AI model (e.g., a convolutional neural network or vision transformer) specialized in image-based feature extraction. The meta-model could then learn to combine the strengths of all three approaches: (i) fuzzy logic for handling uncertainty in clinical scores, (ii) DBN for modeling temporal dependencies in sensor signals, and (iii) computer vision methods for spatial and movement features. This multimodal cooperation allows the system to capture different aspects of fall risk, physiological, behavioral, and contextual, resulting in a more comprehensive and accurate prediction. However, such an extension would require careful data alignment, increased computational resources, and robust meta-model design to avoid overfitting. Moreover, since this research places a strong emphasis on protecting the privacy of older adults, computer vision or any image-based data has deliberately not been used for fall risk prediction.

6.4 AI-Based Co-operative Meta-Model Fall Risk Prediction Algorithm

The fall risk prediction algorithm for the AI-based Cooperate Meta model is built via a combination of the results generated by the AI-1 and AI-2 models, described in the pseudocode of Algorithm I. Weighting is done to every separate model, upon which the final composite risk value is computed. The training labels are set with reference to the combined risk variables alongside MFS. This is where the Meta-Model is trained and the final fall risk prediction is obtained by learning from the stored data (past data), and the current inputs (present data).

AI-Based Co-operative Meta Model Fall Risk Prediction Algorithm: Pseudocode of the Proposed Model (Figure 6.4)

---

1. **Input Mapping:**

Let:

- X_{AI1} = Output of AI_1 Model – *Normal, Low, Moderate, High, Emergency*
- X_{AI2} = Output of AI_2 Model - *Low, Moderate, High*

Assign weights W_{AI1} and W_{AI2} to the outputs:

$$\text{For } X_{AI1}:\ W_{AI1} = \begin{cases} 0.2\ if\ Normal \\ 0.4\ if\ Low \\ 0.6\ if\ Moderate \\ 0.8\ if\ High \\ 1.0\ if\ Emergency \end{cases}$$

$$\text{For } X_{AI2}:\ W_{AI2} = \begin{cases} 0.3\ \ if\ Low \\ 0.6\ if\ Moderate \\ 0.9\ if\ High \end{cases}$$

2. **Combined Risk Score:**

The combined risk score $S_{combined}$ is calculated as:

$$S_{combined} = \frac{W_{AI1}+W_{AI2}}{2}$$

3. **Define Risk Levels:**

Risk level *R* is defined based on $S_{combined}$:

$$R = \begin{cases} Low\ \ if\ 0 \leq\ S_{combined} \leq 0.40 \\ Moderate\ \ if\ 0.41 \leq\ S_{combined} \leq 0.80 \\ High\ \ 0.81 \leq\ S_{combined} \leq 1.00 \end{cases}$$

4. **Train Random Forest Meta Model**

Let the dataset consist of

- Training features $X_{train} = \{W_{AI1}, W_{AI2}\}$
- Training labels Y_{train} = MFS-based risk levels {Low, Moderate, High}

5. **Random Forest Model:**

Initialize *T*, the number of decision trees.

For each tree *t* in *T:*

- Select a random subset X_t from X_{train}
- Build a decision tree using X_t and Y_{train}
- Split data at each node using features $\{W_{AI1}, W_{AI2}\}$
- Aggregate predictions from all *T* trees by majority voting.

6. **Predict Fall Risk:**

For testing data $X_{test} = \{W_{AI1}, W_{AI2}\}$

- Pass each test instance through all *T* decision trees.
- Compute the predicted risk level R_{pred} based on a majority vote from the *T* trees.

7. **Output Results**

For each participant *i*, output: Participant i: $\{S_{combined}, R_{pred}\}$

6.5 Data Collection and Ground Truth Selection

This section evaluates the effectiveness of the proposed AI-based Co-operative Meta-Model for Fall Risk Prediction according to its data acquisition process and experimental result. Its accuracy is calculated based on the correctness of its predictions in comparison to the Morse Fall Scale. Its efficiency is also benchmarked against existing current advanced studies in this field. The simulations were executed using Visual Studio Code on Windows 10 Enterprise, based on an 11th Gen Intel Core i7 processor (3.00 GHz) with 32 GB RAM.

6.5.1 Evaluation Metrics

The proposed framework is evaluated using data from PhysioNet [127], which includes,

- Age
- History of Falls
- Vital sign Data
- ADL Data

The Confusion Matrix is used as an evaluation approach for fall risk prediction. These measurements are Accuracy, Sensitivity, and Specificity, with TP, TN, FP, and FN representing True Positive, True Negative, False Positive, and False Negative, respectively [183].

The result analysis integrates data from both the AI-1 and AI-2 models to ensure a comprehensive assessment of fall risk prediction. However, due to the unavailability of a dataset containing both vital signs and ADLs from the same participants, an indirect approach was adopted. In this method, two different participants with the same age, a similar history of falls, and comparable health conditions were selected, one from the AI-1 model database and the other from the AI-2 model database. To help guarantee consistency, both participants also shared the same MFS score. For the meta-model, these two participants were merged as a single entity to simulate the presence of both vital signs and ADL data. Following such a systematic process, a training dataset of 30 participants was established, while another 10 participants were held out for testing, this is detailed in Section B.2 of the Appendix Section. The effectiveness of the developed model was tested by comparing its prediction with MFS to determine its accuracy and reliability. The MFS scoring system categorizes the risk of falls into three levels: Low risk (below 25), Moderate risk (between 25 and 45), and High risk (above 45). To attain compatibility with the scoring system utilized in the proposed AI-based model, the MFS scores were converted into their equivalent numerical values: Low risk (0.3), Moderate risk (0.6), and High risk (0.9). This step allowed for a homogeneous and standardized evaluation, whereby a direct comparison of the AI-based Co-operative meta-model predictions with the traditional MFS-based fall risk prediction could be made. Through this method, the proposed model demonstrates its ability to provide valid and accurate fall risk prediction in the elderly.

6.6 Evaluation of the Developed AI-Based Meta Model with MFS

The process of result evaluation integrates information from the AI-1 and AI-2 models to provide a comprehensive overview of fall risk assessment [186, 221]. The key components for the same, i.e., age of participants, history of falls, vital signs, and ADLs, were considered with care so that uniformity as well as reliability was maintained while evaluating. For creating a representative data set, 10 participants from the AI-1 model database and 10 participants from the AI-2 model database with matching ages, history of falls, and medical history were selected. This procedure was adopted to ensure that the selected individuals possess comparable health status to perform the fair and systematic evaluation. Since each dataset contained either vital sign data (AI-1 model) or ADL data (AI-2 model), an indirect pairing approach was employed (as stated above), where Participant P1 of the AI-1 model was matched with Participant P1 of the AI-2 model, forming a single Participant 1 to be assessed. This was applied consistently to all the selected participants, essentially combining the two different data dimensions into a single evaluation dataset. As a result, the total number of participants to be involved in the testing phase was narrowed down to 10. The full differential analysis of the Co-operative Meta-Model and the MFS is given in Table 6.5, comparing the results of classification obtained from both frameworks.

Table 6. 5: Comparative Result Analysis on the Meta Model and MFS Prediction

Participant	**Fall History**	**Input**		**Output: Prediction Results**	
		AI-1	**AI-2**	**Co-operative Meta Model Prediction**	**MFS prediction**
P1	2 (Y)	Moderate	Low	Moderate	Moderate
P2	2 (Y)	Moderate	Low	Moderate	Moderate
P3	0 (N)	Moderate	Low	Moderate	Low
P4	5 (Y)	Moderate	Moderate	Moderate	High
P5	0 (N)	Normal	Low	Low	Low
P6	6 (Y)	High	Moderate	Moderate	Moderate
P7	2 (Y)	High	Low	Moderate	Moderate
P8	1 (Y)	Low	Low	Low	Moderate
P9	0 (N)	Low	Low	Low	Low
P10	2 (Y)	Moderate	Moderate	Moderate	Moderate

The proposed AI-based model predicted participants P5, P8, and P9 with "*Low fall risk*", whereas other participants were placed in the "*Moderate fall risk*" category. By comparison, the MFS outcomes positioned participants P3, P5, and P9 in "*Low risk of fall*", P4 in "*High risk of fall*", with the rest in "*Moderate risk of fall*". Figure 6.5 shows the simulation result of Participant P1, where the input from AI-1 is "*Moderate risk of fall*" the input from AI-2 is "*Low* *risk of fall*” and the final estimated result from the Co-operative Meta-Model is “*Moderate risk of fall*”.

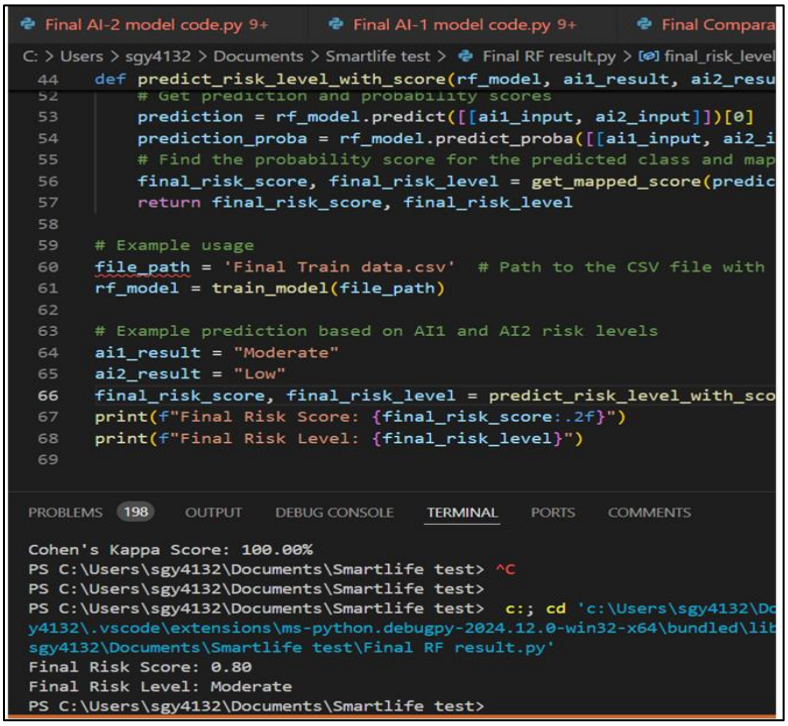


Figure 6.5: Simulation Results for Participant P1.

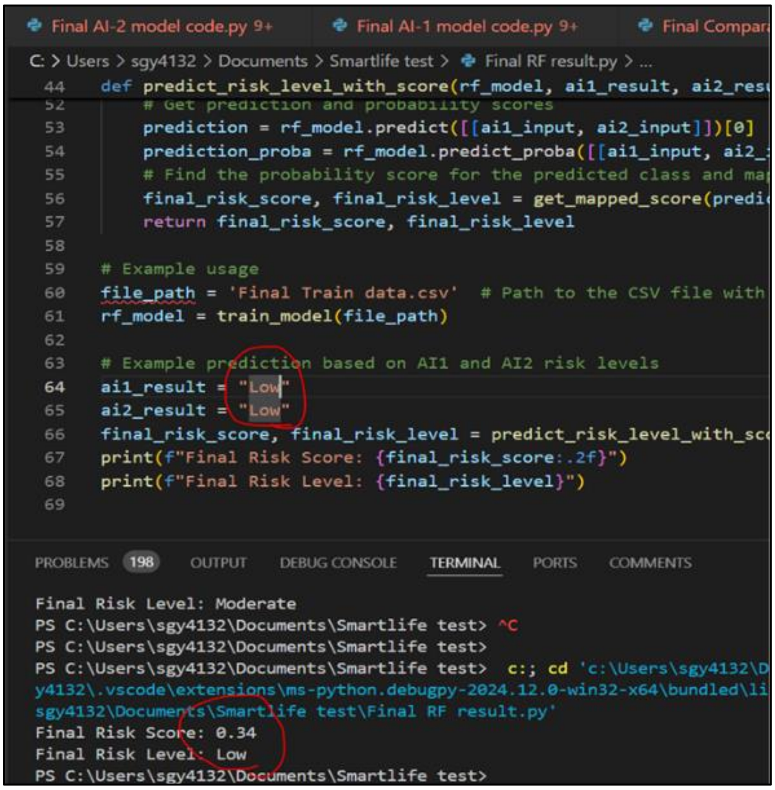


Figure 6.6: Simulation Results for Participant P9.

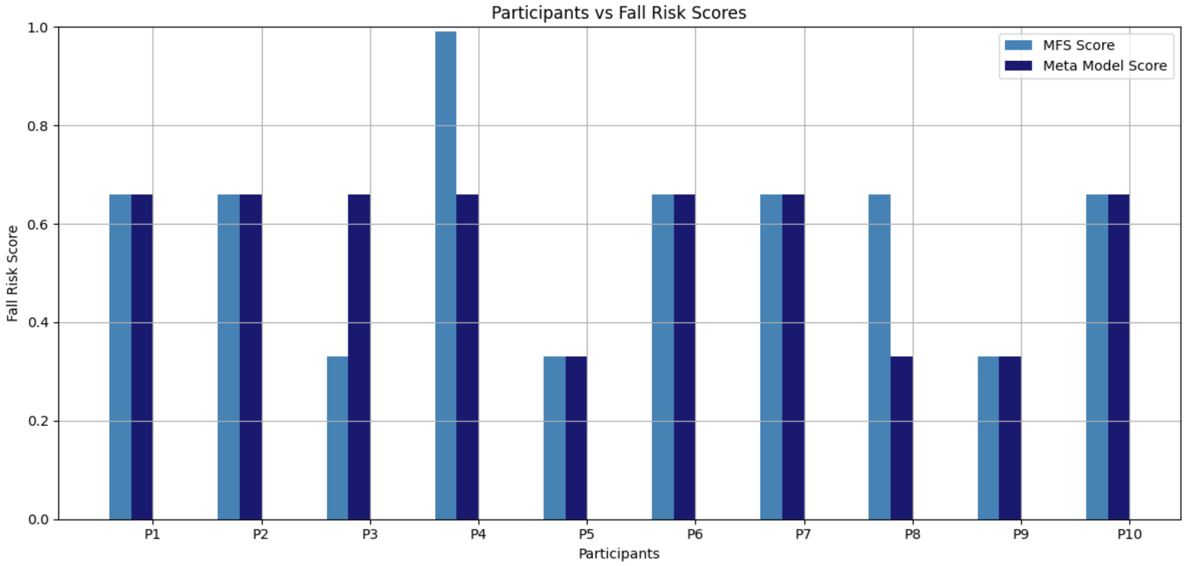


Figure 6.7: Fall Risk Prediction Evaluation Results.

Similarly, Figure 6.6 depicts the simulation results of Participant P9, where the input from AI-1 is "*Low risk of fall*" and the input from AI-2 is "*Low risk of fall*" and the final prediction result from the Co-operative meta-model is "*Low risk of fall*". A comparison of the Co-operative Meta-Model and MFS predictions showed a high correlation, indicating the model's good predictive strength. There were, however, discrepancies in the case of P3, P4, and P8, where model predictions were different from the MFS classifications. Such discrepancies can be due to factors such as the variability of participants' fall history over the last year, or the small size of the training dataset used for AI model development.

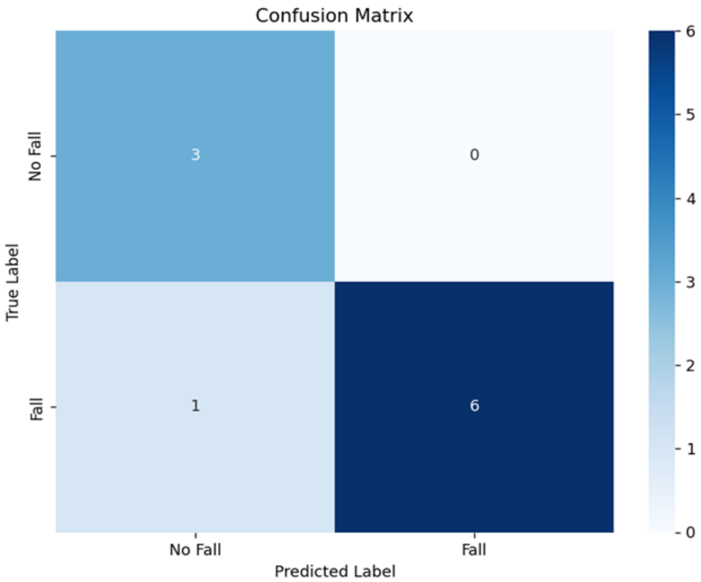


Figure 6.8: Confusion Matrix Outcome.

Figure 6.7 provides a graphical comparison of the simulation outcome of Co-operative Meta-Model and MFS-based risk assessment. In comparison to the MFS, Co-operative Meta-Model was found to have a remarkable accuracy of 90.00%, a sensitivity of 85.75%, and a specificity of 100%. For improved clarity on the effectiveness of the model, Figure 6.8 displays the confusion matrix indicating the breakdown of the TP (6), TN (3), FP (0), and FN (1). The final results confirm the performance and reliability of the developed model as an indicator of falls in older adults, highlighting its viability towards practical application for proactive fall prevention.

6.7 Conclusion

The Co-operative Meta-Model for AI-based Fall Risk Prediction is a very advanced model that is specially developed to recognize elderly individuals at risk of falls through the continuous observation of their vital and behavioural parameters. The model concentrates on two very important predictive parameters: ADLs and vital signs, to enable a complete and very accurate fall risk assessment. This model is different from usual fall detection systems that only react after the fall has occurred because it acts proactively based on the detection of potential risks to allow timely intervention and greatly reduce fall likelihood. By incorporating fuzzy logic in assessing physiological measures (AI-1 model) and deep belief networks in analyzing behaviour patterns (AI-2 model) the proposed model most efficiently picks up on momentary changes in indicators of health and ongoing changes in mobility patterns with increased fall risk. By combining these artificial intelligence models into a meta-learning system, prediction accuracy is optimally enhanced through result fusion, learning from previous cases, and repetitively refining decision processes. Final performance testing validates high predictive accuracy for this model, with 90.00% accuracy, 100% specificity, and 85.75% sensitivity. These metrics point to the systems success in both accurately identifying individuals at risk and keeping both false positives and false negatives low. The 100% specificity guarantees that individuals assessed as low risk truly have minimal risk and the high sensitivity guarantees that the system detects the great majority of individuals who are truly at risk of falling. Moreover, more than two AI methods can cooperate to achieve better performance. While the meta-model combines the results of the fuzzy model and the DBN model, the approach is not limited to just these two methods. Ensemble and hybrid learning frameworks are specifically designed to integrate multiple AI techniques such as support vector machines, convolutional neural networks, reinforcement learning, and decision trees into a single predictive framework. By incorporating more than two models, the system can exploit the complementary strengths of different algorithms, reduce variance and bias, and ultimately enhance prediction accuracy and robustness. For fall-risk prediction, integrating additional AI methods could capture different dimensions of the problem, such as temporal dependencies, uncertainty handling, or nonlinear feature interactions, leading to improved overall performance. However, the trade-off lies in increased system complexity, computational cost, and the challenge of designing an effective meta-model to balance the contributions of multiple methods. Hence, due to its foresight nature, advanced learning abilities, and high predictive effectiveness, this novel Co-operative Meta-Model developed using artificial intelligence marks the evolution of fall risk prediction in geriatric care, ensuring a scalable, data-driven, and highly effective method of minimizing fall-related injuries and improving overall healthcare outcomes.

Chapter 7. Conclusion and Future Directions

7.1 Introduction

This chapter provides a summary of the research findings on the innovative Co-operative AI-based future fall risk prediction model, focusing on its key features and outcomes. The combination of cutting-edge technology, such as AI-based analysis, system integration, and software solutions, is heavily emphasized to create a flexible and adaptive fall prediction model. This developed prediction system is intended to identify the risk of falls among older adults in advance, allowing precautions to be implemented before a fall occurs. Furthermore, this chapter outlines future research directions for the system's functionality.

One of the most crucial areas for development is the incorporation of real-time prediction models, which allow the model to change and instantly adapt to new data. This allows the model to gradually improve its forecast based on real-time ADL and vital sign data. Subsequent work will also result in a more advanced and comprehensive fall risk prediction system by allowing Co-operative AI models to communicate with one another, exchange ideas, and fine-tune their predictive capabilities continuously. The goal is to create an intelligent, self-learning system that can enhance and adjust its fall risk prediction, providing older adults with more accurate and customized future fall risk predictions.

7.2 Conclusion

This thesis provided the motivational background for developing a Co-operative AI-based fall risk prediction system and its feasibility in dynamically assessing and responding to potential fall risks among older adults. Considering the problem space, the key building blocks necessary for the improvement of a plausible, adaptive, and proactive fall prediction system are critically examined with a focus on two areas: ongoing health monitoring and intelligent risk assessment. The study points out the integration of significant vital signs and behaviour information to yield a robust predictive model that can effectively identify at-risk individuals, thus enabling early intervention to prevent falls and enhance care for the elderly.

The first part relates to the proposed Fall Risk Prediction Model, derived from the principles of Fuzzy Logic, which has been designed meticulously to determine the senior citizens at risk of falls. The main motive for developing the model was to design a valid and efficient model for fall prediction, thereby assisting in the decrease of the economic cost and personal difficulties related to fall-related injuries in the elderly population. By monitoring vital signs continuously, the model is integrated using three important physiological parameters such as blood pressure, heart rate, and blood oxygenation to detect early deviations that can indicate a heightened risk of falls. Unlike existing approaches that rely on a synthesis of multiple health parameters, the developed model is distinct in its exclusive reliance on vital signs, making it a compact and efficient fall risk prediction tool. In comparison with the MFS and using data from three sources, the model attained an accuracy of 95.24%, a specificity of 100%, and a sensitivity of 93.75%. These performance indicators point to the efficiency and reliability of the model in assessing fall risk levels with very few false positives and false negatives. Different research about fall risk assessment highlights that the large percentage of falls among the older population can be prevented by acting at the earliest possible moment.

Despite the developed AI-1 model's very good accuracy, the model under discussion has yet to be applied to large real-time-series data. The incorporation of real-time continuous monitoring of older adults is essential to make the model more robust and its prediction more accurate. A key component that remains to be verified is the emergency risk level indicator which can only be validated through empirical implementation. The procedure of acquiring real-time data and tests may generate new variants that could influence the defined fuzzy rules, thus calling for further adjustment.

The second section pertains to the suggested fall risk prediction model based on DBN, which is especially intended for the elderly population and aims to detect risks of falls by continuously observing behavioural patterns, particularly for specific ADLs. The model only predicts fall risks based on behavioural data. With an accuracy of 91.67%, specificity 100%, and sensitivity 90%, the model is capable of accurately categorizing individuals who are at risk of falling against those who are not. A significant limitation of the current study is that the model only incorporates four ADLs instead of the five that should be considered. Although it was trained on a large dataset over 75 hours of observation, the lack of jumping actions limited the total prediction potential for high accuracy. As a result, the model achieved less than 95% accuracy, indicating that including the missing ADL could influence prediction results: either increase accuracy further or drop it below 90% and hence the outcome of this addition is unknown. To amend this, future research will focus on expanding the dataset through the inclusion of all five ADLs and conducting further validation using real-time monitoring. This will determine if the expanded dataset results in greater predictive reliability.

Despite these limitations, this proposed Co-operative model aims to interact with the 2 AI models and learn from the past and present data to provide the future fall risk prediction outcome with good accuracy. Some of the benefits of this research work:

- *Saves Life* - avoids the risk of future falls and injury.
- *Independent Living* – the older adult need not depend on anyone or be afraid of falling.
- *Easy Wearable* – the model can be integrated with wearable devices (Smartwatches, Pendants, Smart Bracelet).

- *Easy Smart Device Integration* - this research idea can be extended to other health-related applications.
- *Secure and Safe* - harmless and notifies the caregiver in terms of any emergency or fall risk.
- *Privacy and Accuracy* - Since no cameras are used for monitoring, the privacy of older adults remains protected while the model still provides accurate fall predictions.
- *Simple Infrastructure and Low cost* - do not require more complex infrastructure hence it is easily affordable.

7.3 Future Directions

The contribution made in this thesis necessitates some additional study to improve the overall concept. Future efforts in terms of expanding this research can be categorized into three stages.

Stage 1: By integrating the AI-1model with the smartwatch, older adults and carers can receive timely alerts based on vital indicators and fall risk predictions. Figure 7.1 depicts the future plan to integrate the developed model into a smartwatch and connect it with intelligent technology to offer timely alerts.

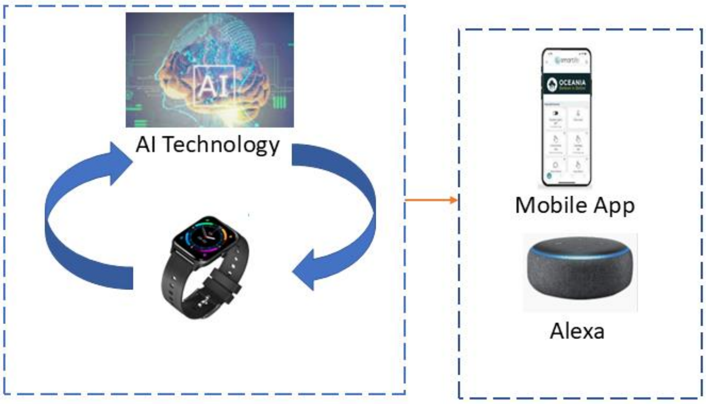


Figure 7.1: Integration of AI-1 Model with Smart App and Voice Models.

Stage 2: Similar to the AI-1 model, the AI-2 model can also be integrated into the prototype to enhance the overall system functionality. Integration of the two models enables the system to be extended further in a way that real-time data acquisition can be supported using the newest wearable technologies, such as motion sensors and smartwatches. These sensors monitor the key physiological and behavioural parameters continuously, facilitating comprehensive fall risk assessment in elderly individuals. By utilizing the merits of the suggested AI-based methods such as Fuzzy Logic and Deep Belief Networks, the hybrid model can foresee the future risk of falling. The advanced ability of the system's AI allows for the creation of a health chart unique to an individual that reflects the changing patterns of his or her fall risk over a given time. For immediate voice alerts to elderly invalids and caregivers regarding fall-related risks, immediate precautionary measures can be instituted. In effect, the integrated arms of alerting and prediction capabilities mentioned above create an additional level of security and safety for older adults in averting falls and promoting well-being. This integrated system contributes a great deal to fall prevention technology by integrating artificial intelligence, wearable monitoring, and real-time health management. Figure 7.2 gives a systematic overview of the combined integration structure.

Figure 7.2: Combined Integration Structure of Future Work.

Stage 3: To prepare for future developments, the model proposes an additional development phase that integrates real-time monitoring systems with transfer learning approaches. This future addition will incorporate additional key signs of health and mobility to enable the model to adapt and tune prediction accuracy in real-time. Upon incorporating continuous learning algorithms will make the system learn the risk factors associated with falls in greater depth and maintain a measure of accuracy that is impossible to beat in the prediction of future falls. At this final stage, the 3 main areas that are focused are as follows,

- Elderly in New Zealand without any major disease.
- Elderly in New Zealand with dimensions such as Dementia, Parkinson's Disease, and Alzheimer's disease, as they are at high risk of fall.
- Māori populations with and without conditions.

The extension of this research (future work) aims to develop an advanced, non-invasive, continuous fall risk monitoring system for elderly individuals that doesn't interrupt their daily routines. The model will utilize a multi-model AI architecture comprising the existing 2 models (improved version) with the third AI model using Transfer Learning to integrate outputs from the first two models into a consolidated fall risk assessment. Figure 7.3 depicts the future direction of the fall risk prediction system using Transfer learning.

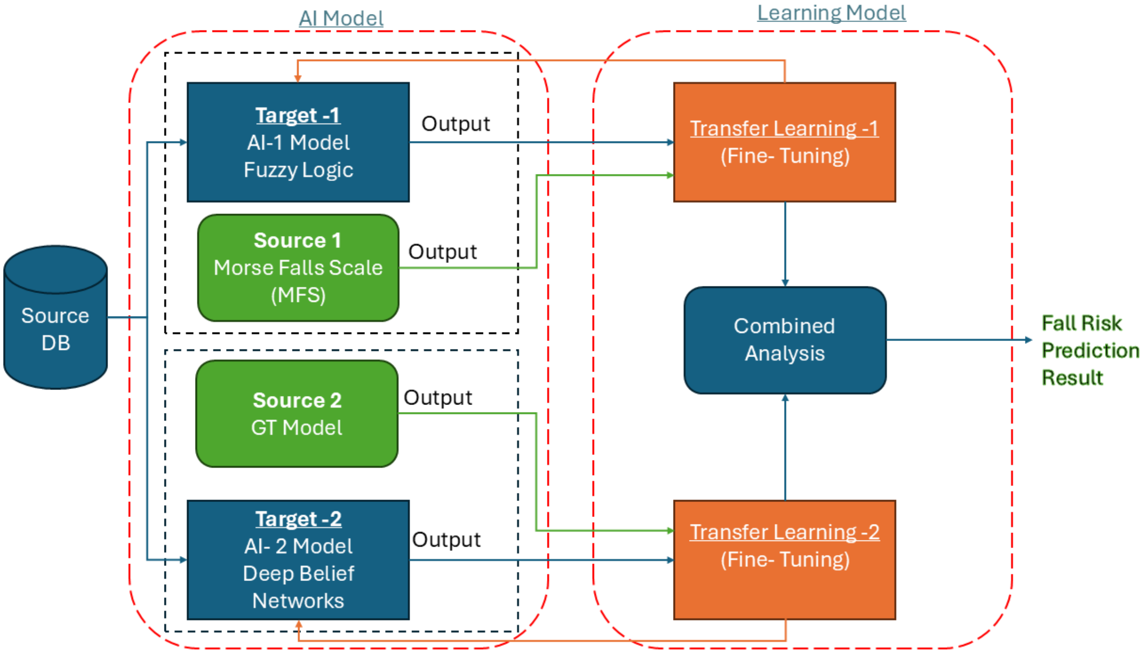


Figure 7.3: Fall Risk Prediction Model using Transfer Learning – Future Directions.

This architecture is based on and will allow continuous information exchange between the two models, strengthening the fall risk prediction by aligning physiological and behavioural indicators. Furthermore, its continuous learning capability will enable real-time detection of changes in an individual's health and behavioural patterns, supporting the timely detection of impending fall risk. It will generate a personalized and dynamically updated fall risk profile. This is especially valuable because it will provide clinicians and caregivers with accurate, actionable insights to develop, test, and measure proactive and tailored fall prevention interventions. Dual Transfer Learning (DTL) is a relatively recent and emerging methodology. It is not mainstream yet, but it has been explored in academic literature, especially in domain adaptation, cross-domain learning, and semi-supervised learning [242]. Its most basic definition is employing two models helping each other learn. The two models mutually support each other in transferring knowledge between two distributions across domains. This enhances the representation of features and minimizes classification errors. Results demonstrate that the proposed hybrid approach can outperform conventional deep learning methods e.g. early work in emotion recognition [243] or deep transfer learning hybrid techniques to enhance the accuracy of breast cancer tumor classification on histopathology images [244].

The uniqueness of this proposed approach lies in the use of two standalone AI models. The outputs from both AI models will be combined based on a transfer learning model, and the output of the transfer learning model is fed to another transfer learning model for further learning to provide the final prediction output. This approach operates independently while enabling interaction among all three AI models. Based on ground truth, historical data, and current forecasts, the model will continuously learn and refine its predictions.

The interactive and Co-operative character of the system allows continuous sharing of information between the models, which is the basis for robust risk prediction based on the synchronization of physiological and behavioural markers. Additionally, the ability of such a model would be to learn continuously allowing continuous adaptation to evolving health and behavioural patterns of the user, thereby allowing for timely capture of change in risk. With real-time, actionable data, the transfer learning model can provide patient-specific fall risk profiles that allow caregivers and healthcare providers to make informed proactive decisions. Preventative care is the priority of this research, and that is a giant leap beyond the traditional way of forecasting falls; eventually, it means safer and better wellness for older adults. Besides, due to its multi-model and transfer learning design, the model learns from the current and past data, and its GT and produces more accurate predictions than current fall risk assessment methods. The proposed framework solves the urgent requirement for a clear, effective, and scalable fall risk prediction system for older adults.

References

[1] C. Wu, C. H. LAM, F. XHAFA, V. TANG, and W. Ip, "The vision of the healthcare industry for supporting the aging population," in *IoT for Elderly, Aging and eHealth: Quality of Life and Independent Living for the Elderly*: Springer, 2022, pp. 5-15.

[2] K. Sarmiento and R. Lee, "STEADI: CDC's approach to make older adult fall prevention part of every primary care practice," *Journal of safety research,* vol. 63, pp. 105-109, 2017. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC6239204/pdf/nihms-993852.pdf.

[3] N. Stats. "Home." NZ.govt.nz. https://www.stats.govt.nz/ (accessed 2024).

[4] "Topic 1 – Falls in older people: the impacts." e Tāhū Hauora Health Quality & Safety Commission. https://www.hqsc.govt.nz/our-work/system-safety/reducing-harm/falls/10-topics/topic-1-falls-in-older-people-the-impacts/#:~:text=Topic%201%20%E2%80%93%20Falls%20in%20older%20people%3A%20the...,interventions.%20Published%3A%2027%20Oct%202021Modified%3A%2031%20Jan%202022 (accessed.

[5] M. o. Health. "Publicly funded hospital discharges – 1 July 2018 to 30 June 2019." https://www.health.govt.nz/publications/publicly-funded-hospital-discharges-1-july-2018-to-30-june-2019 (accessed.

[6] ACC. "Injuries from falls." https://www.acc.co.nz/newsroom/media-resources/injuries-from-falls/#:~:text=Find%20statistics%20on%20injury%20claims%20relating%20to%20injuries,for%20fall-related%20injuries%20in%202024%20by%20injury%20type. (accessed.

[7] K. Chaccour, R. Darazi, A. H. El Hassani, and E. Andres, "From fall detection to fall prevention: A generic classification of fall-related systems," *IEEE Sensors Journal,* vol. 17, no. 3, pp. 812-822, 2016.

[8] R. Tanwar, N. Nandal, M. Zamani, and A. Manaf, "Pathway of Trends and Technologies in Fall Detection: A Systematic Review. Healthcare 2022, 10, 172," *Cybersecurity and the Digital Health,* p. 59, 2022.

[9] A. Agrawal, J. Gans, and A. Goldfarb, "Economic policy for artificial intelligence," *Innovation policy and the economy,* vol. 19, no. 1, pp. 139-159, 2019.

[10] P. Hamet and J. Tremblay, "Artificial intelligence in medicine," *metabolism,* vol. 69, pp. S36-S40, 2017.

[11] K. Qian, Z. Zhang, Y. Yamamoto, and B. W. Schuller, "Artificial intelligence internet of things for the elderly: From assisted living to health-care monitoring," *IEEE Signal Processing Magazine,* vol. 38, no. 4, pp. 78-88, 2021.

[12] L. Ren and Y. Peng, "Research of fall detection and fall prevention technologies: A systematic review," *IEEE Access,* vol. 7, pp. 77702-77722, 2019.

[13] Y. Zhang, P. Xiong, Y. Luo, and L. Li, "Design of remote home environment monitoring and health care monitoring system based on data confusion," in *2011 IEEE International Conference on Automation and Logistics (ICAL)*, 2011: IEEE, pp. 35-39.

[14] S. K. Dhar, S. S. Bhunia, and N. Mukherjee, "Interference aware scheduling of sensors in IoT enabled health-care monitoring system," in *2014 Fourth International Conference of Emerging Applications of Information Technology*, 2014: IEEE, pp. 152-157.

[15] W. Wu, J. Cao, Y. Zheng, and Y.-P. Zheng, "WAITER: A wearable personal healthcare and emergency aid system," in *2008 Sixth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2008: IEEE, pp. 680-685.

[16] Z. Lv, F. Xia, G. Wu, L. Yao, and Z. Chen, "iCare: a mobile health monitoring system for the elderly," in *2010 IEEE/ACM Int'l Conference on Green Computing and Communications & Int'l Conference on Cyber, Physical and Social Computing*, 2010: IEEE, pp. 699-705.

[17] D. D. Luxton, "Recommendations for the ethical use and design of artificial intelligent care providers," *Artificial intelligence in medicine,* vol. 62, no. 1, pp. 1-10, 2014.

[18] A. Arcelus, M. H. Jones, R. Goubran, and F. Knoefel, "Integration of smart home technologies in a health monitoring system for the elderly," in *21st international conference on advanced information networking and applications workshops (AINAW'07)*, 2007, vol. 2: IEEE, pp. 820-825.

[19] A. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," *New England Journal of Medicine,* vol. 380, no. 14, pp. 1347-1358, 2019.

[20] J. L. Speiser *et al.*, "Machine learning in aging: an example of developing prediction models for serious fall injury in older adults," *The Journals of Gerontology: Series A,* vol. 76, no. 4, pp. 647-654, 2021.

[21] G. Gürsel, "Healthcare, uncertainty, and fuzzy logic," *Digital Medicine,* vol. 2, no. 3, pp. 101-112, 2016.

[22] R. Rajagopalan, I. Litvan, and T.-P. Jung, "Fall prediction and prevention systems: recent trends, challenges, and future research directions," *Sensors,* vol. 17, no. 11, p. 2509, 2017.

[23] T. Tsukiyama, "In-home health monitoring system for solitary elderly," *Procedia Computer Science,* vol. 63, pp. 229-235, 2015.

[24] S. Vimal, Y. H. Robinson, S. Kadry, H. V. Long, and Y. Nam, "IoT based smart health monitoring with CNN using edge computing," *Journal of Internet Technology,* vol. 22, no. 1, pp. 173-185, 2021.

[25] L. NZ. "Falls in advanced age: Findings from LiLACS NZ." Ministry of Health. https://www.fmhs.auckland.ac.nz/en/faculty/lilacs.html (accessed.

[26] B.-S. Lin, T. Yu, C.-W. Peng, C.-H. Lin, H.-K. Hsu, I.-J. Lee, and Z. Zhang, "Fall detection system with artificial intelligence-based edge computing," *IEEE Access,* vol. 10, pp. 4328-4339, 2022.

[27] K. S. Chan and N. Zary, "Applications and challenges of implementing artificial intelligence in medical education: integrative review," *JMIR medical education,* vol. 5, no. 1, p. e13930, 2019.

[28] C. Krittanawong, A. S. Bomback, U. Baber, S. Bangalore, F. H. Messerli, and W. Wilson Tang, "Future direction for using artificial intelligence to predict and manage hypertension," *Current hypertension reports,* vol. 20, pp. 1-16, 2018.

[29] M. o. Health. "Māori Health Action Plan 2020-2025 " https://www.health.govt.nz/publication/whakamaua-maori-health-action-plan-2020-2025 (accessed.

[30] T. E. Lockhart, R. Soangra, H. Yoon, T. Wu, C. W. Frames, R. Weaver, and K. A. Roberto, "Prediction of fall risk among community-dwelling older adults using a wearable system," *Scientific reports,* vol. 11, no. 1, p. 20976, 2021.

[31] B. Chen *et al.*, "Computer vision and machine learning-based gait pattern recognition for flat fall prediction," *Sensors,* vol. 22, no. 20, p. 7960, 2022.

[32] F. Buisseret, L. Catinus, R. Grenard, L. Jojczyk, D. Fievez, V. Barvaux, and F. Dierick, "Timed up and go and six-minute walking tests with wearable inertial sensor: one step further for the prediction of the risk of fall in elderly nursing home people," *Sensors,* vol. 20, no. 11, p. 3207, 2020.

[33] R. Schniepp *et al.*, "Fall prediction in neurological gait disorders: differential

contributions from clinical assessment, gait analysis, and daily-life mobility monitoring," *Journal of neurology,* vol. 268, pp. 3421-3434, 2021.

[34] A. Sampath Dakshina Murthy, T. Karthikeyan, and R. Vinoth Kanna, "Gait-based person fall prediction using deep learning approach," *Soft computing,* vol. 26, no. 23, pp. 12933-12941, 2022.

[35] X. Cheng, M. Ran, B. Chen, and H. Yin, "Image channel and spatial information integrated method for fall detection," *Multimedia Systems,* vol. 31, no. 1, p. 67, 2025.

[36] Y. Chen, W. Dai, L. Ju, and C. Zhou, "Detection of human fall behavior based on YOLOv5," in *Fourth International Conference on Computer Vision, Application, and Algorithm (CVAA 2024)*, 2025, vol. 13486: SPIE, pp. 293-299.

[37] H. Tashiro, S. Hirosaki, Y. Sato, H. Ihira, M. Toki, and N. Kozuka, "Concern about falling is related to threat-induced changes in emotions and postural control in older adults," *Gait & Posture,* vol. 115, pp. 1-6, 2025.

[38] M. Luštrek and B. Kaluža, "Fall detection and activity recognition with machine learning," *Informatica,* vol. 33, no. 2, 2009.

[39] A. G. S. Panel on Prevention of Falls in Older Persons and B. G. Society, "Summary of the updated American Geriatrics Society/British Geriatrics Society clinical practice guideline for prevention of falls in older persons," *Journal of the American Geriatrics Society,* vol. 59, no. 1, pp. 148-157, 2011.

[40] F. Clay, G. Yap, and A. Melder, "Risk factors for in hospital falls: Evidence Review," *Centre for Clinical Effectiveness, Monash Health, Melbourne, Australia,* 2018.

[41] M. Oh-Park, T. Doan, C. Dohle, V. Vermiglio-Kohn, and A. Abdou, "Technology utilization in fall prevention," *American journal of physical medicine & rehabilitation,* vol. 100, no. 1, pp. 92-99, 2021.

[42] J. A. Stevens, R. K. Noonan, and L. Z. Rubenstein, "Older adult fall prevention: Perceptions, beliefs, and behaviors," *American Journal of Lifestyle Medicine,* vol. 4, no. 1, pp. 16-20, 2010.

[43] A. Aliverti, "Wearable technology: role in respiratory health and disease," *Breathe,* vol. 13, no. 2, pp. e27-e36, 2017.

[44] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing,* vol. 100, pp. 144-152, 2013.

[45] X. Hu and X. Qu, "Pre-impact fall detection," *Biomedical engineering online,* vol. 15, pp. 1-16, 2016.

[46] N. Pannurat, S. Thiemjarus, and E. Nantajeewarawat, "A hybrid temporal reasoning framework for fall monitoring," *IEEE Sensors Journal,* vol. 17, no. 6, pp. 1749-1759, 2017.

[47] I. Lee and K. Lee, "The Internet of Things (IoT): Applications, investments, and challenges for enterprises," *Business horizons,* vol. 58, no. 4, pp. 431-440, 2015.

[48] G. Premalatha and V. T. Bai, "Design and implementation of intelligent patient in-house monitoring system based on efficient XGBoost-CNN approach," *Cognitive Neurodynamics,* vol. 16, no. 5, pp. 1135-1149, 2022.

[49] S. D. Choi, L. Guo, D. Kang, and S. Xiong, "Exergame technology and interactive interventions for elderly fall prevention: A systematic literature review," *Applied ergonomics,* vol. 65, pp. 570-581, 2017.

[50] X. Yu, H. Qiu, and S. Xiong, "A novel hybrid deep neural network to predict pre-impact fall for older people based on wearable inertial sensors," *Frontiers in bioengineering and biotechnology,* vol. 8, p. 63, 2020.

[51] M. H. Sarowar, M. F. K. Khondakar, H. S. Roy, H. Ullah, R. Ahmed, and Q. D.

Hossain, "Internet of things based fall detection and heart rate monitoring system for senior citizens," *International Journal of Electrical and Computer Engineering (IJECE),* vol. 12, no. 3, pp. 3204-3216, 2022.

[52] A. A. R. Richard, M. F. Sadman, U. H. Mim, I. Rahman, and M. S. R. Zishan, "Health monitoring system for elderly and disabled people," in *2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, 2019: IEEE, pp. 677-681.

[53] M. M. Islam, A. Rahaman, and M. R. Islam, "Development of smart healthcare monitoring system in IoT environment," *SN computer science,* vol. 1, pp. 1-11, 2020.

[54] C.-Y. Hsieh, W.-T. Shi, H.-Y. Huang, K.-C. Liu, S. J. Hsu, and C.-T. Chan, "Machine learning-based fall characteristics monitoring system for strategic plan of falls prevention," in *2018 IEEE International Conference on Applied System Invention (ICASI)*, 2018: IEEE, pp. 818-821.

[55] J. S. Raj, "A novel information processing in IoT based real time health care monitoring system," *Journal of Electronics,* vol. 2, no. 03, pp. 188-196, 2020.

[56] M. Mayilvaganan and K. Rajeswari, "Health care analysis based on fuzzy logic control system," *Blood pressure,* vol. 180, no. 110, p. 70, 2014.

[57] B. J. Powell *et al.*, "A refined compilation of implementation strategies: results from the Expert Recommendations for Implementing Change (ERIC) project," *Implementation science,* vol. 10, pp. 1-14, 2015.

[58] K. Turner, V. S. Staggs, C. Potter, E. Cramer, R. I. Shorr, and L. C. Mion, "Fall prevention practices and implementation strategies: examining consistency across hospital units," *Journal of patient safety,* vol. 18, no. 1, pp. e236-e242, 2022.

[59] V. Carande-Kulis, J. A. Stevens, C. S. Florence, B. L. Beattie, and I. Arias, "A cost–benefit analysis of three older adult fall prevention interventions," *Journal of safety research,* vol. 52, pp. 65-70, 2015.

[60] C. WU, C. H. LAM, F. XHAFA, V. TANG, and W. IP, "Case study in fall prevention in indoor environments," in *IoT for Elderly, Aging and eHealth: Quality of Life and Independent Living for the Elderly*: Springer, 2022, pp. 87-98.

[61] A.-M. Hill *et al.*, "Falls after hospital discharge: a randomized clinical trial of individualized multimodal falls prevention education," *The Journals of Gerontology: Series A,* vol. 74, no. 9, pp. 1511-1517, 2019.

[62] A. C. Tricco *et al.*, "Comparisons of interventions for preventing falls in older adults: a systematic review and meta-analysis," *Jama,* vol. 318, no. 17, pp. 1687-1699, 2017.

[63] D. A. Scherle, "Germany's lonely dead," DW, Ed., ed: DW, 2018.

[64] J. Kim, S. Chi, and J. Seo, "Interaction analysis for vision-based activity identification of earthmoving excavators and dump trucks," *Automation in Construction,* vol. 87, pp. 297-308, 2018.

[65] E. Stone and M. Skubic, "Evaluation of an inexpensive depth camera for in-home gait assessment," *Journal of Ambient Intelligence and Smart Environments,* vol. 3, no. 4, pp. 349-361, 2011.

[66] A. Mokhber, C. Achard, and M. Milgram, "Recognition of human behavior by space-time silhouette characterization," *Pattern Recognition Letters,* vol. 29, no. 1, pp. 81-89, 2008.

[67] D. Mohan, D. Z. Al-Hamid, P. H. J. Chong, K. L. K. Sudheera, J. Gutierrez, H. C. Chan, and H. Li, "Artificial Intelligence and IoT in Elderly Fall Prevention: A Review," *IEEE Sensors Journal,* 2024.

[68] B. Kaluža, B. Cvetković, E. Dovgan, H. Gjoreski, M. Gams, M. Luštrek, and V. Mirchevska, "A multi-agent care system to support independent living," *International*

journal on artificial intelligence tools, vol. 23, no. 01, p. 1440001, 2014.

[69] D. Weinland and E. Boyer, "Action recognition using exemplar-based embedding," in *2008 IEEE Conference on Computer Vision and Pattern Recognition*, 2008: IEEE, pp. 1-7.

[70] M. V. Albert, K. Kording, M. Herrmann, and A. Jayaraman, "Fall classification by machine learning using mobile phones," *PloS one,* vol. 7, no. 5, p. e36556, 2012.

[71] J. Kim, K. Min, M. Jung, and S. Chi, "Occupant behavior monitoring and emergency event detection in single-person households using deep learning-based sound recognition," *Building and Environment,* vol. 181, p. 107092, 2020.

[72] M. Hosseinzadeh *et al.*, "An elderly health monitoring system based on biological and behavioral indicators in internet of things," *Journal of Ambient Intelligence and Humanized Computing,* pp. 1-11, 2023.

[73] J. Aidemark and L. Askenäs, "Fall Prevention as personal learning and changing behaviors: systems and technologies," *Procedia Computer Science,* vol. 164, pp. 498-507, 2019.

[74] S. A. Mostafa, A. Mustapha, M. A. Mohammed, M. S. Ahmad, and M. A. Mahmoud, "A fuzzy logic control in adjustable autonomy of a multi-agent system for an automated elderly movement monitoring application," *International journal of medical informatics,* vol. 112, pp. 173-184, 2018.

[75] P. Peursum, S. Venkatesh, and G. West, "Tracking-as-recognition for articulated full-body human motion analysis," in *2007 IEEE Conference on Computer Vision and Pattern Recognition*, 2007: IEEE, pp. 1-8.

[76] A. Baniukevic, C. S. Jensen, and H. Lu, "Hybrid indoor positioning with wi-fi and bluetooth: Architecture and performance," in *2013 IEEE 14Th international conference on mobile data management*, 2013, vol. 1: IEEE, pp. 207-216.

[77] M. Ogawa, R. Suzuki, S. Otake, T. Izutsu, T. Iwaya, and T. Togawa, "Long term remote behavioral monitoring of elderly by using sensors installed in ordinary houses," in *2nd Annual International IEEE-EMBS Special Topic Conference on Microtechnologies in Medicine and Biology. Proceedings (Cat. No. 02EX578)*, 2002: IEEE, pp. 322-325.

[78] N. Bhargava, G. Sharma, R. Bhargava, and M. Mathuria, "Decision tree analysis on j48 algorithm for data mining," *Proceedings of international journal of advanced research in computer science and software engineering,* vol. 3, no. 6, 2013.

[79] E. Kańtoch and P. Augustyniak, "Human activity surveillance based on wearable body sensor network," in *2012 computing in cardiology*, 2012: IEEE, pp. 325-328.

[80] O. C. Ann and L. B. Theng, "Human activity recognition: A review," in *2014 IEEE international conference on control system, computing and engineering (ICCSCE 2014)*, 2014: IEEE, pp. 389-393.

[81] O. D. Lara, and Miguel A. Labrador, " survey on human activity recognition using wearable sensors," *IEEE communications surveys & tutorials* vol. 15(3), , no. 15(3), , pp. 1192-1209., 2012.

[82] F. J. Ordóñez and D. Roggen, "Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition," *Sensors,* vol. 16, no. 1, p. 115, 2016.

[83] G. Forbes, S. Massie, and S. Craw, "Fall prediction using behavioural modelling from sensor data in smart homes," *Artificial Intelligence Review,* vol. 53, no. 2, pp. 1071-1091, 2020.

[84] A. Albu-Shamah and J. Zhan, "Towards an optimizing model for older people at risk of falls," in *2012 ASE/IEEE International Conference on BioMedical Computing (BioMedCom)*, 2012: IEEE, pp. 55-58.

[85] Q. V. Vo, G. Lee, and D. Choi, "Fall detection based on movement and smart phone

technology," in *2012 IEEE RIVF International Conference on Computing & Communication Technologies, Research, Innovation, and Vision for the Future*, 2012: IEEE, pp. 1-4.

[86] J.-Y. Kim, C.-H. Chu, and M.-S. Kang, "IoT-based unobtrusive sensing for sleep quality monitoring and assessment," *IEEE Sensors Journal,* vol. 21, no. 3, pp. 3799-3809, 2020.

[87] V. Di Lecce, C. Guaragnella, R. Dario, and T. D'ORAZIO, "Smart postural monitor for elderly people," *19th IMEKO TC,* vol. 4, pp. 18-19, 2013.

[88] I. De Falco, G. De Pietro, and G. Sannino, "RETRACTED ARTICLE: Evaluation of artificial intelligence techniques for the classification of different activities of daily living and falls," *Neural Computing and Applications,* vol. 32, no. 3, pp. 747-758, 2020.

[89] J. E. Fulton *et al.*, "Strategic priorities for physical activity surveillance in the United States," *Translational Journal of the American College of Sports Medicine,* vol. 1, no. 13, pp. 111-123, 2016.

[90] B. M. Haas and A. M. Burden, "Validity of weight distribution and sway measurements of the Balance Performance Monitor," *Physiotherapy research international,* vol. 5, no. 1, pp. 19-32, 2000.

[91] J. E. Visser, M. G. Carpenter, H. van der Kooij, and B. R. Bloem, "The clinical utility of posturography," *Clinical neurophysiology,* vol. 119, no. 11, pp. 2424-2436, 2008.

[92] D. B. Matchar *et al.*, "Randomized controlled trial of screening, risk modification, and physical therapy to prevent falls among the elderly recently discharged from the emergency department to the community: the steps to avoid falls in the elderly study," *Archives of physical medicine and rehabilitation,* vol. 98, no. 6, pp. 1086-1096, 2017.

[93] Y.-H. Pua, P.-H. Ong, R. A. Clark, D. B. Matcher, and E. C.-W. Lim, "Falls efficacy, postural balance, and risk for falls in older adults with falls-related emergency department visits: prospective cohort study," *BMC geriatrics,* vol. 17, pp. 1-7, 2017.

[94] T. Amundsen, M. Rossman, I. Ahmad, A. Clark, and M. Huber, "Fall risk assessment and visualization through gait analysis," *Smart Health,* vol. 25, p. 100284, 2022.

[95] B. Hu, P. Dixon, J. Jacobs, J. Dennerlein, and J. Schiffman, "Machine learning algorithms based on signals from a single wearable inertial sensor can detect surface- and age-related differences in walking," *Journal of biomechanics,* vol. 71, pp. 37-42, 2018.

[96] D. Brulin, Y. Benezeth, and E. Courtial, "Posture recognition based on fuzzy logic for home monitoring of the elderly," *IEEE transactions on information technology in biomedicine,* vol. 16, no. 5, pp. 974-982, 2012.

[97] O. Oluwadare, *Gait analysis on a smart floor for health monitoring*. The University of Texas at Arlington, 2015.

[98] A. Baghdadi, L. A. Cavuoto, A. Jones-Farmer, S. E. Rigdon, E. T. Esfahani, and F. M. Megahed, "Monitoring worker fatigue using wearable devices: A case study to detect changes in gait parameters," *Journal of quality technology,* vol. 53, no. 1, pp. 47-71, 2021.

[99] S. Wang *et al.*, "A spatio-temporal graph neural network for fall prediction with inertial sensors," *Knowledge-Based Systems,* vol. 293, p. 111709, 2024.

[100] M. Savadkoohi, T. Oladunni, and L. A. Thompson, "Deep neural networks for human's fall-risk prediction using force-plate time series signal," *Expert systems with applications,* vol. 182, p. 115220, 2021.

[101] M. Piirtola and P. Era, "Force platform measurements as predictors of falls among older people–a review," *Gerontology,* vol. 52, no. 1, pp. 1-16, 2006.

[102] J. Howcroft, E. D. Lemaire, J. Kofman, and W. E. McIlroy, "Elderly fall risk prediction

using static posturography," *PLoS one,* vol. 12, no. 2, p. e0172398, 2017.

[103] M. J. Hilliard, K. M. Martinez, I. Janssen, B. Edwards, M.-L. Mille, Y. Zhang, and M. W. Rogers, "Lateral balance factors predict future falls in community-living older adults," *Archives of physical medicine and rehabilitation,* vol. 89, no. 9, pp. 1708-1713, 2008.

[104] A. Nait Aicha, G. Englebienne, K. S. Van Schooten, M. Pijnappels, and B. Kröse, "Deep learning to predict falls in older adults based on daily-life trunk accelerometry," *Sensors,* vol. 18, no. 5, p. 1654, 2018.

[105] C. P. Carty *et al.*, "Reactive stepping behaviour in response to forward loss of balance predicts future falls in community-dwelling older adults," *Age and ageing,* vol. 44, no. 1, pp. 109-115, 2015.

[106] E. R. Burns, R. Lee, S. E. Hodge, V. J. Pineau, B. Welch, and M. Zhu, "Validation and comparison of fall screening tools for predicting future falls among older adults," *Archives of gerontology and geriatrics,* vol. 101, p. 104713, 2022.

[107] K. Cleary and E. Skornyakov, "Predicting falls in older adults using the four square step test," *Physiotherapy theory and practice,* vol. 33, no. 10, pp. 766-771, 2017.

[108] R. Ng *et al.*, "Increasing complexity of new nursing home residents in Ontario, Canada: A serial cross-sectional study," *Journal of the American Geriatrics Society,* vol. 68, no. 6, pp. 1293-1300, 2020.

[109] B. Homann *et al.*, "The impact of neurological disorders on the risk for falls in the community dwelling elderly: a case-controlled study," *BMJ open,* vol. 3, no. 11, p. e003367, 2013.

[110] A. C. Scheffer, M. J. Schuurmans, N. Van Dijk, T. Van Der Hooft, and S. E. De Rooij, "Fear of falling: measurement strategy, prevalence, risk factors and consequences among older persons," *Age and ageing,* vol. 37, no. 1, pp. 19-24, 2008.

[111] S. J. Lloyd, M. Malek-Ahmadi, K. Barclay, M. R. Fernandez, and M. S. Chartrand, "Emotional intelligence (EI) as a predictor of depression status in older adults," *Archives of Gerontology and Geriatrics,* vol. 55, no. 3, pp. 570-573, 2012.

[112] G. H. Bjørkløf, K. Engedal, G. Selbæk, S. E. Kouwenhoven, and A.-S. Helvik, "Coping and depression in old age: a literature review," *Dementia and geriatric cognitive disorders,* vol. 35, no. 3-4, pp. 121-154, 2013.

[113] I. Delhom, M. Gutierrez, T. Mayordomo, and J. C. Melendez, "Does emotional intelligence predict depressed mood? A structural equation model with elderly people," *Journal of happiness studies,* vol. 19, pp. 1713-1726, 2018.

[114] M. J. Al Nahian, T. Ghosh, M. N. Uddin, M. M. Islam, M. Mahmud, and M. S. Kaiser, "Towards artificial intelligence driven emotion aware fall monitoring framework suitable for elderly people with neurological disorder," in *International conference on brain informatics*, 2020: Springer, pp. 275-286.

[115] M. R. Landers, C. Durand, D. S. Powell, L. E. Dibble, and D. L. Young, "Development of a scale to assess avoidance behavior due to a fear of falling: the Fear of Falling Avoidance Behavior Questionnaire," *Physical therapy,* vol. 91, no. 8, pp. 1253-1265, 2011.

[116] M. C. Chung *et al.*, "Posttraumatic stress disorder in older people after a fall," *International Journal of Geriatric Psychiatry: A journal of the psychiatry of late life and allied sciences,* vol. 24, no. 9, pp. 955-964, 2009.

[117] W. R. Young and A. M. Williams, "How fear of falling can increase fall-risk in older adults: applying psychological theory to practical observations," *Gait & posture,* vol. 41, no. 1, pp. 7-12, 2015.

[118] H. L. Urry and J. J. Gross, "Emotion regulation in older age," *Current Directions in*

Psychological Science, vol. 19, no. 6, pp. 352-357, 2010.

[119] D. Miranda, M. Calderón, and J. Favela, "Anxiety detection using wearable monitoring," in *Proceedings of the 5th Mexican Conference on Human-computer Interaction*, 2014, pp. 34-41.

[120] K. Rennert and E. Karapanos, "Faceit: Supporting reflection upon social anxiety events with lifelogging," in *CHI'13 Extended Abstracts on Human Factors in Computing Systems*, 2013, pp. 457-462.

[121] K. Delbaere, J. C. Close, H. Brodaty, P. Sachdev, and S. R. Lord, "Determinants of disparities between perceived and physiological risk of falling among elderly people: cohort study," *Bmj,* vol. 341, 2010.

[122] L. Scarlett, E. Baikie, and S. W. Chan, "Fear of falling and emotional regulation in older adults," *Aging & mental health,* vol. 23, no. 12, pp. 1684-1690, 2019.

[123] K. Edginton Bigelow and N. Berme, "Development of a protocol for improving the clinical utility of posturography as a fall-risk screening tool," *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences,* vol. 66, no. 2, pp. 228-233, 2011.

[124] T. Namba and Y. Yamada, "Risks of deep reinforcement learning applied to fall prevention assist by autonomous mobile robots in the hospital," *Big Data and Cognitive Computing,* vol. 2, no. 2, p. 13, 2018.

[125] R. Y. Lee and A. J. Carlisle, "Detection of falls using accelerometers and mobile phone technology," *Age and ageing,* vol. 40, no. 6, pp. 690-696, 2011.

[126] C.-L. Lin, W.-C. Chiu, F.-H. Chen, Y.-H. Ho, T.-C. Chu, and P.-H. Hsieh, "Fall monitoring for the elderly using wearable inertial measurement sensors on eyeglasses," *IEEE Sensors Letters,* vol. 4, no. 6, pp. 1-4, 2020.

[127] N. I. o. B. I. a. B. N. u. N. g. n. R01EB030362. "PhysioNet." https://physionet.org/ (accessed.

[128] R. Schwendimann, S. De Geest, and K. Milisen, "Evaluation of the Morse Fall Scale in hospitalised patients," *Age and ageing,* vol. 35, no. 3, pp. 311-313, 2006.

[129] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," *circulation,* vol. 101, no. 23, pp. e215-e220, 2000.

[130] L. A. Bianchi, R. Harris, and J. M. Fitzpatrick, "Barriers to healthcare professionals recognizing and managing delirium in older adults during a hospital stay: A mixed-methods systematic review," *Journal of Advanced Nursing,* vol. 80, no. 7, pp. 2672-2689, 2024.

[131] A. Garrido, "A brief history of fuzzy logic," *BRAIN. Broad Research in Artificial Intelligence and Neuroscience,* vol. 3, no. 1, pp. 71-77, 2012.

[132] Z. Gao, R. Li, C. Ma, L. Rui, and X. Sun, "Core-brain-network-based multilayer convolutional neural network for emotion recognition," *IEEE Transactions on Instrumentation and Measurement,* vol. 70, pp. 1-9, 2021.

[133] Y. Zidoun and A. E. Mardi, "Artificial Intelligence (AI)-Based simulators versus simulated patients in undergraduate programs: A protocol for a randomized controlled trial," *BMC Medical Education,* vol. 24, no. 1, p. 1260, 2024.

[134] B. Khan, H. Fatima, A. Qureshi, S. Kumar, A. Hanan, J. Hussain, and S. Abdullah, "Drawbacks of artificial intelligence and their potential solutions in the healthcare sector," *Biomedical Materials & Devices,* vol. 1, no. 2, pp. 731-738, 2023.

[135] V. A. Lepakshi, "Machine learning and deep learning based AI tools for development of diagnostic tools," in *Computational Approaches for Novel Therapeutic and Diagnostic Designing to Mitigate SARS-CoV-2 Infection*: Elsevier, 2022, pp. 399-420.

[136] J. He and H. Guo, "Study on the Area of Waiting Space in the Old Area of a Tertiary Hospital Based on AnyLogic Simulation," *Scientific and Social Research,* vol. 6, no. 5, pp. 50-57, 2024.

[137] X. Liu, "Research on the application of RFID technology in artificial intelligence medical management," in *AIP Conference Proceedings*, 2024, vol. 3131, no. 1: AIP Publishing.

[138] F. Târcoveanu, F. Leon, C. Lisa, S. Curteanu, A. Feraru, K. Ali, and N. Anton, "The use of artificial neural networks in studying the progression of glaucoma," *Scientific Reports,* vol. 14, no. 1, p. 19597, 2024.

[139] C. S. S.-T. G. D. D. A. S. A. G. J. Zerna. *Heart Rate*. [Online]. Available: https://osf.io/

[140] F. Guo, Y. Li, M. S. Kankanhalli, and M. S. Brown, "An evaluation of wearable activity monitoring devices," in *Proceedings of the 1st ACM international workshop on Personal data meets distributed multimedia*, 2013, pp. 31-34.

[141] Fitbit. "Fitabase Data Dictionary." https://www.fitabase.com/media/1930/fitabasedatadictionary102320.pdf (accessed.

[142] M. Plainer, "Practical Study of Visual Studio Code," 2021.

[143] T. Kahlert and K. Giza, "Visual Studio Code Tips & Tricks Vol. 1," *Microsoft Deutschland GmbH,* 2016.

[144] B. Ikeda and D. Szafir, "Advancing the design of visual debugging tools for roboticists," in *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 2022: IEEE, pp. 195-204.

[145] G. B. Smith, D. R. Prytherch, S. Jarvis, C. Kovacs, P. Meredith, P. E. Schmidt, and J. Briggs, "A comparison of the ability of the physiologic components of medical emergency team criteria and the UK National Early Warning Score to discriminate patients at risk of a range of adverse clinical outcomes," *Critical care medicine,* vol. 44, no. 12, pp. 2171-2181, 2016.

[146] M. Mansoor Baig, H. Gholamhosseini, M. Lindén, and M. J. Connolly, "Review of vital signs monitoring systems–patient's acceptability, issues and challenges," *Neuroscience and Biomedical Engineering,* vol. 2, no. 1, pp. 2-13, 2014.

[147] N. Levy, J. Sturgess, and P. Mills, "“Pain as the fifth vital sign” and dependence on the “numerical pain scale” is being abandoned in the US: why?," *British journal of anaesthesia,* vol. 120, no. 3, pp. 435-438, 2018.

[148] J. G. Chester and J. L. Rudolph, "Vital signs in older patients: age-related changes," *Journal of the American Medical Directors Association,* vol. 12, no. 5, pp. 337-343, 2011.

[149] A. J. Campbell and M. C. Robertson, "Implementation of multifactorial interventions for fall and fracture prevention," *Age and Ageing,* vol. 35, no. suppl_2, pp. ii60-ii64, 2006.

[150] E. Oluokun, "Classification and analysis of blood pressure characteristics using fuzzy logic approach," *Preprint,* 2022.

[151] R. D. Langer, M. H. Criqui, E. L. Barrett-Connor, M. R. Klauber, and T. G. Ganiats, "Blood pressure change and survival after age 75," *Hypertension,* vol. 22, no. 4, pp. 551-559, 1993.

[152] D. DeMers and D. Wachs, "Physiology, mean arterial pressure," 2019.

[153] T. D. Homan, S. J. Bordes, and E. Cichowski, "Physiology, pulse pressure," 2018.

[154] P. Carlos Tello. "Pulse Pressure (Wide, Narrow & Normal) + How to Calculate." https://health.selfdecode.com/blog/pulse-pressure/ (accessed.

[155] S. Medical, "How to calculate heart rate from ECG," ed, 2023.

[156] A. H. Association. "All About Heart Rate." https://www.heart.org/en/health-topics/high-blood-pressure/the-facts-about-high-blood-pressure/all-about-heart-rate-pulse (accessed.

[157] J. D. a. J. Seladi-Schulman. "What is a Dangerous Heart Rate?" https://www.healthline.com/health/dangerous-heart-rate#for-adults. (accessed.

[158] Andrejs. "3 Ways To Calculate Max Heart Rate And How To Use It." https://theathleteblog.com/calculate-maximum-heart-rate/#google_vignette. (accessed.

[159] J. Chertoff. "Running Heart Rate: What's Safe and What's Too High?" https://www.healthline.com/ (accessed.

[160] D. Berwal, A. Kuruba, A. M. Shaikh, A. Udupa, and M. S. Baghini, "Spo 2 measurement: Non-idealities and ways to improve estimation accuracy in wearable pulse oximeters," *IEEE Sensors Journal,* vol. 22, no. 12, pp. 11653-11664, 2022.

[161] "What Is A Normal Blood Oxygen Level? | Kinetik Wellbeing." https://www.kinetikwellbeing.com/what-is-a-normal-blood-oxygen-level-and-how-can-i-test-mine/. (accessed.

[162] M. Z. Dini, A. Rakhmatsyah, and A. A. Wardana, "Detection of oxygen levels (SpO2) and heart rate using a pulse oximeter for classification of hypoxemia based on fuzzy logic," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika,* vol. 8, no. 1, p. 17, 2022.

[163] T. R. Razak, J. M. Garibaldi, C. Wagner, A. Pourabdollah, and D. Soria, "Toward a framework for capturing interpretability of hierarchical fuzzy systems—a participatory design approach," *IEEE Transactions on Fuzzy Systems,* vol. 29, no. 5, pp. 1160-1172, 2020.

[164] Y. Zheng, S. Wang, Q. Li, and B. Li, "Fringe projection profilometry by conducting deep learning from its digital twin," *Optics express,* vol. 28, no. 24, pp. 36568-36583, 2020.

[165] A. D. Dwivedi, L. Malina, P. Dzurenda, and G. Srivastava, "Optimized blockchain model for internet of things based healthcare applications," in *2019 42nd international conference on telecommunications and signal processing (TSP)*, 2019: IEEE, pp. 135-139.

[166] J. Swanenburg, E. D. de Bruin, D. Uebelhart, and T. Mulder, "Falls prediction in elderly people: a 1-year prospective study," *Gait & posture,* vol. 31, no. 3, pp. 317-321, 2010.

[167] R. Thapa *et al.*, "Predicting falls in long-term care facilities: machine learning study," *JMIR aging,* vol. 5, no. 2, p. e35373, 2022.

[168] S. Dutta, A. J. Maeder, and J. Basilakis, "Using Fuzzy Logic for Decision Support in Vital Signs Monitoring," in *AIH+ CARE@ AUS-AI*, 2013: Citeseer, pp. 29-33.

[169] D. E. Iakovakis, F. A. Papadopoulou, and L. J. Hadjileontiadis, "Fuzzy logic-based risk of fall estimation using smartwatch data as a means to form an assistive feedback mechanism in everyday living activities," *Healthcare technology letters,* vol. 3, no. 4, pp. 263-268, 2016.

[170] M. Kowsigan, A. C. Jebamalar, S. Shobika, R. Roshini, and A. Saravanan, "Heart disease prediction by analysing various parameters using fuzzy logic," *Pakistan Journal of Biotechnology,* vol. 14, no. 2, pp. 157-161, 2017.

[171] N. Bhatla and K. Jyoti, "A Novel Approach for heart disease diagnosis using Data Mining and Fuzzy logic," *International Journal of Computer Applications,* vol. 54, no. 17, 2012.

[172] T. R. Razak, N. F. Mahadi, I. H. Abd Halim, M. N. F. Jamaluddin, M. H. Ismail, S. S. M. Fauzi, and R. A. J. Gining, "Towards designing a hierarchical fuzzy system for early diagnosis of heart disease," *Journal of Computing Research and Innovation,* vol. 4, no.

2, pp. 31-41, 2019.

[173] M. F. Ganji and M. S. Abadeh, "A fuzzy classification system based on Ant Colony Optimization for diabetes disease diagnosis," *Expert systems with applications,* vol. 38, no. 12, pp. 14650-14659, 2011.

[174] C.-S. Lee and M.-H. Wang, "A fuzzy expert system for diabetes decision support application," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics),* vol. 41, no. 1, pp. 139-153, 2010.

[175] M. Phillips *et al.*, "Prediction of breast cancer using volatile biomarkers in the breath," *Breast cancer research and treatment,* vol. 99, pp. 19-21, 2006.

[176] H. GholamHosseini, M. M. Baig, M. J. Connolly, and M. Lindén, "A multifactorial falls risk prediction model for hospitalized older adults," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2014: IEEE, pp. 3484-3487.

[177] B. W. Nelson and N. B. Allen, "Accuracy of consumer wearable heart rate measurement during an ecologically valid 24-hour period: intraindividual validation study," *JMIR mHealth and uHealth,* vol. 7, no. 3, p. e10828, 2019.

[178] Healthy-ojas. "Blood Pressure & Heart Rate." https://healthy-ojas.com/pressure/pressure-heart-rate.html (accessed.

[179] C. Prendergast, "Normal Resting Heart Rate By Age (Chart)," ed: Forbes, 2023.

[180] H. Machine, "PULSE OXIMETER," 2022. [Online]. Available: https://gruasyaparejos.com/en/pulse-oximeter/.

[181] T. Siddiqui and B. I. Morshed, "Severity Exploratory Model Analysis of Chronic Obstructive Pulmonary Disease and Asthma with Heart Rate and SpO 2," in *2018 IEEE International Conference on Electro/Information Technology (EIT)*, 2018: IEEE, pp. 0913-0916.

[182] S. Radhakrishnan, S. G. Nair, and J. Isaac, "Analysis of parameters affecting blood oxygen saturation and modeling of fuzzy logic system for inspired oxygen prediction," *Computer methods and programs in biomedicine,* vol. 176, pp. 43-49, 2019.

[183] D. Mohan, D. Z. Al-Hamid, P. H. J. Chong, J. Gutierrez, and H. Li, "Fall Prediction in Elderly Through Vital Signs Monitoring–A Fuzzy–Based Approach," *IEEE Internet of Things Journal,* 2024.

[184] P. Anooj, "Clinical decision support system: Risk level prediction of heart disease using weighted fuzzy rules," *Journal of King Saud University-Computer and Information Sciences,* vol. 24, no. 1, pp. 27-40, 2012.

[185] M. M. Baig, "Smart vital signs monitoring and novel falls prediction system for older adults," *Auckland University of Technology in fulfilment of the requirements for the degree of Doctor of Philosophy (PhD),* 2014.

[186] A. Johnson, T. Pollard, O. Badawi, and J. Raffa, "eICU collaborative research database demo (version 2.0. 1)," *PhysioNet,* 2021.

[187] M. A. Reyna *et al.*, "Early prediction of sepsis from clinical data: the PhysioNet/Computing in Cardiology Challenge 2019," *Critical care medicine,* vol. 48, no. 2, pp. 210-217, 2020.

[188] D. I. R. Maria Matarese MNS RN, Francesco Bartolozzi MD, Michela Piredda MNS RN, Maria Grazia De Marinis MNS RN, "Systematic review of fall risk screening tools for older patients in acute hospitals," *JAN,* Review paper no. https://doi.org/10.1111/jan.12542, 2014, doi: https://doi.org/10.1111/jan.12542. Wiley Online Library.

[189] S. Baek, J. Piao, Y. Jin, and S. M. Lee, "Validity of the Morse Fall Scale implemented in an electronic medical record system," *Journal of clinical nursing,* vol. 23, no. 17-18,

pp. 2434-2441, 2014.

[190] A. Mehmood, A. Nadeem, M. Ashraf, M. S. Siddiqui, K. Rizwan, and K. Ahsan, "A fall risk assessment mechanism for elderly people through muscle fatigue analysis on data from body area sensor network," *IEEE Sensors Journal,* vol. 21, no. 5, pp. 6679-6690, 2020.

[191] S. D. Devi, "A Study to Find Out the Fear of Falling Between Fallers and Non-Fallers in Elderly Population," Rajiv Gandhi University of Health Sciences (India), 2013.

[192] N. King and I. Asquith, "An evaluation of behaviour monitoring charts for behaviours that challenge in an older adult inpatients dementia service," *Working with Older People,* vol. 28, no. 3, pp. 247-257, 2024.

[193] A. Saffa. "New Zealand: AI for Medication Management for Elderly." Open Gov. https://opengovasia.com/2024/06/03/new-zealand-ai-for-medication-management-for-elderly/ (accessed.

[194] Q. Xu, G. Huang, M. Yu, and Y. Guo, "Fall prediction based on key points of human bones," *Physica A: Statistical Mechanics and its Applications,* vol. 540, p. 123205, 2020.

[195] S. McCall *et al.*, "Computer vision based transfer learning-aided transformer model for fall detection and prediction," *IEEE Access,* 2024.

[196] A. K. Mishra *et al.*, "Explainable fall risk prediction in older adults using gait and geriatric assessments," *Frontiers in digital health,* vol. 4, p. 869812, 2022.

[197] R. Keramati Hatkeposhti, M. Yadollahzadeh-Tabari, and M. Golsorkhtabariamiri, "Providing an approach for early prediction of fall in human activities based on wearable sensor data and the use of deep learning algorithms," *The Computer Journal,* vol. 67, no. 2, pp. 658-673, 2024.

[198] S. H. Mohammed, Y. Fan, G. Lv, and S. Liu, "A Mathematical model for fall detection predication in elderly people," *IEEE Sensors Journal,* 2023.

[199] N. Thakur and C. Y. Han, "Country-specific interests towards fall detection from 2004–2021: An open access dataset and research questions," *Data,* vol. 6, no. 8, p. 92, 2021.

[200] N. Salari, N. Darvishi, M. Ahmadipanah, S. Shohaimi, and M. Mohammadi, "Global prevalence of falls in the older adults: a comprehensive systematic review and meta-analysis," *Journal of orthopaedic surgery and research,* vol. 17, no. 1, p. 334, 2022.

[201] M. Ferreira, J. Rodrigues, A. Rezende, A. Pereira, L. Lemos, and L. Cunha, "Intrinsic risk factors for falls among institutionalized older adults," *Acta Fisiátr,* vol. 30, no. 2, pp. 73-80, 2023.

[202] Ž. Kozinc, S. Löfler, C. Hofer, U. Carraro, and N. Šarabon, "Diagnostic balance tests for assessing risk of falls and distinguishing older adult fallers and non-fallers: a systematic review with meta-analysis," *Diagnostics,* vol. 10, no. 9, p. 667, 2020.

[203] M. Tago, N. E. Katsuki, Y. Oda, E. Nakatani, T. Sugioka, and S.-i. Yamashita, "New predictive models for falls among inpatients using public ADL scale in Japan: A retrospective observational study of 7,858 patients in acute care setting," *PloS one,* vol. 15, no. 7, p. e0236130, 2020.

[204] J. M. Negrete Ramírez, C. Martinie, P. Palanque, and Y. Cardinale, "ADL Monitoring of Elderly People in Smart Homes Based on Task Models," in *Workshop Proceedings of the 19th International Conference on Intelligent Environments (IE2023)*, 2023: IOS Press, pp. 216-225.

[205] N. Camp, M. Lewis, K. Hunter, J. Johnston, M. Zecca, A. Di Nuovo, and D. Magistro, "Technology used to recognize activities of daily living in community-dwelling older adults," *International Journal of Environmental Research and Public Health,* vol. 18, no. 1, p. 163, 2021.

[206] M. Pashmdarfard and A. Azad, "Assessment tools to evaluate Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL) in older adults: A systematic review," *Medical journal of the Islamic Republic of Iran,* vol. 34, p. 33, 2020.

[207] M. Jacob Rodrigues, O. Postolache, and F. Cercas, "Physiological and behavior monitoring systems for smart healthcare environments: A review," *Sensors,* vol. 20, no. 8, p. 2186, 2020.

[208] S. Shenbagavalli and D. Shanthi, "Optimized deep belief network and unsupervised deep learning methods for disease prediction," *Journal of Intelligent & Fuzzy Systems,* vol. 45, no. 6, pp. 9571-9589, 2023.

[209] M. K. Gourisaria, G. Harshvardhan, R. Agrawal, S. S. Patra, S. S. Rautaray, and M. Pandey, "Arrhythmia detection using deep belief network extracted features from ECG signals," *International Journal of E-Health and Medical Communications (IJEHMC),* vol. 12, no. 6, pp. 1-24, 2021.

[210] D. C. R. Novitasari, A. Z. Foeady, M. Thohir, A. Z. Arifin, K. Niam, and A. H. Asyhar, "Automatic approach for cervical cancer detection based on deep belief network (DBN) using colposcopy data," in *2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, 2020: IEEE, pp. 415-420.

[211] S. A. Ali, B. Raza, A. K. Malik, A. R. Shahid, M. Faheem, H. Alquhayz, and Y. J. Kumar, "An optimally configured and improved deep belief network (OCI-DBN) approach for heart disease prediction based on Ruzzo–Tompa and stacked genetic algorithm," *IEEE Access,* vol. 8, pp. 65947-65958, 2020.

[212] K. Lim, B. M. Lee, U. Kang, and Y. Lee, "An optimized DBN-based coronary heart disease risk prediction," *International Journal of Computers Communications & Control,* vol. 13, no. 4, pp. 492-502, 2018.

[213] X. Zhang, F.-L. Chung, and S. Wang, "An interpretable fuzzy DBN-based classifier for indoor user movement prediction in ambient assisted living applications," *IEEE Transactions on Industrial Informatics,* vol. 16, no. 1, pp. 42-53, 2019.

[214] A. Jahanjoo, M. Naderan, and M. J. Rashti, "Detection and multi-class classification of falling in elderly people by deep belief network algorithms," *Journal of Ambient Intelligence and Humanized Computing,* vol. 11, no. 10, pp. 4145-4165, 2020.

[215] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural computation,* vol. 18, no. 7, pp. 1527-1554, 2006.

[216] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy layer-wise training of deep networks," *Advances in neural information processing systems,* vol. 19, 2006.

[217] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, 2019, pp. 4171-4186.

[218] M. A. Carreira-Perpinan and G. Hinton, "On contrastive divergence learning," in *International workshop on artificial intelligence and statistics*, 2005: PMLR, pp. 33-40.

[219] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson, "How transferable are features in deep neural networks?," *Advances in neural information processing systems,* vol. 27, 2014.

[220] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *nature,* vol. 323, no. 6088, pp. 533-536, 1986.

[221] A. Weiss, M. Brozgol, M. Dorfman, T. Herman, S. Shema, N. Giladi, and J. M. Hausdorff, "Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings," *Neurorehabilitation and neural repair,* vol. 27, no. 8, pp. 742-752, 2013.

[222] I. M. Pires, N. M. Garcia, E. Zdravevski, and P. Lameski, "Activities of daily living with motion: A dataset with accelerometer, magnetometer and gyroscope data from mobile devices," *Data in brief,* vol. 33, p. 106628, 2020.

[223] A. Cella *et al.*, "Development and validation of a robotic multifactorial fall-risk predictive model: A one-year prospective study in community-dwelling older adults," *PLoS One,* vol. 15, no. 6, p. e0234904, 2020.

[224] W.-M. Chu *et al.*, "A model for predicting fall risks of hospitalized elderly in Taiwan-A machine learning approach based on both electronic health records and comprehensive geriatric assessment," *Frontiers in medicine,* vol. 9, p. 937216, 2022.

[225] N. Dormosh, M. C. Schut, M. W. Heymans, N. van der Velde, and A. Abu-Hanna, "Development and internal validation of a risk prediction model for falls among older people using primary care electronic health records," *The Journals of Gerontology: Series A,* vol. 77, no. 7, pp. 1438-1445, 2022.

[226] A. S. Doorduijn *et al.*, "Nutritional status is associated with clinical progression in Alzheimer's disease: the NUDAD project," *Journal of the American Medical Directors Association,* vol. 24, no. 5, pp. 638-644. e1, 2023.

[227] M. Ullrich *et al.*, "Fall risk prediction in Parkinson's disease using real-world inertial sensor gait data," *IEEE journal of biomedical and health informatics,* vol. 27, no. 1, pp. 319-328, 2022.

[228] G. Cuaya-Simbro, A.-I. Perez-Sanpablo, A. Muñoz-Meléndez, I. Q. Uriostegui, E.-F. Morales-Manzanares, and L. Nuñez-Carrera, "Comparison of machine learning models to predict risk of falling in osteoporosis elderly," *Foundations of Computing and Decision Sciences,* vol. 45, no. 2, pp. 66-77, 2020.

[229] Y. T. Tang and R. Romero-Ortuno, "Using explainable AI (XAI) for the prediction of falls in the older population," *Algorithms,* vol. 15, no. 10, p. 353, 2022.

[230] B. Lindholm, C. Brogårdh, P. Odin, and P. Hagell, "Longitudinal prediction of falls and near falls frequencies in Parkinson's disease: a prospective cohort study," *Journal of neurology,* vol. 268, pp. 997-1005, 2021.

[231] Y. Wang, X. Wu, and X. Mo, "A novel adaptive-weighted-average framework for blood glucose prediction," *Diabetes technology & therapeutics,* vol. 15, no. 10, pp. 792-801, 2013.

[232] A. Zemirline, L. Lecornu, and B. Solaiman, "Rule-based diagnostic system fusion," in *2007 10th International Conference on Information Fusion*, 2007: IEEE, pp. 1-7.

[233] S. Sarkar, R. Raj, S. Vinay, J. Maiti, and D. K. Pratihar, "An optimization-based decision tree approach for predicting slip-trip-fall accidents at work," *Safety science,* vol. 118, pp. 57-69, 2019.

[234] P. Mahajan, S. Uddin, F. Hajati, and M. A. Moni, "Ensemble learning for disease prediction: A review," in *Healthcare*, 2023, vol. 11, no. 12: MDPI, p. 1808.

[235] F. Matloob *et al.*, "Software defect prediction using ensemble learning: A systematic literature review," *IEEe Access,* vol. 9, pp. 98754-98771, 2021.

[236] X. Dong, Z. Yu, W. Cao, Y. Shi, and Q. Ma, "A survey on ensemble learning," *Frontiers of Computer Science,* vol. 14, pp. 241-258, 2020.

[237] I. D. Mienye and Y. Sun, "A survey of ensemble learning: Concepts, algorithms, applications, and prospects," *Ieee Access,* vol. 10, pp. 99129-99149, 2022.

[238] I. D. Mienye, Y. Sun, and Z. Wang, "An improved ensemble learning approach for the prediction of heart disease risk," *Informatics in Medicine Unlocked,* vol. 20, p. 100402, 2020.

[239] C. Fernandez-Lozano *et al.*, "Random forest-based prediction of stroke outcome," *Scientific reports,* vol. 11, no. 1, p. 10071, 2021.

[240] R. Couronné, P. Probst, and A.-L. Boulesteix, "Random forest versus logistic regression: a large-scale benchmark experiment," *BMC bioinformatics,* vol. 19, pp. 1-14, 2018.

[241] V. R. Rae, "A Random Forest-Based Q-Learning Algorithm: Toward Interpretable Artificial Intelligence," 2024.

[242] Z. Guo, J. Wang, B. Zhang, Y. Ku, and F. Ma, "A dual transfer learning method based on 3D-CNN and vision transformer for emotion recognition," *Applied Intelligence,* vol. 55, no. 2, p. 200, 2025.

[243] Q. Zhang and L. Yang, "Cross-Subject Emotion Classification based on Dual-Attention Mechanism and Meta-Transfer Learning," in *Proceedings of the Annual Meeting of the Cognitive Science Society*, 2024, vol. 46.

[244] J. De Matos, A. d. S. Britto, L. E. Oliveira, and A. L. Koerich, "Double transfer learning for breast cancer histopathologic image classification," in *2019 international joint conference on neural networks (IJCNN)*, 2019: IEEE, pp. 1-8.

Appendices:

A. AI-1 and AI-2 Model Development Analysis:

A.1 AI-1 Model - Formulated Fuzzy Rules (111- Fuzzy rules)

Blood Pressure Status	Rule	Blood Pressure Readings	Pulse Pressure	Heart Rate Readings	O2 Readings	Risk Level
Normal	1.	Normal	Normal	Normal	Normal	Normal
	2.	Normal	Normal	Normal	Moderate	Normal
	3.	Normal	Normal	Moderate	Normal	Normal
	4.	Normal	Normal	Moderate	Moderate	Low
	5.	Normal	Normal	Moderate	High	Low
	6.	Normal	Normal	High	Normal	Low
	7.	Normal	Normal	High	Moderate	Low
	8.	Normal	Normal	High	High	Low
	9.	Normal	Normal	Emergency	High	Moderate
	10.	Normal	Normal	Emergency	Emergency	Moderate
		Hypothetical Rule 8-10				
Low	11.	Low	Low	Normal	Normal	Normal
	12.	Low	Low	Normal	Moderate	Low
	13.	Low	Low	Normal	High	Low
	14.	Low	Low	Moderate	Normal	Low
	15.	Low	Low	Moderate	Moderate	Low
	16.	Low	Low	Moderate	High	Moderate
	17.	Low	Low	High	Moderate	Moderate
	18.	Low	Low	High	High	Moderate
	19.	Low	Low	High	Emergency	Moderate
	20.	Low	Low	Emergency	Moderate	Moderate
	21.	Low	Low	Emergency	High	Moderate
	22.	Low	Low	Emergency	Emergency	Moderate
	23.	Moderate	High	Normal	Normal	Low
	24.	Moderate	High	Normal	Moderate	Moderate
	25.	Moderate	High	Normal	High	Moderate
	26.	Moderate	High	Normal	Emergency	Moderate
	27.	Moderate	High	Moderate	Normal	Moderate
	28.	Moderate	High	Moderate	Moderate	Moderate
	29.	Moderate	High	Moderate	High	Moderate
	30.	Moderate	High	Moderate	Emergency	High
	31.	Moderate	High	High	Moderate	Moderate
	32.	Moderate	High	High	High	High
	33.	Moderate	High	High	Emergency	High
	34.	Moderate	High	Emergency	Moderate	High
	35.	Moderate	High	Emergency	High	High
	36.	Moderate	High	Emergency	Emergency	High
	37.	High	High	Normal	Moderate	Moderate
	38.	High	High	Normal	High	Moderate
	39.	High	High	Normal	Emergency	Moderate
	40.	High	High	Moderate	Moderate	Moderate
	41.	High	High	Moderate	High	High

	42.	High	High	Moderate	Emergency	High
	43.	High	High	High	Moderate	High
	44.	High	High	High	High	High
	45.	High	High	High	Emergency	High
	46.	High	High	Emergency	Moderate	High
	47.	High	High	Emergency	High	High
	48.	High	High	Emergency	Emergency	High
	49.	Emergency	High	Normal	Moderate	Moderate
	50.	Emergency	High	Normal	High	Moderate
	51.	Emergency	High	Normal	Emergency	High
	52.	Emergency	High	Moderate	Moderate	High
	53.	Emergency	High	Moderate	High	High
	54.	Emergency	High	Moderate	Emergency	High
	55.	Emergency	High	High	Moderate	High
	56.	Emergency	High	High	High	High
	57.	Emergency	High	High	Emergency	High
	58.	Emergency	High	Emergency	Moderate	High
	59.	Emergency	High	Emergency	Emergency	Emergency
High	60.	Low	Normal	Normal	Normal	Normal
	61.	Low	Normal	Normal	Moderate	Low
	62.	Low	Normal	Normal	High	Low
	63.	Low	Normal	Moderate	Normal	Low
	64.	Low	Normal	Moderate	Moderate	Low
	65.	Low	Normal	Moderate	High	Low
	66.	Low	Normal	Moderate	Emergency	Moderate
	67.	Low	Normal	High	Normal	Low
	68.	Low	Normal	High	Moderate	Low
	69.	Low	Normal	High	High	Moderate
	70.	Low	Normal	High	Emergency	Moderate
	71.	Low	Normal	Emergency	Moderate	Moderate
	72.	Low	Normal	Emergency	High	Moderate
	73.	Low	Normal	Emergency	Emergency	Moderate
	74.	Moderate	Normal	Normal	Normal	Normal
	75.	Moderate	Normal	Normal	Moderate	Low
	76.	Moderate	Normal	Normal	High	Low
	77.	Moderate	Normal	Normal	Emergency	Low
	78.	Moderate	Normal	Moderate	Normal	Low
	79.	Moderate	Normal	Moderate	Moderate	Low
	80.	Moderate	Normal	Moderate	High	Moderate
	81.	Moderate	Normal	Moderate	Emergency	Moderate
	82.	Moderate	Normal	High	Moderate	Moderate
	83.	Moderate	Normal	High	High	Moderate

	84.	Moderate	Normal	High	Emergency	Moderate
	85.	Moderate	Normal	Emergency	Moderate	Moderate
	86.	Moderate	Normal	Emergency	High	Moderate
	87.	Moderate	Normal	Emergency	Emergency	Moderate
	88.	High	High	Normal	Moderate	Moderate
	89.	High	High	Normal	High	Moderate
	90.	High	High	Normal	Emergency	Moderate
	91.	High	High	Moderate	Moderate	Moderate
	92.	High	High	Moderate	High	High
	93.	High	High	Moderate	Emergency	High
	94.	High	High	High	Moderate	High
	95.	High	High	High	High	High
	96.	High	High	High	Emergency	High
	97.	High	High	Emergency	Moderate	High
	98.	High	High	Emergency	High	High
	99.	High	High	Emergency	Emergency	High
	100.	Emergency	High	Normal	Moderate	Moderate
	101.	Emergency	High	Normal	High	Moderate
	102.	Emergency	High	Normal	Emergency	High
	103.	Emergency	High	Moderate	Moderate	High
	104.	Emergency	High	Moderate	High	High
	105.	Emergency	High	Moderate	Emergency	High
	106.	Emergency	High	High	Moderate	High
	107.	Emergency	High	High	High	High
	108.	Emergency	High	High	Emergency	High
	109.	Emergency	High	Emergency	Moderate	High
	110.	Emergency	High	Emergency	High	High
	111.	Emergency	High	Emergency	Emergency	Emergenc y

A.2 AI-2 Model - Raw Data to ADL Conversion

A comprehensive process for converting raw accelerometer data into ADLs as outlined in Section 5.7.2 is presented here.

ADL Data Extraction: This research utilizes ADL data to predict falls, which is derived from the raw data collected from a 3D accelerometer placed on the lower back of each participant to monitor gait. The raw recordings are then processed using an ADL conversion algorithm that extracts meaningful activity classifications based on predefined threshold values.

ADL Conversion Algorithm - Pseudocode

Input: 3D Accelerometer Raw Data

Output: ADL (Sitting, Standing, Walking, Running, Jumping) and Unknown

Initialization:

CLOCK_FREQUENCY=100 ticks/second

WINDOW_SIZE=100

Data Frame → df

Time Parsing:

For each entry in the 'Time (elapsed)' column

Parse_time (h:m:s) = h x 3600 + m x 60 + s

Remove NaN rows.

Feature Extraction:

For each sliding window of size n from df:

mean_v = $\frac{1}{n}\sum_{i=1}^{n} v_{acceleration}[i]$

mean_ml = $\frac{1}{n}\sum_{i=1}^{n} ml_{acceleration}[i]$

mean_ap = $\frac{1}{n}\sum_{i=1}^{n} ap_{acceleration}[i]$

std_v = $\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(v_{acceleration}[i]-mean\_v)^2}$

std_ml = $\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(ml_{acceleration}[i]-mean\_ml)^2}$

std_ap = $\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(ap_{acceleration}[i]-mean\_ap)^2}$

Activity Classification:

- Sitting
- Standing
- Walking
- Running
- Jumping

A.3 AI-2 Model - Long-Term Movement Monitoring Database

#	Date of Evaluation	Gender(0-	Age	Year Fall	6 Months	yr almost	Time (m/s	TUG		BERG		Risk Level
FL-001	7/04/2010	0	79.2	5	2	1	23.72	8.56	Normal	55	Low	Low
FL-004	30/01/2011	0	81.99	2	2	1	78.48	11.01	Low	48	Low	Low
FL-005	23/03/2011	0	77.96	2	0	na	80.56	11.05	Low	51	Low	Low
FL-006	8/05/2011	0	84.46	2	2	7	58.26	18.18	Low	50	Low	Low
FL-007	15/05/2011	1	75.44	2	1	0	20.94	11.05	Low	54	Low	Low
FL-008	22/05/2011	1	74.37	0	0	0	25.99	11.68	Low	55	Low	Low
FL-009	24/05/2011	1	70.23	2	0	4	28.27	10.83	Low	52	Low	Low
FL-010	24/05/2011	0	75.18	10	6	don't remember	69.24	10.3	Low	54	Low	Low
FL-011	5/06/2011	1	78.24	8	4	234	148.57	14.5	Low	53	Low	Low
FL-013	30/05/2011	1	74.49	7	6	4	56.3	13.08	Low	48	Low	Low
FL-014	30/08/2011	1	80.74	at least 2	yes, but ca	can't tell	0	22.5	High	41	Low	Low
FL-015	25/09/2011	1	84	2	1	0	0	26.25	0	40		Low
FL-016	14/09/2011	1	72.46	6	2	yes, no number	36.93	8.53	Normal	56	Low	Low
FL-017	11/09/2011	1	77.43	3	2	0	32.63	21.1	High	40	Moderate	Moderate
FL-018	26/07/2011	1	69.16	6	3	5	52.82	12.06	Low	47	Low	Low

B. Result Evaluation and Dataset Information:

B.1 AI-2 Model - GT Evaluation

# Participant	TUG Score	MFS Score	Final GT
CO-002	Low	Low	Low
CO-003	Low	Low	Low
CO-004	Low	Low	Low
CO-005	Low	Low	Low
CO-006	Low	Low	Low
CO-007	Low	Low	Low
CO-008	Low	Low	Low
CO-009	Low	Low	Low
CO-010	Low	Low	Low
CO-011	Low	Low	Low
CO-012	Low	Moderate	Moderate
CO-013	Low	Low	Low
CO-014	Low	Moderate	Moderate
CO-015	Low	Low	Low
CO-016	Low	Low	Low
CO-017	Low	Moderate	Moderate
CO-018	Low	Moderate	Moderate
CO-019	Low	Low	Low
CO-020	Low	Moderate	Moderate
CO-021	Low	Low	Low
CO-022	Low	Low	Low
CO-023	Low	Low	Low

B.2 Meta-Model -Training Data (15 Participants)

Age	Fall History	AI-1	AI-2	MFS
77	0 (N)	Normal	Low	Low
81	0 (N)	Low	Low	Low
84	2 (Y)	Low	Moderate	Moderate
77	0 (N)	Normal	Low	Low
84	2 (Y)	Low	Moderate	Moderate
75	5 (Y)	High	Low	High
83	9 (Y)	Moderate	Moderate	Moderate
70	0 (N)	Low	Low	Low
81	2 (Y)	Low	Moderate	Moderate
74	3 (Y)	Low	Moderate	Low
76	10 (Y)	High	Low	High
89	5 (Y)	Moderate	Moderate	Moderate
81	2 (Y)	Normal	High	Moderate
81	2 (Y)	Low	High	Moderate
80	2 (Y)	Moderate	High	Moderate