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Deep Belief Network-based Activity of Daily Living Monitoring for Fall Risk Prediction in Elderly

Deepika Mohan, *Student Member, IEEE*, Peter Han Joo Chong, *Senior Member, IEEE,* Jairo Gutierrez, Mirza Mansoor Baig*, IEEE and* Hui Li*, Senior Member, IEEE*

***Abstract*— Despite advancements in healthcare and emerging technologies, falls among older adults remain a significant health issue. Recent research has increasingly focused on developing advanced monitoring methods, predicting, and preventing falls in this population. Achieving high performance in fall prediction requires a clear understanding of relevant features such as gait patterns, balance metrics, muscle strength, and environmental factors. Identifying these key indicators and incorporating data from wearable sensors, medical histories, and demographic information can significantly enhance predictive accuracy. This study proposes an intelligent fall prediction model that anticipates future falls in older adults by continuously monitoring their Activities of Daily Living (ADLs) and detecting abnormalities. The model uses a Deep Belief Network (DBN) that incorporates contrastive divergence for pre-training, backpropagation for fine-tuning, and the Adam Optimizer to minimize loss. Evaluation of the proposed model shows it achieved an accuracy of 91.67%, specificity of 100%, and sensitivity of 90.00% when compared to the Ground Truth (GT) and existing fall prediction approaches. These results suggest that advanced deep learning techniques can effectively assist in early fall risk prediction, potentially reducing the likelihood and severity of falls among older adults.**

***Index Terms*— Fall Prediction, Deep Belief Networks, Risk analysis, Morse Falls Scale, AI, ML, and ADLs**

I. INTRODUCTION

FALLS in older adults represent a major public health issue worldwide, particularly in New Zealand, where approximately 30% of individuals aged 65 and older living in the community experience at least one fall each year [1]. Notably, 10 to 20% of individuals who experience falls require hospitalization, highlighting the serious consequences that can arise from a fall. The risk of severe outcomes increases substantially for those over the age of 85, who are 15 times more likely to sustain a hip fracture compared to 65–84-year-old adults. This group is especially at risk because falls make up a large number of Accident Compensation Corporation (ACC) injury claims as stated in [2], and many of these cases lead to extended hospital stays. As individuals age, they experience a decline in physical health, characterized by a reduction in muscle fibers and overall muscle strength, which contributes to balance issues [3]. These physiological changes can be exacerbated by environmental factors, including inadequate lighting, unsafe footwear, slippery surfaces, and various tripping hazards such as rugs and electrical cords. Such conditions create a perfect storm for falls, making it critical to address both intrinsic and extrinsic risk factors [4].

One of the most significant effects is the potential for bone fractures, which often leads to a loss of mobility and independence. According to statistics provided by ACC New Zealand [5] approximately 22–60% of individuals aged over 65 who fall sustain injuries, while 10–15% incur serious injuries. Furthermore, 2–6% of these falls result in fractures and 0.2–5% lead to hip fractures. These injuries can create a cycle of dependency, as many older adults may begin to rely more heavily on family members for assistance in daily activities. Additionally, the psychological impact of falling stated in [6] can lead to an increased fear of falling again, which may cause individuals to limit their activities and social interactions, further diminishing their quality of life. Thus, falls among the elderly are not only a leading cause of illness and disability but also a significant contributor to mortality. Preventive measures are essential for lowering the number of falls and their impacts, highlighting the importance of strategies that address both health and safety in the environment. One critical approach to enhancing safety is through fall detection and fall prediction technologies.

As mentioned in [7], fall detection refers to the capability of identifying when an individual has fallen, utilizing various technologies such as wearable devices, cameras, or motion sensors. These systems can automatically alert caregivers, family members, or emergency services, ensuring timely assistance and significantly reducing the adverse effects of injuries by facilitating quicker medical intervention. Meanwhile, fall prediction involves assessing an individual's risk of falling before it occurs (potential future falls). This can be achieved by monitoring factors such as physical activity levels, medical history, balance assessments, and environmental conditions. Predictive models often use

Deepika Mohan, and Peter Han Joo Chong are with the Department of Electrical and Electronic Engineering, Auckland University of Technology, Auckland 1010, New Zealand (e-mail: deepika.mohan@autuni.ac.nz; Corresponding Author: peter.chong@aut.ac.nz)

Jairo Gutierrez is with the Department of Computer Science and Software Engineering, Auckland University of Technology, Auckland 1010, New Zealand (e-mail: jairo.gutierrez@aut.ac.nz)

Mirza Mansoor Baig is with Consumer Engagement Solutions, Orion Health, Auckland 1010, New Zealand (e-mail: mirzamansoor01@gmail.com)

Hui Li is with the Shenzhen Graduate School, Peking University, Shenzhen 100871, China (e-mail: huilihuge@163.com).

statistical analysis and machine learning algorithms to identify patterns and risk factors associated with falls. Integrating advanced technologies into these systems is important for making them work better. From [8], the traditional monitoring methods might not be fast or accurate enough to stop serious problems, hence Artificial Intelligence (AI) and Machine Learning (ML) can help solve this issue. These technologies significantly enhance fall detection and prediction systems in terms of data analysis, real-time monitoring, continuous improvements, and smart integration. The use of AI and ML in fall prediction is crucial because these technologies provide a level of sophistication and adaptability that traditional methods cannot match. They allow for continuous learning and improvement, enabling more accurate assessments of fall risks and timely responses to falls, ultimately leading to better outcomes for older adults [9]. As technology advances, the effectiveness of these solutions is expected to grow, empowering older adults to live more independently and safely.

A study in [10] investigates methods to improve real-time fall detection and prediction using ML and deep learning (DL) models like Convolutional Neural Networks (CNNs), Long-Short Term Memory (LSTM), K-Nearest Neighbors (KNN), and Support Vector Machines (SVMs), applied to the UPFALL dataset. By combining ML and DL methods and optimizing them using techniques like Grid Search and Maximum Voting, the study achieved a detection accuracy of 93.5%. Random Forest and Gradient Boosting provided the best performance, with CNNs and LSTMs adding predictive capabilities for early fall detection. A promising model presented in [11] combines two algorithms: one that predicts the likelihood of a fall based on ADL and another that classifies the activity as either a fall or not. This model uses three Inertial Measurement Unit (IMU) sensors placed on the thoracic, hip, and knee joints, utilizing quaternions for orientation representation. It calculates joint angles with a T-pose skeleton as a reference for coordinates. When evaluated with the IMU, which includes real-time human motion data, the model demonstrated efficiency achieving an average sensitivity of 70.4% in training and 71.4% in testing, with specificity averaging 75.3% during training and 75.5% during testing. The logistic regression model attained an overall accuracy of 88% in training and 87.75% in testing. Based on Human Body Kinematics (HBK), this model effectively differentiates between falls and non-falls in elderly individuals.

Research and development in fall detection have expanded significantly in recent years, with numerous countries conducting active studies, as discussed in [12]. Recent research in the field of fall detection has focused on detecting fall events after they happen, leading to extremely high classification accuracies. For example, a fall detection system was developed in [13] for assisted living facilities by a thorough comparative analysis employing 19 distinct machine learning techniques. A k-NN classifier optimised with an AdaBoost framework beat other models, achieving performance accuracies of 99.87% and 99.66% across the two benchmark datasets on which they tested several classifiers. In order to detect fall-like motions and transitions, their method went beyond binary fall/non-fall categorisation. This helps to infer richer activity in smart home situations.

Similar to this, in [14], a workable fall detection system was presented that uses six-axis inertial features (three axes of acceleration and three axes of rotational acceleration) and an AdaBoost classifier with single-layer decision trees. Their model achieves an overall accuracy of 99.08% with high sensitivity and specificity on their gathered dataset by using a small collection of time-domain features and using a lightweight classification approach targeted at high accuracy and low computing complexity. Because of its design, the approach can be used in real-time fall detection systems and embedded implementations. These high accuracy rates are typical in fall detection research, where the primary goal is to recognize falls from sensor streams immediately after they occur. However, it is important to differentiate this from fall prediction, which aims to forecast risk before a fall and generally involves more complex temporal modeling and greater uncertainty.

While many modern smartphones and smart systems now incorporate AI-based fall detection features, there has been a notable shift toward fall prediction. This area has garnered significant research interest since 2020, recognizing that predicting falls before they happen is more advantageous than detecting them afterward. Fig. 1. illustrates the worldwide statistics of fall detection and prediction research from 2020 to 2024, as sourced from Google Trends [15]. A review work in [16] underscores that advancements in sensor technologies and machine learning algorithms are increasingly enhancing the predictive capabilities of intelligent systems. Globally, as well as in specific regions like New Zealand, there's a growing body of research focused on improving fall prediction strategies for the elderly, as discussed in [17]. The overall trajectory shows a shift towards prevention, driven by the idea that preventing falls is more beneficial than treating them aftermath.

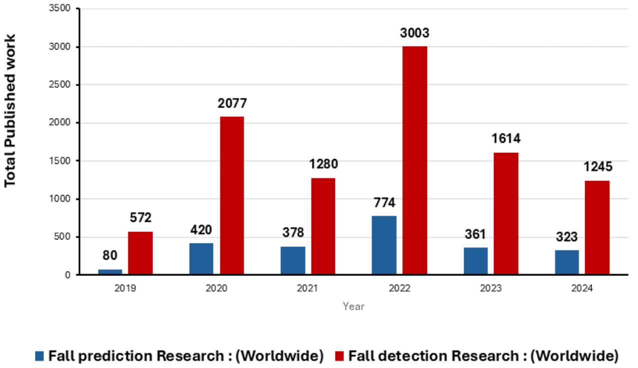

Fig. 1. Worldwide Statistics of Fall Detection and Fall Prediction Research from 2020-2024

Fall prediction is a critical and sensitive area for maintaining a healthy lifestyle, particularly for older adults, as any imbalance can increase the risk of falls. AI and ML serve as valuable tools for predicting potential falls in this demographic. The goal of AI is to address challenges by analyzing all available information. In this paper, we introduce an activity monitoring system aimed at predicting potential falls among older adults. Initially, we validate this model using data collected from public repositories. Following verification, we plan to incorporate real-time data from older adults in the subsequent phase. Our work focuses on predictive modeling of fall risk rather than post-fall detection, highlighting a distinct and clinically meaningful challenge beyond traditional detection benchmarks. To the best of our knowledge, this is the first research study that specifically utilizes ADLs and introduces a three-stage DBN model to predict the risk of future falls in older adults which is explained in Section III.

To the best of our knowledge, no previous study has used Activities of Daily Living (ADL) as the only input modality in conjunction with a Deep Belief Network (DBN) for fall-risk prediction. This makes this work innovative. The majority of previous studies have either used traditional machine learning classifiers, relied on alternative deep learning architectures like CNNs and LSTMs, or combined ADL data with extra clinical, biomechanical, or demographic information. Our suggested method is motivated by this obvious vacuum in the literature. In addition, this study is the first to present a 3-stage DBN architecture created especially to forecast future fall risk as opposed to identifying falls after they happen. The comparison of TUG and MFS scores as ground truth measures for multi-class fall-risk prediction, which offers clinically meaningful risk stratification, is another significant contribution. The proposed method also offers a structured risk categorisation technique with its 3-stage DBN design, allowing classification into low, moderate, and high fall-risk categories. It is non-invasive and supports continuous, round-the-clock monitoring. All of these contributions show how the suggested fall-risk prediction methodology is innovative, clinically relevant, and practically applicable.

The structure of the remainder of the paper is as follows: Section II provides a review of relevant work, Section III details the selection of behavior parameters and DBN, Section IV discusses the proposed framework development strategy and the three-stage Deep Belief Network (DBN) model, Section V presents experimental findings, and Section VI summarizes the results and outlines future research directions.

II. RELATED WORKS

A. AI/ML-based Fall Prediction using Human Activity Recognition with Computer Vision

Vision-based techniques focus on representing, segmenting, and recognizing human actions that involve hand and body gestures and facial expressions. Consequently, computer vision encompasses diverse methods that operate across both temporal and spatial dimensions. A study in [18] tackles the important challenge of predicting falls, specifically flat falls, which can cause serious injuries in older adults. It presents a novel method that employs computer vision and machine learning techniques to recognize gait patterns, aiming to improve the accuracy of fall predictions. The study utilizes a dataset comprising 750 video recordings of individuals engaged in various activities, including walking and simulated falls, designed to capture a wide range of gait patterns. Pose estimation and feature extraction techniques are used to identify key points from the human body in the videos and to analyze relevant gait dynamics features such as stride length, speed, and body posture. Four classification methods such as CNN, SVM, KNN, and LSTM neural networks are employed to classify three distinct gait patterns. The proposed approach achieves an impressive accuracy of 94.5% in predicting flat falls, significantly outperforming traditional methods.

Similarly, a study in [19] presents a deep learning method for predicting falls in older persons by using a real-time dataset that was generated by watching 50 participants' walking patterns. Each video was captured at 50 frames per second for 60 seconds. This dataset, which consists of recordings of people engaging in a variety of activities, including simulated falls and regular walking, is crucial for teaching the model to distinguish between normal and abnormal gait patterns. Normalisation and segmentation of gait sequence data are part of pre-processing analysis to improve quality and get it ready for deep learning model input. In order to efficiently learn from time-series data, CNN is utilised to extract features from the gait images, and LSTM networks are employed to capture temporal relationships in the gait sequences. Comparing the suggested Deep CNN (DCNN) model's performance to that of the traditional CNN and ResNet50 architectures shows that the DCNN has a high detection probability and few false positives. The suggested DCNN outperforms the traditional models with a maximum prediction ratio of 98.64%. In order to anticipate falls in elderly persons, research was done in [20] that focused on improving the accuracy of fall prediction systems by examining important features of human bones. Motion capture techniques were used to gather data on skeletal important points when walking and falling, among other activities. The study makes use of the University of Montreal's Multiple Cameras Fall dataset, which was made publicly available. It consists of 192 movies that use eight cameras to record 24 distinct fall events from different perspectives. Important skeletal locations, like joints and limbs, are identified by the model and serve as indicators of a person's posture and gait. The researchers use OPENPOSE to construct bone maps from 2D pictures and produce an analytical dataset. This dataset is then utilised to train the CNN using transfer learning to create a new fall prediction model. The CNN is then trained on this dataset using transfer learning to create a new fall prediction model. The novel aspect of this study is the use of image-derived bone maps for fall prediction. According to the final experimental results, the new model achieves 91.7% accuracy.

A study in [21] combines transformer models and transfer learning to present a sophisticated method for fall detection and prediction. 15,429 samples from 100 people completing 20 actions, such as walking, jogging, etc., make up the MPOSE dataset. ResNet and other pre-trained CNNs are used to extract features from video frames. By employing attention mechanisms to concentrate on significant frames associated with falls, these features are fed into a transformer model, which is highly effective at temporal sequence analysis. Effective and efficient fall detection and prediction outcomes are made possible by the combination of transformers and transfer learning. By identifying frames with a higher fall risk in sequential video data, the transformer model enhances the predictive power of the system. The model's remarkable performance level of 96.4% in fall detection was ascribed to the potent combination of transformers for temporal analysis and transfer learning for feature extraction. Both 2-D and 3-D body model patterns were created using machine vision in [22], where a 2-D model achieves 100% accuracy in behavioural identification and a 3-D model estimates motion capture.

B. AI/ML-based Fall Prediction using Wearable Sensors and Gait Features

One of the most important indicators for predicting falls and assessing fall risk is gait. The stability and symmetry of a person's stride are indicators of consistent, safe movement when gait is monitored. In order to address the growing worry of falls that can result in significant consequences including fractures and hospitalisations, a study in [23] investigates the use of wearable technology to assess fall risks in older persons living independently. The average age of the 171 participants, who ranged in age from 56 to 90, was 74.3 ± 7.6 years. With a wireless sensor fastened to their chest, each participant walked ten meters. In order to create the model, 127 participants' trunk movements were examined in order to determine fall risk and differentiate between fallers and non-fallers using both linear and nonlinear techniques. Without being intrusive, the wearable technology continuously tracked movement, gait, balance, and other biomechanical parameters. Machine learning algorithms, including SVM, neural networks, and decision trees, were used to process the gathered data and categorise the fall risk (low or high). The neural network achieved the best accuracy of 87% when these models were evaluated against actual fall events that were recorded during the study.

A study in [24] employs geriatric evaluations and gait analysis to predict fall risk in older persons, with a focus on developing predictions that can be explained. In order to make well-informed judgements regarding interventions, this aids clinicians and carers in understanding how particular circumstances contribute to fall risks. The study integrates geriatric evaluations, which include physical, cognitive, and clinical ageing measures, with gait-related characteristics, such as step length, walking speed, and body sway. ADL and Instrumental ADL (IADL) scores from standardised geriatric assessments were employed. Based on fall history, spatiotemporal gait metrics, and geriatric assessments, data from 92 participants were examined to forecast 6-month fall risk. According to the study, gait speed, IADL, and ADL were all generally better indicators of fall risk. Clinicians could save time by using fall risk models to analyse individual assessments and offer early interventions to stop falls in the future. Which gait metrics or geriatric assessment scores had the biggest effects on fall risk prediction were determined using explainability techniques like SHAP (SHapley Additive Explanations). The use of explainability provides value by enabling more individualised interventions to avoid falls in older persons, and the machine learning models showed a high accuracy of 85% in predicting fall risk overall.

A fall prediction system using wearable devices was developed in [25] to address the growing concerns over older adult's safety, especially regarding falls, which present a serious health risk as people age. The system begins by collecting motion data from wearable devices, which can indicate the potential for a fall. This data is then pre-processed, and features are extracted to prepare it for further analysis. The researchers introduced an improved Convolutional Long Short-Term Memory (ConvLSTM) network, which considers both spatial and temporal dynamics to improve fall prediction accuracy. ConvLSTM is well-suited for time-series data, such as movement patterns, as it captures both spatial information (like body posture) and temporal dependencies (how these postures change over time). The proposed model aims to support older adult's independence while simultaneously reducing medical costs linked to fall injuries. By providing early fall warnings, the system allows older adults to adjust their posture or seek help before an incident occurs.

A fall-prediction algorithm was proposed in [26] that utilizes a neural network to enhance safety for older adults, developing a reliable system capable of predicting potential falls and providing timely alerts to caregivers or individuals themselves. Five subjects performed a series of falls while walking on a fixed floor in an indoor environment without obstacles. The subjects were instructed to fall forward onto a supporting object equipped with elasticity. To prevent injuries, they braced themselves against a supporting object with an airbag designed to inflate upon falling. The fall-prediction system incorporates wearable sensors to monitor the participants' movements, and the neural network used for the algorithm consists of three layers: input, hidden, and output. The fall-prediction algorithm predicts falls 0.4 seconds in advance, allowing enough time to inflate an airbag to protect the head, trunk, and hip, reducing injuries in older adults.

C. AI/ML-based Fall Prediction using Assessment Tools

A study in [27] uses a variety of machine learning algorithms to analyse kinematic data from the Timed Up and Go (TUG) test in order to predict fall risk in older persons. It includes 98 participants with various physiological characteristics and medical disorders, such as physical and mental disabilities. IMU sensors record data while participants get out of a chair, walk three meters at their typical pace, turn around, walk back, and sit down again during the TUG test. Utilising MPU-9255 Micro-Electro-Mechanical Systems (MEMS), the RunScribe pods gather 3D kinematic data at a sampling rate of 250 Hz. They record roll, pitch, and yaw angular velocity signals in addition to acceleration in the superior-inferior, mediolateral, and anterior-posterior directions. In order to extract high-level gait features, the study uses a CNN model with four 1-D convolutional layers, each of which is followed by batch normalisation and ReLU activation. With an accuracy of 89.4% in predicting fall risk based on TUG test kinematics, the machine learning models outperform the classic TUG test by at least 19% in sensitivity and a 4% increase in F1-score. 73 senior care home residents over 65 participated in a different study described in [28] that looked at the application of AI to predict fall risk in two different ways. Participants, which included both fallers and non-fallers, completed the 6-minute walk test and the TUG test over the course of six months while wearing an IMU

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sensor. The data collected from the sensors was used to train a deep learning-based AI algorithm, which enhanced gait analysis accuracy from 68% to 76% and achieved a fall prediction precision of 75%. Similarly, the Fall Risk Assessment in Older Adults (FARAO) group conducted a study [29] to collect data on fall risk in the elderly population using wearable sensors, physical examinations, and questionnaires. The findings indicated that DL models can accurately identify participants when utilized with single-task learning techniques. However, these models exhibit improved performance when integrated with multitask learning. Specifically, DL models demonstrate superior performance when combined with multitask learning, achieving an impressive accuracy of 75%. As a result, DL models, particularly within the multitask learning framework, can effectively predict fall risk by leveraging data from wearable sensors and screening tools.

Wearable technology, when paired with cutting-edge AI and machine learning algorithms, can greatly improve fall prediction tactics, allowing for prompt interventions to lower incidences and enhance older folks' quality of life, according to the thorough background analysis. But visual monitoring is computationally demanding; even low-resolution video needs a lot of preprocessing because of the amount of information it conveys. Many video monitoring systems on the market today only pay attention to some aspects of the data, failing to use all of the data that is available in real-time. While computer vision systems are able to recognise objects in video footage, they are unable to comprehend all the information at once. Using a variety of techniques, such as wearable sensors, gait patterns, skeletal imaging, human activity recognition (HAR), or evaluation tools, the majority of studies successfully predicts fall risk using everyday activities, such as ADLs. The importance of ADLs in predicting fall risks especially future falls is thus highlighted. Furthermore, CNN, DCNN, and SVM are frequently used in autumn prediction research for classification and prediction, frequently using simulated data gathered from actors or younger people.

Our study specifically focuses on using ADL monitoring to predict future falls in the elderly. With the help of ADL data, the created Fall Risk Prediction Algorithm (FRPA) easily combines with our suggested 3-stage DBN model to produce extremely accurate results that nearly match the ground truth derived by the TUG and the Morse Falls Scale (MFS). In order to predict the likelihood of future falls, our method uses a dataset of daily activity measurements from a public repository. This dataset includes real-time data from older persons who were tracked for 75 hours. By using real-time data in the next stage of our research, this creative method demonstrates that our built model may deliver timely alarms for predicting falls in older adults.

III. RATIONALE BEHIND SELECTED ADLS AND DBN: A JUSTIFICATION

A. ADL Parameter Selection

Older adults often experience a decline in their ability to perform personal ADLs, exacerbated by factors such as physical weakness, overweightness, health issues, and the emotional toll of losing loved ones like spouses, relatives, or friends. These circumstances can result in social isolation and significantly increase the risk of falling, especially when they are alone. Evaluating an individual’s health and physical condition is closely tied to their capacity to carry out daily activities, which are essential for maintaining routines and overall well-being. In the past decade, numerous studies have focused on the continuous monitoring of ADLs in elderly individuals. Monitoring ADLs can significantly enhance elder care by improving safety, and quality of life, and allowing for the timely detection of critical events such as disease onset or falls, enabling prompt intervention. Additionally, long-term monitoring offers valuable insights to healthcare professionals, helping them make informed decisions regarding the progression of health issues. Elderly adults who struggle with essential ADLs such as preparing meals, eating, bathing, or climbing stairs or who have poor medication adherence are at a higher risk of experiencing a rapid decline in both quality of life and health status, as well as a greater likelihood of falling.

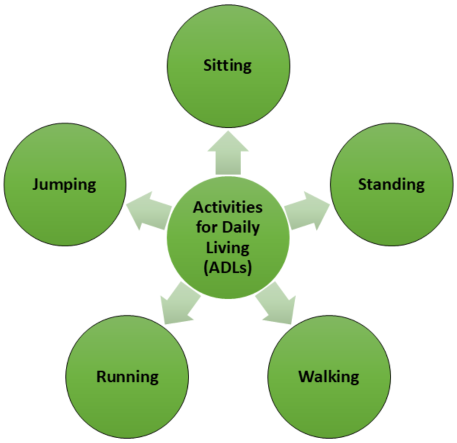

Fig. 2. Behaviour Parameter Selection

Based on the background research conducted in [30] on monitoring abnormal behavior in the elderly, we gain a clear understanding of the significance of ADLs in fall prediction. Therefore, this study focuses on five key ADLs that are instrumental in predicting future falls among older adults.

- Sitting
- Standing
- Walking
- Running
- Jumping

All five ADLs are vital for the essential functioning of older adults. Our research focuses on assessing the risk of falls in older adults during their daily activities and exercises, as these are closely linked to their health parameters. Fig. 2 depicts the selected behavioral parameters for our proposed study. Since health influences behavior patterns and vice versa, monitoring these parameters will yield valuable inputs for the DBN model used to predict fall risk. In our study, activities such as lying down and sleeping are excluded, as they may trigger fall-detection scenarios that are beyond the scope of this research.

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The long-term activity monitoring dataset is obtained from a public repository, containing recordings of older adults performing their ADLs. This raw data is then transformed into the corresponding ADLs using the ADL conversion algorithm detailed in the Appendix. These ADLs are subsequently used as input for the DBN model to predict the risk of future falls.

B. Deep Belief Networks (DBN)

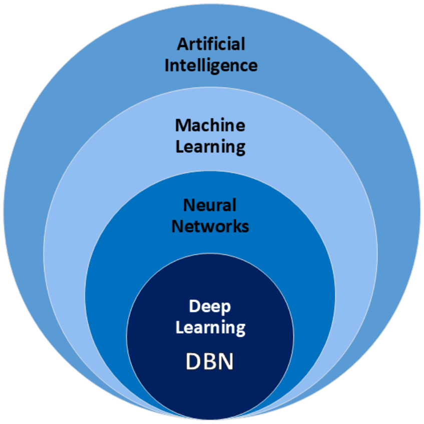

Fig. 3. DBN Overview

DBNs are models that use multiple layers of random variables to learn features from data. As mentioned in [31] they connect the top two layers in a way that allows them to remember information and use direct connections from the upper layers to the lower layers. DBNs have two main advantages: they can efficiently learn the relationships between layers and can infer values in the hidden layers from observed data in one step. Learning happens one layer at a time, where the output of one layer becomes the training data for the next layer (Unsupervised learning). This method can be improved by fine-tuning the model to make it more accurate (Supervised Learning). DBNs are particularly effective for processing complex data, by initializing feature detectors with learned information. Additionally, DBNs facilitate transfer learning and can integrate both supervised and unsupervised learning methods, making them effective across various complex tasks, including data, image, and speech recognition. Overall, DBNs' unique architecture and learning capabilities make them a versatile tool for predictive applications in diverse fields. An overview of the DBN structure in AI is shown in Fig. 3.

A study in [32] focuses on improving the detection and categorization of arrhythmias, which are heart disorders caused by irregular heartbeats due to failures in electrical signal conduction in the heart. The authors use an unsupervised DBN for effective feature extraction from electrocardiogram (ECG) signals, followed by a simple logistic regression (LR) classifier. They compare the results of this feature extraction against plain, non-enriched data using metrics such as precision, recall, specificity, and F1-score. Significant performance improvements are observed, with the DBN-LR pipeline achieving a 5% increase in accuracy over a 1D convolution technique and a 10% increase compared to a method without feature extraction. This indicates the effectiveness of DBN in enriching data features for better arrhythmia detection. A novel method for detecting cervical cancer using a DBN model is presented in [33]. The study aims to automate the diagnostic process by analyzing colposcopy images, which are critical for identifying pre-cancerous lesions. A multi-layer architecture is implemented to extract relevant features from the images, facilitating the classification of cervical cancer stages. The DBN is employed to automatically learn hierarchical features from the colposcopy images, enhancing the model's ability to differentiate between normal and abnormal tissues. The model's performance is evaluated against traditional methods, demonstrating significant improvements in classification accuracy, sensitivity, and specificity. The proposed DBN-based approach shows promising results, indicating its potential as an effective tool for the early detection of cervical cancer, which could lead to better patient outcomes.

Based on the results discussed, DBN demonstrates superior prediction accuracy compared to other neural networks. The DBN was chosen because of its capacity for unsupervised hierarchical feature learning, which is especially well-suited for healthcare datasets with complicated, non-linear patterns and minimal labelled data. Compared to purely supervised deep learning models, DBNs' layer-wise pretraining mechanism offers reliable parameter initialization, lowering overfitting and enhancing generalizability. Given the unrestricted and highly variable nature of activity patterns, this is particularly crucial for ADL-based fall risk prediction. DBN is a suitable choice for this study because it provides a balanced trade-off between model complexity, robustness, and predictive performance when compared to more data-intensive architectures like CNNs and LSTMs. For these reasons, we are undertaking our initial attempt to combine ADLs with DBN to predict the risk of future falls in older adults. Our study highlights the significance of monitoring ADLs and implementing DBN models in forecasting future falls among older adults, which will be further detailed in the following sections.

IV. PROPOSED DBN-BASED 3-STAGE FALL PREDICTION MODEL

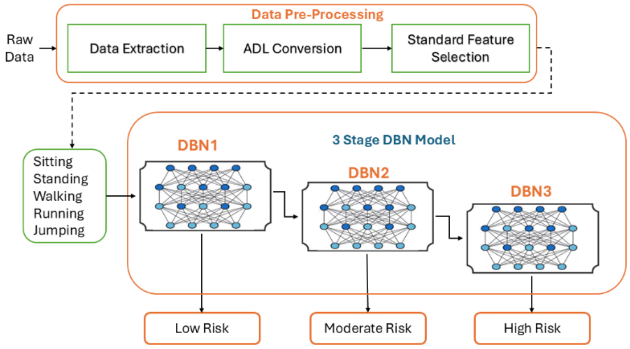

Fig. 4. Architecture of the proposed 3-stage DBN-based Fall Risk Prediction system.

Our study aims to predict future falls in older adults and to classify the different levels of fall risk namely Low, Moderate, and High. An alert about the possibility of a future fall will then be sent to the older adults and their family members, which will be discussed further in the future work section of this paper. The major focus of our study is on older adults (60 years and older) living alone, but the data from older adults residing in assisted living facilities are also taken into consideration. Initially, the data of the older adults in this study was collected from public repositories for model training and testing. An overview of the proposed DBN-based fall prediction model is shown on Fig. 4 which explains the process of Data Pre-Processing, 3-Stage DBN Desing and DBN Training.

A. Data-Pre-Processing

The proposed model employs ADL datasets from older adults aged 65 to 87 years, sourced from the Long-term Monitoring Database available on Physionet [34]. This dataset consists of 3-day 3D accelerometer recordings from 71 elderly community residents, who were continuously monitored for 75 hours to assess gait, stability, and fall risk. However, recordings are only available for 66 participants in the repository. In this study, data from 50 participants, each with 65 to 75 hours of recordings, are used for training. Data from 12 additional participants are used for testing. Four datasets are excluded due to having less than 30 hours of recordings. Participants are divided into two groups: Participants were classified as fallers or non-fallers based on their self-reported fall history. Specifically, individuals who experienced two or more falls within the past year were categorized as fallers, while those with fewer than two falls were considered non-fallers. Hence, Fallers (Fx), who experienced more than two falls within a year, and Non-Fallers or the Control Group (Cx), who either did not fall or had fewer than two falls per year. A detailed overview of the participants' recordings used in this study is provided in Table I. The raw data collected from the 3D accelerometer is categorized into six types of signals: vertical (v)_acceleration, medial-lateral (ml)_acceleration, anterior-posterior (ap)_acceleration, yaw_velocity, pitch_velocity, and roll_velocity.

TABLE I
Overview of the Participant's Recordings

Data Analysis	**Participant count**
Total older adults 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)

The clock frequency is set to 100 ticks per second, with one tick representing a sample for each of the six signal categories recorded over time. Visual Studio Code is used to process and convert this raw accelerometer data into corresponding ADLs using threshold-based algorithms. Each participant's dataset in our study contains over 10,000 recordings from the 3D accelerometer sensor. The data conversion follows the method described in [35], which outlines how to identify ADLs from the raw recordings. The specific ADLs of interest for our research sitting, standing, walking, running, and jumping were then used to train and test our developed DBN model. Data from both fallers and non-fallers was collected at 10-minute intervals (10 minutes x 60 minutes per hour x 75 hours over 3 days) and subsequently converted into the corresponding ADLs. This processed information serves as input for our proposed model. A detail of the ADL conversion algorithm is provided in the Appendix section.

B. 3 -Stage DBN Model Design

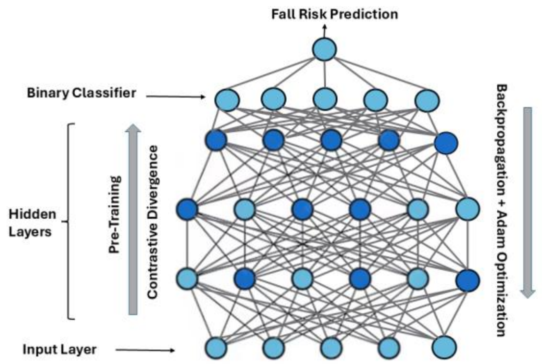

Fig. 5. Network Structure of the proposed 3-stage DBN-based Fall Risk Prediction System.

The input data used in the DBN model includes ADLs correlated with time for each participant. The model considers five ADLs → Sitting, Standing, Walking, Running, and Jumping, obtained from the older adults as input variables. Each ADL is assigned a specific weight based on its significance in fall risk prediction: Sitting (0.2), Standing (0.4), Walking (0.6), Running (0.8), and Jumping (1.0). These weighted inputs are evaluated within each of the three DBN-based fall prediction systems using a developed algorithm. Each DBN model is pre-trained using different Restricted Boltzmann Machine (RBM) architectures: DBN 1 consists of RBM 1 layer with hidden nodes [128, 64, 32], DBN 2 contains RBM 2 layer with hidden nodes [64, 32, 16], and DBN 3 has RBM 3 layer with hidden nodes [32, 16, 8]. The input data is first passed through DBN 1, where it is transformed and analyzed for low fall risk. DBN 2 processes the data to classify moderate fall risk, while DBN 3 classifies high fall risk. 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. To improve prediction accuracy, several enhancements are proposed for the unsupervised training models and fine-tuning procedures. The network structure of the proposed DBN model is shown in Fig. 5.

DBN-based Fall Risk Prediction Algorithm 1 (DBN-FRPA): Pseudocode of the Proposed Model (Fig. 5)

```
Input: $X$ → ADLs (Sitting, Standing, Walking, Running, Jumping)
    $Y$ → Fall risk level (Low, Moderate, High)
```

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```
Output: $\hat{Y}$→ Predicted fall risk levels
1. Data extraction from the input parameters
2. Feature extraction → Feed 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) LabelEncoding: $Y \rightarrow$ 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 labeled 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:
    $X_{test\_rbm1} = RBM1.transform(X_{test})$
    $X_{test\_rbm2} = RBM2.transform(X_{test\_rbm1})$
    $X_{test\_rbm3} = RBM3.transform(X_{test\_rbm2})$
7. Cross-validation using testing dataset → Determine the accuracy, specificity, and sensitivity of the model.
        metrics={accuracy,specificity,sensitivity}
8. Result Evaluation → validate the findings and predict fall risk levels Ŷ
```

C. DBN Training

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.

1) *Unsupervised Pre-Training:* As detailed in Section II, our model takes ADL data as input for the visible layer. The proposed DBN model consists of three RBM layers: RBM_1, RBM_2, and RBM_3, containing [128, 64, 32], [64, 32, 16], and [32, 16, 8] hidden units, respectively. These configurations were optimized through extensive trials and iterative training to maximize accuracy. The RBM layers are trained successively using contrastive divergence, starting from the bottom layer to the top. Each trained RBM layer serves as the input for the subsequent layer; for instance, RBM_1, which is trained with the visible layer as input, transitions to become the visible layer for RBM_2 after its training, and this process continues for RBM_3. This training follows the greedy layer-by-layer algorithm, as described in [36]. The unsupervised learning approach allows each layer to effectively learn from the input data, with weights assigned based on fall risk analysis: Sitting - 0.2, Standing - 0.4, Walking - 0.6, Running - 0.8, Jumping – 1.0. Risk levels are categorized with corresponding weights: Low risk – 0.3, Moderate risk - 0.6, and High risk - 0.9. The unsupervised layers facilitate feature extraction and pre-training, allowing each RBM layer to capture progressively higher-order features from the data. This architecture enables the DBN to learn complex data features, with the output of each RBM serving as the input for the next layer.
2) *Backpropagation and Adam Optimizer-based Fine-Tuning:* After the RBM pre-training, the weights are fine-tuned using 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 based on the prediction errors. The network computes the difference between its prediction and the actual labels (y_train) using a binary cross-entropy loss function. The error is then propagated back through the network, updating the weights using an Adam optimizer to minimize the loss. 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 is applied to scale the output of all predicted risk levels to align with the risk indicators: Low – 0.3, Moderate – 0.6, and High – 0.9.

The model learns meaningful representations from the input sensor data using an unsupervised pretraining technique before supervised fall-risk prediction. In this stage, the network is trained on unlabelled raw data, which enables it to identify broad temporal and spatial patterns. The network is optimised using backpropagation after pretraining, and the predicted accuracy is increased by fine-tuning with labelled fall-risk data. Although this method is similar to self-supervised learning, it is categorised as unsupervised pretraining instead of self-supervised learning because it does not include self-generated labels or explicit pretext tasks. In order to improve feature representation and model performance even further, future research will investigate the incorporation of self-supervised techniques such contrastive or reconstruction-based pretext challenges. Early intervention

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and individualised care planning are made possible by the three-stage DBN architecture, which permits progressive and understandable risk categorisation into low, moderate, and high-risk categories. These additions improve the suggested fall-risk prediction framework's clinical relevance, scalability, and practicality when taken as a whole.

V. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed DBN-based fall risk prediction framework by analyzing the experimental results. The system's accuracy is first assessed by comparing it against the Ground Truth, which is derived from a combination of the MFS and TUG tests. Subsequently, the proposed model's performance is benchmarked against other similar existing works in the field. The simulations were executed in Visual Studio Code on a system running Windows 10 Enterprise, powered by an 11th Gen Intel Core i7 processor (3.00 GHz) with 32 GB of RAM.

A. Evaluation Metrics

The proposed model is evaluated using real-time data from a previous study which was obtained from PhysioNet. The features of these datasets include,

- Age
- Sex
- History of Falls
- ADL Data

The evaluation method of fall risk prediction is done by using the metrics from Table II. These measures are Accuracy, Sensitivity, and Specificity, where TP, TN, FP, and FN refer to True Positive, True Negative, False Positive, and False Negative respectively [37] as shown in (1), (2), and (3),

$$Sensitivity = \frac{TP}{TP+FN} \tag{1}$$

$$Specificity = \frac{TN}{TN+FP} \tag{2}$$

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{3}$$

TABLE II
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

B. Verification of the Proposed DBN-Based Fall Risk Prediction Model with Ground Truth (GT)

As explained in Section IV, the real-time activity monitoring data were collected from the PhysioNet long-term monitoring database. Participants were observed over three days to analyze their gait, stability, and fall risk. During the study period, participants underwent several clinical assessments, including the Berg Balance Scale (BBS), Four Square Step Test (FSST), Timed Up and Go (TUG), Mini-Mental State Examination (MMSE), and the Activities-Specific Balance Confidence (ABC) scale. Among these measures, the TUG test demonstrated the strongest alignment with the predictions of our fall risk model. TUG is a widely used and clinically validated screening tool for assessing mobility and fall risk, categorizing individuals into low, moderate, or high risk based on the time required to complete a standardized mobility task. Owing to this close correspondence in risk stratification, TUG was selected as the primary metric for generating ground truth (GT) labels. In addition, the Morse Fall Scale (MFS) was incorporated as a secondary reference standard, as it is a reliable and well-established tool for predicting future falls in older adults. A study cited in [38] details how MFS has been used for fall risk assessment, categorizing fall risks into low, moderate, and high, which aligns with our proposed model's outcomes. Therefore, the combined use of TUG and MFS as GT measures ensures clinical validity, consistency with the dataset, and meaningful interpretation of ADL-based fall risk predictions. Hence, we selected MFS as our second metric for deriving GT.

TABLE III
INTEGRATING 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

To generate GT, we compared the risk levels from both TUG and MFS as shown in Table III. If both assessment tools (TUG/MFS) indicated 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 the GT for all participants.

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TABLE IV
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

TABLE V
CONFUSION MATRIX LAYOUT

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

To evaluate the performance of our developed DBN-based fall risk prediction model, we utilized data recordings from 12 participants, which included 5 non-fallers (Cx) and 7 fallers (Fx). Among the non-fallers, participants C18 and C36, aged 84 and 80, respectively, reported experiencing one fall in the past 12 months. The other non-fallers C2, C30, and C37 are healthy individuals with no recorded falls in that period. In the fallers group, which included participants with more than two falls within the last year, F1 experienced 5 falls, while F9 and F21 each had 2 falls. Participants F8 and F29 recorded 3 falls, and F10 and F27 had a significantly higher number of falls, with 10 falls in the past 12 months. The ADL data from all 12 participants served as input for testing our model, and the results were subsequently compared against the derived ground truth. Table IV presents the comparison results from our model against the ground truth (GT).

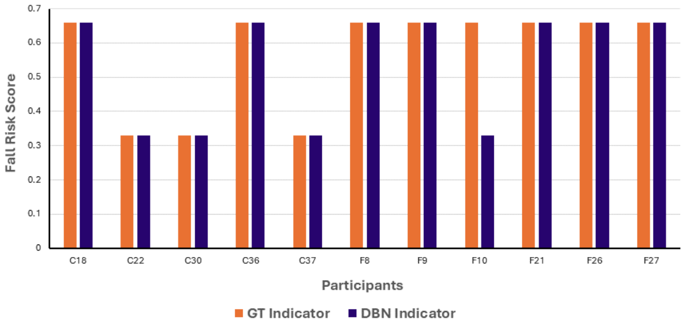

Fig. 6. DBN-based Fall risk prediction evaluation results.

The results obtained from our proposed DBN model indicate a low fall risk for participants C22, C30, C37, and F10, while a moderate fall risk is identified for C18, C36, F1, F8, F9, F21, F26, and F27. Notably, no participants were classified as having a high fall risk. The ground truth outcomes reflect a low prediction risk for C22, C30, and C37, and a moderate risk for C18, C36, F1, F8, F9, F10, F21, F26, and F27, with no high-risk classifications noted. This alignment between our DBN model's predictions and the GT results demonstrates that the model accurately identifies most non-fallers. However, for participant F10, the DBN model predicts a low fall risk, while the GT categorizes them as moderate risk, likely due to their history of falls within the past year. Fig. 6. 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 V shows the confusion matrix layout of the predicted outcome, where 1 (Positive) indicates the positive class, or the occurrence of the event, and 0 (Negative) indicates the negative class, or the non-occurrence of the event.

C. Accuracy comparison of our proposed DBN model with the existing works

The findings of our study were methodically contrasted with those of six closely related fall risk prediction studies that have been published in the literature. These studies were chosen because they shared similar goals, sensing techniques, feature representations, and machine learning frameworks for assessing the risk of falls. Important elements including input data type, activity context, modelling methodology, and prediction performance were the focus of the comparative study. A crucial finding from this comparison is that the majority of previous research relies on a mix of multi-sensor physiological data, vision-based features, gait-specific parameters, and clinical assessment scores. Although a number of methods use deep learning and machine learning models to predict fall risk, their analyses are typically restricted to predetermined movements or controlled gait tasks rather than routine functional activities.

Our framework shows that accurate fall risk prediction can be accomplished without relying on clinical scores, laboratory-based gait assessments, or intricate multi-modal sensing setups by utilising only ADL-based inertial sensor data and modelling the underlying temporal and probabilistic patterns using a DBN. In addition to making data collection easier, this improves the suggested system's viability and scalability for ongoing, real-world monitoring in homes and communities. Therefore, the comparative results confirm our method's efficacy and uniqueness, establishing it as a unique and complementary addition to the current body of research on fall risk prediction. It also has a high potential for use in non-intrusive, real-world applications related to elder care.

In the study [39], a predictive model for fall risk was developed using both clinical and robotic parameters. This research involved community-dwelling older adults aged 65 and above, with a total of 100 participants assessed over one year using real-time data collected through a robotic platform.

TABLE VI
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 (%)**
[39]	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
[40]	Utilizing artificial intelligence to predict fall risks in hospitalized elderly patients.	≥ 65	1 year	vital signs, visual ability, hearing ability, previous medication, and ADLs	XGBoost	73.2
[41]	Developing a fall prediction model for community-dwelling older adults using electronic health records (EHR) data.	≥ 65	1 year	age, sex, history of falls, 2 medications, and 5 medical conditions	Bootstrap-enhanced penalized logistic regression	70
[42]	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
[43]	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	85
[44]	To examine the effectiveness of various machine learning models based on spatiotemporal gait parameters in predicting falls among elderly individuals with osteoporosis.	≥68	12 months	spatiotemporal gait parameters and prospective registration of falls	Dynamic Bayesian Networks	80
Our Proposed DBN-based Fall Risk Prediction Model	To predict future falls in older adults	≥60	75 hours	ADL	DBN	91.67

The model integrated 20 robotic parameters and 8 clinical variables, resulting in an improved fall risk prediction accuracy of 81%. Similarly, a study in [40] explores machine learning applications in predicting fall risks among hospitalized older adult patients in Taiwan. This research combines electronic health records (EHR) and comprehensive geriatric assessments (CGA) to create a fall risk prediction model, utilizing real-time hospital data. The study applied the XGBoost algorithm and achieved an accuracy of 73.2%.

In a study [41], the aim is to develop and internally validate a model to predict fall risk in older adults using primary care EHR data. The study focuses on improving fall prediction accuracy by leveraging both structured data and free-text notes in EHRs. This analysis included 36,470 participants aged 65 and older, and used real-time data extracted from primary care EHRs. The model, developed using Bootstrap-enhanced penalized logistic regression, achieved an accuracy of 70%.

Research in [42] aims to create a predictive tool for identifying individuals with dementia at increased risk of falling over a short-term period. Real-time data is collected through continuous movement monitoring over a week, and this data is utilized to predict falls within the next 30 days. The Random Forest algorithm and other classification models were applied, yielding a strong predictive performance with an accuracy of 82%.

Similarly, the study in [43] focuses on identifying gait characteristics associated with fall risk among older adults with Parkinson's disease, typically aged 60 to 80 years. Machine learning techniques, specifically feature extraction from gait data, are employed alongside classification algorithms such as Random Forest and Support Vector Machines (SVM). This model achieved an accuracy of approximately 85%, demonstrating its potential utility in clinical settings for identifying high-risk falls individuals.

Finally, in a study [44], various machine learning models built on spatiotemporal gait parameters evaluated to predict falls in older adults, particularly those with osteoporosis. The study demonstrates that the Dynamic Bayesian Network can effectively complement expert knowledge for predicting fall risk over a period of up to 12 months, achieving an accuracy of 80%. Out of all the compared existing works, our proposed DBN-based fall risk prediction model uniquely utilizes only five ADLs as key parameters to predict future fall risk in older adults, achieving a higher accuracy of 91.67% compared to all other existing studies. Fig. 7. displays the comparison results of our proposed DBN model with other existing works. The summary of the accuracy comparisons of the discussed existing work and our proposed work is elaborated in Table VI.

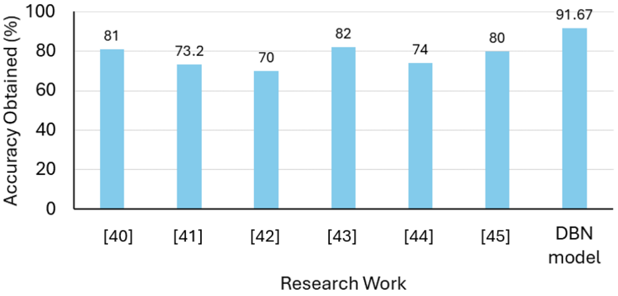

Fig. 7. Accuracy Comparision between different Fall Risk Prediction Models

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Despite the model's high accuracy, additional testing with real-time data is essential for providing timely fall risk alerts in the future. Some limitations of our proposed fall-risk prediction model stem from its reliance on relatively limited datasets, despite the extensive monitoring period of 75 hours. The dataset's size and diversity might not adequately reflect the great variation in movement and gait characteristics across various groups or real-world settings, even though it offers enough preliminary insights into fall patterns. Taking this limitation into account, the next stage of our study will concentrate on testing the model with bigger and more varied datasets that were gathered in real-time situations. Cross-validation and comparison with real ground truth (GT) data are two of the stringent validation processes that will be used to make sure the model's predictive abilities extend well beyond the current dataset. Additionally, we will be able to evaluate the model's resilience and practical usefulness by testing it in real-world scenarios, especially in dynamic and uncontrolled contexts that are characteristic of daily living activities. Our model has already shown consistent and dependable results when compared to the GT data, suggesting its potential for successful fall-risk prediction despite the present dataset size constraints. In order to improve the model's clinical relevance and usefulness in fall prevention interventions, future research will also investigate methods for optimising model performance with larger datasets. The findings from these extended evaluations are planned for publication, contributing to both the scientific community and practical healthcare solutions.

VI. CONCLUSION AND FUTURE WORK

The proposed DBN-based Fall Risk Prediction Model aims to identify older adults at risk of falls by continuously monitoring their physical activities, specifically focusing on ADLs. This model exclusively utilizes behavioral data to forecast future falls and exhibits impressive predictive accuracy. Our initial evaluation indicates an accuracy of 91.67%, with a specificity of 100% and a sensitivity of 90.00%. In the future, we plan to enhance this system by integrating additional parameters such as vital signs, a broader range of ADLs, fall history, and medication data. Furthermore, we intend to compare our prediction outcomes using different algorithms and transfer learning models, as well as test these outcomes in real-time scenarios.

We acknowledge some limitations of the current study and require further investigation. Addressing this will involve securing external funding and obtaining ethical approval, which is expected to take approximately 12 months or more. As such, it is not feasible to incorporate this aspect within the scope and timeline of the present work. However, it has been identified as a key priority for future research. This study represents the initial phase of a multi-stage research project. While the current work focuses on the proposed concept and methodology, subsequent phases with system development, followed by comprehensive validation through clinical trials in real-world healthcare environments. The overall research is expected to progress over the next two years toward full clinical implementation.

In addition, it is important to note that commonly used assessment tools such as the MFS and TUG test are based on periodic clinical or survey-based evaluations, making them unsuitable for continuous or frequent monitoring. This highlights a critical gap in long-term, real-time fall risk assessment. To address this, our proposed system is designed to enable continuous, real-time monitoring of fall risk, allowing assessment anytime and anywhere. Our ongoing and future work will focus on refining the system, improving robustness, and validating its effectiveness in practical settings to better support fall prevention among older adults.

REFERENCES

1. Health Quality & Safety Commission, "Falls," June 2020. [Online]. Available:https://www.hqsc.govt.nz/assets/Our-work/System-safety/Reducing-harm/Falls/Projects/Topics-1-10-reupload/Topic-ONE-June-2020.pdf.
2. ACC, "Preventing falls for over 65s," *Accident Compensation Corporation*, Sep. 17, 2024. [Online]. Available: https://www.acc.co.nz/preventing-injury/trips-falls/preventing-falls-for-over-65s.
3. K. A. Yasa, A. A. G. A. Puspa Negara, and I. D. G. A. Kamayoga, "Hypertension and falls in the elderly: a literature review," *Bachelor and Professional Program of Physical Therapy, College of Medicine, Universitas Udayana*, Bali, Indonesia, 2020.
4. Healthdirect Australia, "Falls," *Healthdirect*, [Online]. Available: https://www.healthdirect.gov.au/falls.
5. Accident Compensation Corporation (ACC), "Falls prevention: Information for health professionals," ACC, 2009. Available: www.acc.co.nz/preventing-injuries/at-home/older-people/information-for-health-professionals/index.htm.
6. S. S. Rao, "Prevention of falls in older patients," *Am. Fam. Physician*, vol. 72, no. 1, pp. 81-88, 2005.
7. 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. [Online]. Available: https://doi.org/10.3390/s17112509.
8. S. K. Gharghan and H. A. Hashim, "A comprehensive review of elderly fall detection using wireless communication and artificial intelligence techniques," *Measurement*, vol. 2024, no. 114186, Jan. 20, 2024.
9. 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. 15, 2024.
10. M. Mahmoud, M. Osama, A. Milad, J. Raafat, P. Elkafrawy, and S. Fawzi, "Sudden fall detection and prediction using AI techniques," in *Proc. 21st Learning and Technology Conference (L&T)*, Jeddah, Saudi Arabia, pp. 308-312, 2024
11. S. H. Mohammed, Y. Fan, G. Lv, and S. Liu, "A mathematical model for fall detection prediction in elderly people," *IEEE Sensors Journal*, Sep. 19, 2023
12. 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, Aug. 15, 2021.
13. N. Thakur and C. Y. Han, “A study of fall detection in assisted living: Identifying and improving the optimal machine learning method,” *J. Sens. Actuator Netw.*, vol. 10, no. 3, p. 39, Jun. 2021.
14. W. Cai, L. Qiu, W. Li, J. Yu, and L. Wang, “Practical fall detection algorithm based on Adaboost,” in *Proc. 4th Int. Conf. Biomedical Signal and Image Processing (ICBIP ’19)*, pp. 117–121, 2019.
15. Google, "Google Trends," Google Trends, 2024. [Online]. Available: https://trends.google.com/trends/.
16. N. Dormosh, B. van de Loo, M. W. Heymans, M. C. Schut, S. Medlock, N. M. van Schoor, N. van der Velde, and A. Abu-Hanna, "A systematic review of fall prediction models for community-dwelling older adults: comparison between models based on research cohorts and models based on routinely collected data," *Age and Ageing*, vol. 53, no. 7, p. afae131, Jul. 2024.
17. 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, Jun. 28, 2022.

18. B. Chen, C. Chen, J. Hu, Z. Sayeed, J. Qi, H. F. Darwiche, B. E. Little, S. Lou, M. Darwish, C. Foote, and C. Palacio-Lascano, "Computer vision and machine learning-based gait pattern recognition for flat fall prediction," *Sensors*, vol. 22, no. 20, p. 7960, Oct. 19, 2022.
19. 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, Dec. 2022.
20. 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, Feb. 15, 2020.
21. S. McCall, S. S. Kolawole, A. Naz, L. Gong, S. W. Ahmed, P. S. Prasad, M. Yu, J. Wingate, and S. P. Ardakani, "Computer Vision Based Transfer Learning-Aided Transformer Model for Fall Detection and Prediction," *IEEE Access*, Feb. 20, 2024.
22. 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*, pp. 1-8, Jun. 17, 2007.
23. 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, Oct. 25, 2021.
24. A. K. Mishra, M. Skubic, L. A. Despins, M. Popescu, J. Keller, M. Rantz, C. Abbott, M. Enayati, S. Shalini, and S. Miller, "Explainable fall risk prediction in older adults using gait and geriatric assessments," *Frontiers in Digital Health*, vol. 4, p. 869812, May 6, 2022.
25. S. Guo, Y. Xie, and Y. Li, "Research on the prediction model of elderly fall," in *MATEC Web of Conferences*, vol. 336, p. 07019, 2021.
26. S. H. Yang, W. Zhang, Y. Wang, and M. Tomizuka, "Fall-prediction algorithm using a neural network for safety enhancement of elderly," in *2013 CACS International Automatic Control Conference (CACS)*, pp. 245-249, Dec. 2, 2013.
27. V. Roshdibenam, G. J. Jogerst, N. R. Butler, and S. Baek, "Machine learning prediction of fall risk in older adults using timed up and go test kinematics," *Sensors*, vol. 21, no. 10, p. 3481, May 17, 2021.
28. 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, Jun. 5, 2020.
29. 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)*, pp. 35-39, Aug. 15, 2011.
30. 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.
31. G. E. Hinton, "Deep belief networks," *Scholarpedia*, vol. 4, no. 5, p. 5947, May 31, 2009.
32. M. K. Gourisaria, G. M. 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, Nov. 1, 2021.
33. D. C. 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)*, pp. 415-420, Feb. 19, 2020.
34. 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, Oct. 2013.
35. 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, Dec. 1, 2020.
36. S. M. Elkholy, A. Rezk, and A. A. Saleh, "Early prediction of chronic kidney disease using deep belief network," *IEEE Access*, vol. 9, pp. 135542-135549, Sep. 21, 2021.
37. D. Mohan, D. Z. Al-Hamid, P. H. Chong, J. Gutierrez, and H. Li, "Fuzzy based Fall Risk Prediction in Older Adults," in *2024 3rd International Conference on Artificial Intelligence for Internet of Things (AIIoT)*, pp. 1-6, May 3, 2024.
38. 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, Oct. 15, 2024
39. A. Cella, A. De Luca, V. Squeri, S. Parodi, F. Vallone, A. Giorgeschi, B. Senesi, E. Zigoura, K. L. Quispe Guerrero, G. Siri, and L. De Michieli, "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, Jun. 25, 2020.
40. W. M. Chu, E. Kristiani, Y. C. Wang, Y. R. Lin, S. Y. Lin, W. C. Chan, C. T. Yang, and Y. T. Tsan, "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, Aug. 9, 2022.
41. 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, Jul. 1, 2022.
42. A. S. Doorduijn, M. A. de Van Der Schueren, O. van de Rest, F. A. de Leeuw, H. M. Hendriksen, C. E. Teunissen, P. Scheltens, W. M. van der Flier, and M. Visser, "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, May 1, 2023.
43. M. Ullrich, N. Roth, A. Küderle, R. Richer, T. Gladow, H. Gaßner, F. Marxreiter, J. Klucken, B. M. Eskofier, and F. Kluge, "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, Oct. 19, 2022.
44. 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.

DEEPIKA MOHAN received her master's degree in Telecommunications from Auckland University of Technology (AUT), New Zealand in 2020. She has completed and graduated with a Ph.D. degree in Artificial Intelligence from the Department of Electrical and Electronic Engineering at Auckland University of Technology (AUT). From 2020 to 2022, she was a Research Assistant with the Auckland University of Technology (AUT) and with the University of Auckland (UoA). Since early 2023 she has been working as a Teaching Assistant with the Department of Electrical and Electronics Engineering, Auckland University of Technology, Auckland, New Zealand. Her research interests include Artificial Intelligence, the Internet of Things (IoT), Smart Devices, Machine Learning, millimeter Wave (mmWave), vehicular communication, and 5G.

PETER HAN JOO CHONG (Senior member IEEE) received a Ph.D. degree in Electrical and Computer Engineering from the University of British Columbia, Canada, in 2000. He is the Associate Head of School (Research) at the School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, New Zealand. Between 2016 and 2021, he was the Head of the Department of Electrical and Electronic Engineering at AUT. His research interests are in the areas of wireless/mobile communications systems including radio resource management, multiple access, MANETs/VANETs, green radio networks, and 5G-V2X networks. Dr. Chong is listed in the World's Top 2% Scientists published by Stanford University in 2022.

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JAIRO GUTIERREZ received a systems and computing engineering degree from Universidad de Los Andes in Colombia, a master's degree in computer science from Texas A&M University, College Station, Texas, and a PhD degree in information systems from the University of Auckland, New Zealand. He is currently a professor in the Department of Computer Science and Software Engineering at Auckland University of Technology (AUT), New Zealand. From 2015 until 2020, Professor Gutierrez was the deputy head of the School of Engineering, Computer and Mathematical Sciences also at AUT. His current research is on Internet of Things security, networking and information security, viable business models for ICT-enabled enterprises, next-generation networks, and cloud computing systems.

MIRZA MANSOOR BAIG received his Ph.D. in Biomedical and Medical Informatics from Auckland University of Technology, Auckland, New Zealand. He is currently a Senior Solutions Specialist for Orion Health and an active researcher in the biomedical and healthcare informatics domain. With over 10 years of industrial experience, Dr. Baig has worked on numerous commercial and research projects focused on clinical applications, patient monitoring, and medical device integration on a global scale. His contributions have been recognized through several awards and research grants. In addition to his research and professional work, Dr. Baig serves as an Associate Editor for the Journal of Medical Systems. He is also a member of the IEEE NZ North Section committee, where he provides technical guidance to students and early-career researchers.

Dr. HUI LI is a Professor at Peking University. HUI LI received his Bachelor of Engineering from Tsinghua University in 1986 and Ph.D. from The Chinese University of Hong Kong in 2000. He was the first scholar in the world systematically pointed out the three gene defects of the TCP/IP network：(A) cyberspace sovereignty is monopolized unilaterally. (B) lack of security genes, so security accidents keep breaking, and privacy protection is difficult. (C) The protocol is solidified; evolution or upgrading is a long time and high cost. He first put forward the three conjectural theorems of cyberspace security in the world：(D) No technical solution to ensure security in IP. (E) Taking IP space as a frame of reference, there are security deterministic technical solutions in the future cyberspace that can quantitatively and exponentially improve the performance against network attacks. (F) There may be deterministic security solutions in future cyberspace. He proposed a comprehensive system integrated collaborative solution: Co-governed Multi-identifier Network to solve from（A) to (E）.