electronics

Article

Internet of Things Gateway Edge for Movement Monitoring in a Smart Healthcare System

Khalid Al-Naime [1], Adnan Al-Anbuky [1,*] and Grant Mawston [2]

[1] School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, Auckland 1010, New Zealand; khalid.alnaime@aut.ac.nz
[2] Physiotherapy Department, Health and Rehabilitation Research Institute, Auckland University of Technology, Auckland 1010, New Zealand; grant.mawston@aut.ac.nz
* Correspondence: adnan.anbuky@aut.ac.nz

Abstract: Over the past two decades, there has been a notable and swift advancement in the field of healthcare with regards to the Internet of Things (IoT). This progress has brought forth a substantial prospect for healthcare services to enhance performance, transparency, and cost effectiveness. Internet of Things gateways, such as local computational facilities, mobile devices, or custom miniature computational embedded electronics like the Raspberry Pi (RPi), are crucial in facilitating the required processing and data compression tasks as well as serving as front-end event detectors. Numerous home-based healthcare monitoring systems are currently accessible; however, they have several limitations. This paper examines the role of the Raspberry Pi gateway in the healthcare system, specifically in the context of pre-operative prehabilitation programs (PoPPs). The IoT remote monitoring system employed a Microduino integrated with various supporting boards as a wearable device. Additionally, a Raspberry Pi was utilised as a base station or mobile gateway, while ThingSpeak served as the cloud platform. The monitoring system was developed with the purpose of assisting healthcare personnel in real time, remotely monitoring patients while engaging in one or more of the nine typical physical activities that are often prescribed to individuals participating in a prehabilitation program. Furthermore, an alert notification system was designed to notify the clinician and patient if the values were abnormal (i.e., the patient had not been active for many days). The integration of IOT and Raspberry Pi technology into a pre-operative prehabilitation program yielded a promising outcome with a success rate of 78%. Consequently, this intervention is expected to facilitate the resolution of challenges encountered by healthcare providers and patients, including extended waiting periods and constraints related to staffing and infrastructure.

Keywords: IoT; Raspberry Pi; ambient assisted living; real-time monitoring; pre-operative prehabilitation program

check for updates

Citation: Al-Naime, K.; Al-Anbuky, A.; Mawston, G. Internet of Things Gateway Edge for Movement Monitoring in a Smart Healthcare System. *Electronics* **2023**, *12*, 3449. https://doi.org/10.3390/electronics12163449

Academic Editors: Binod Vaidya, Djuradj Budimir and Byung Rae Cha

Received: 20 May 2023
Revised: 9 August 2023
Accepted: 13 August 2023
Published: 15 August 2023

1. Introduction

The incidence of chronic disease and cancer has increased significantly over the past decade [1]. Traditional models of healthcare do not currently have the resources to cope with the monitoring and the provision of health-related interventions. This is clearly evident in cancer populations awaiting surgical intervention, who present with significant physical deconditioning and loss of function. An important component of healthcare for individuals with cancer is exercise-based training prior to surgical intervention (prehabilitation). Prehabilitation has been shown to improve function and wellbeing as well as reduce the likelihood of morbidity and mortality following surgical interventions [1]. However, because of the complex issues associated with diseases such as cancer, these patients often need guidance and monitoring under the supervision of health professionals. Unfortunately, many cancer patients do not have access to health professionals because of geographical isolation, long waiting times, limited resources and facilities, and travel-related costs. These barriers often mean that many patients have to partake in home-based prehabilitation, which has been shown to have lower adherence and poorer health outcomes than supervised programmes [2].

Integration of wearable devices and the Internet of Things (IoT) into cancer prehabilitation has the potential to address a number of the barriers for cancer patients who cannot regularly partake in supervised exercise programmes. The use of IoT technology, a reduction in the size of wearable sensors, and an increase in the processing capabilities of these sensors have shown to provide significant advantages in the advancement of contemporary medical treatment [2]. For example, RPi has been developed as an interface to send medication reminders to elderly patients with cognitive and memory impairments [3]. Soniya et al. [4] also used Raspberry Pi (RPi) technology as a home-based system for remote monitoring of heart rate and temperature. This was achieved by directly connecting monitoring sensors to the general-purpose input–output pins (GPIO). The output results were then sent to the healthcare provider via the Internet and a liquid-crystal display (LCD) screen was used to provide visual feedback on heart rate and temperature responses. The feasibility of this system was not assessed. However, a major drawback of this system would be the inability of patients to attach multiple electrocardiograph (ECG) electrodes and temperature sensors in correct locations.

Roy and Gupta [5] developed IoT technology for ECG wave monitoring. ECG waves were monitored using an AT Mega 16 L microcontroller that transferred data to the nearest connected system using the ZigBee module. One of the major limitations in this work was that the patient had to be under nursing supervision during the measurement of ECG waves. P. Bora et al. [6] proposed a real-time monitoring system for homes for the elderly by using Arduino and a Raspberry Pi. This system was designed to monitor body temperature and heart rate, while a global positioning system (GPS) module tracked the location, and a camera captured a live feed. A monitoring camera has its limitations, due to the cost and that the patient movement area is limited to the camera range only. Sangeethalakshmi et al. [7] proposed an IoT remote monitoring system for the patient's vital signs (i.e., temperature, heart rate, ECG, and blood pressure). One of the key limitations of the above studies is that the feasibility of the system was not assessed. In some studies, up to seven devices were described, each with its own circuit board. It would be difficult for the patient to deal with the different peripherals at the same time. Furthermore, there was a lack of clarity on the accuracy of these devices to collect vital sign data.

To date, remote real-time monitoring systems have been limited to measuring vital signs with multiple devices within the limits of the home environment. In the area of cancer prehabilitation there have been no studies that have used wearable devices and IoT technology to quantify intensity, duration, frequency, and volume of exercise. A system that is able to detect these exercise parameters is important in prehabilitation because minimal thresholds for exercise parameters need to be attained to improve fitness and reduce perioperative risk in this population. Most studies in the area of exercise monitoring in cancer have used activity diaries, online and printed material, apps, and telehealth interventions [8,9]. Those studies that have used movement detection devices such as Fitbit have focused on step count, limiting activity recognition to walking and providing no indication of the intensity of activity. These devices are also limited by the commercial software, which is often not suited to cancer populations with slow and variable movement characteristics. This may be why a recent systematic review concluded that current home-based remote strategies for improving physical activity had little impact on improving physical activity in colorectal cancer populations [2].

There are currently no systems using IoT technology to remotely monitor prescribed physical activity during the prehabilitation period for cancer suffers awaiting major surgery. The present study aims to describe the development and implementation of a wearable sensor and IoT remote monitoring as a tool to assist pre-operative prehabilitation. We employed a Microduino as a wearable sensor device and an RPi as a gateway for the purpose of real-time data collection, analysis, recognition of physical activity, calculation of physical effort, and data transmission. One important aspect in clarifying the potential for this role was the application of the system in a participant partaking in a home-based unsupervised prehabilitation exercise programme.

2. Overview of the Pre-Operative Prehabilitation Program and the Role of IoT and Remote Monitoring

A pre-operative prehabilitation program (PoPP) is a 4- to 6-week program that primarily focuses on physical activities to improve fitness and reduced postoperative complications in patients who are scheduled to undergo major abdominal surgery [10]. The patient must perform one or more of the common physical activities (walking, running, cycling, treadmill, cross trainer, leg press, rowing, step up, and staircase ascending and descending) prescribed by a doctor or physiotherapist. The duration, intensity, and time period of each activity will often vary among patients and are based on factors such as health condition, fitness level, and remaining time before surgery [10,11]. Research has found that prehabilitation in a hospital setting improves post-surgical health outcomes in patients [12]. However, many patients are unable to attend these sessions due to factors such as availability of local health centres and facilities, long waiting lists, and cost and time of travel for people living in communities that are located a considerable distance from health centres [13–16]. An alternative option for these patients is non-supervised home-based prehabilitation, but exercise adherence and health outcomes in this group are poor when compared to a supervised programme [2]. An IoT remote monitoring system could help the healthcare system and patients overcome a number of barriers associated with home-based prehabilitation and improve health outcomes in patients who currently cannot access hospital services [17].

Prehabilitation in the context of the IoT refers to the use of devices and sensors and the cloud to help patients optimise their functional capacity in preparation for a surgical procedure. The key functionalities and computations required for the IoT process of prehabilitation include data collection via a wearable sensor, physical activity recognition (type and intensity), a simple and reliable Internet gateway, and the development of a user-friendly credit system that can provide feedback to patients and clinicians on patient progress through the prehabilitation period. This tool should also be able to integrate key goals and milestones that the patient needs to achieve in order to progress throughout the prehabilitation process. Such a system should have the flexibility to accurately record physical activity off-line and be able to automatically download this information to the IoT, as many of these patients exercise outside the home environment. Connection with IoT-enabled devices should also allow real-time monitoring of physical activity information by health providers and have the ability to provide feedback in the form of alerts and reminders to patients.

To meet these requirements for remote monitoring of a prehabilitation programme, we propose that an IoT system requires a wearable sensing device (WSD) with data processing and storage capabilities, an Internet gateway (e.g., RPi-based gateway), remote computing, and a facility such as a cloud centre (e.g., ThingSpeak (TS)) [11]. Figure 1 shows the general architecture of the IoT system that we developed to support the remote monitoring of a prehabilitation program. The wearable device is located on a patient's ankle and collects continuous 3D accelerometer data from the patient. The short-term data can be processed in the wearable device and transferred to the gateway (RPi) wirelessly. The RPi (gateway edge device) has the ability to offer medium-term storage and more involved processing. It can pass the data to the cloud computing device on either a continuous basis or as the opportunity arises. The cloud device offers long-term data storage and manages the process of overall computation and interaction with the users (patient and healthcare professionals).

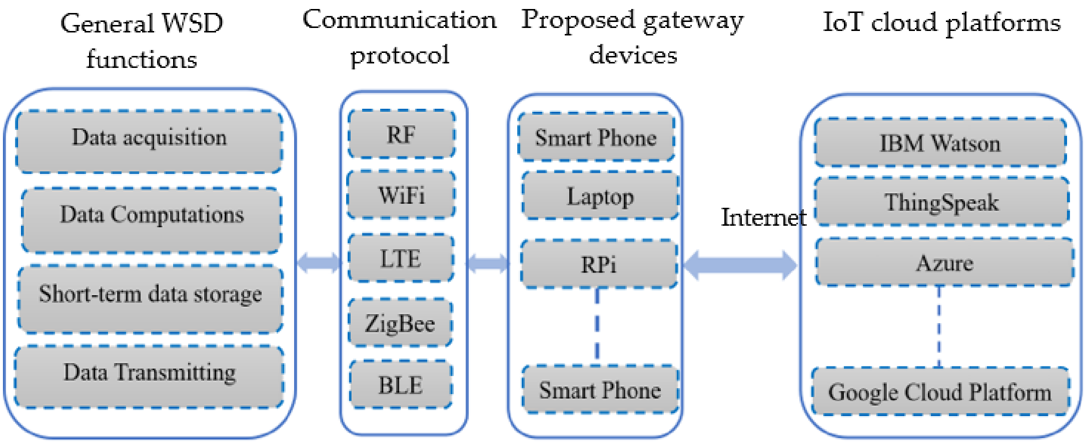


Figure 1. General organization of IoT system supporting the prehabilitation program.

Security Issues and Patients' Data Protection in IoT System

The development of IoT devices necessitates a thorough recognition of the associated security considerations and risks prior to their deployment [18]. One inherent issue associated with the IoT systems is the components that collect environmental data and their links to a microcontroller. These components have the capability to transmit the captured data to external servers for the purposes of storage or subsequent analysis. The issue lies with the non-transparent communication between these devices and the external data servers. These servers can analyse and redistribute the information without direct consent from the user [19]. We have previously addressed this problem by placing a Microduino microcontroller into the WSD that is able to transmit processed data to the gateway using a radio frequency (RF) channel. Both the WSD and gateway RPi utilise identical transceiver devices. Each WSD connected to the RPi is assigned a unique ID [11,12]. Additionally, the data payload accompanying each WSD provides a level of protection for the transmitted data. Furthermore, the data processed in the gateway for cloud upload have a designated channel and are assigned a specific number for data security protection. This level of security is deemed acceptable for the current stage of the study, as security is not the primary focus.

3. Specific Components of the IoT System for Prehabilitation

3.1. Wearable Sensor Device Role

The WSD is the front-end component of the IoT system and is responsible for sensing the movement and capturing raw 3D movement data from the user. Our previous work on WSD movement detection capabilities in different body locations found that the ankle was the best location for the accurate identification of patient movements during physical activities used in cancer prehabilitation programmes [1,10]. The WSD size, power consumption, computation functionality requirements, data storage, and communication requirements have been discussed in detail in a previous studies [1,20,21]. For example, low-power 3D-accelerometer Microduino sensors have been integrated within different supported electronic boards. In a previous study [22] we found that 4 s epochs of data captured at a 128 Hz sampling frequency gave the optimum result for the detection of physical activities performed by elderly subjects [10]. To minimise the amount of data having to be transmitted (128 × 4), digital signal processing using a fast Fourier transform (FFT) was applied on the raw accelerometer data captured at the sensor source to determine the dominant frequency (F) with the maximum power component amplitude (A) of each 4 s data epoch [10]. This means only two components of data (amplitude and frequency) were sent to the gateway, instead of 512 raw data values, as shown in Figure 2 [10].

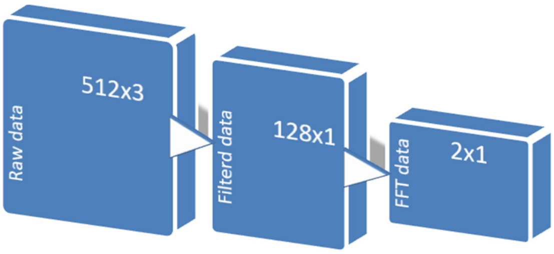
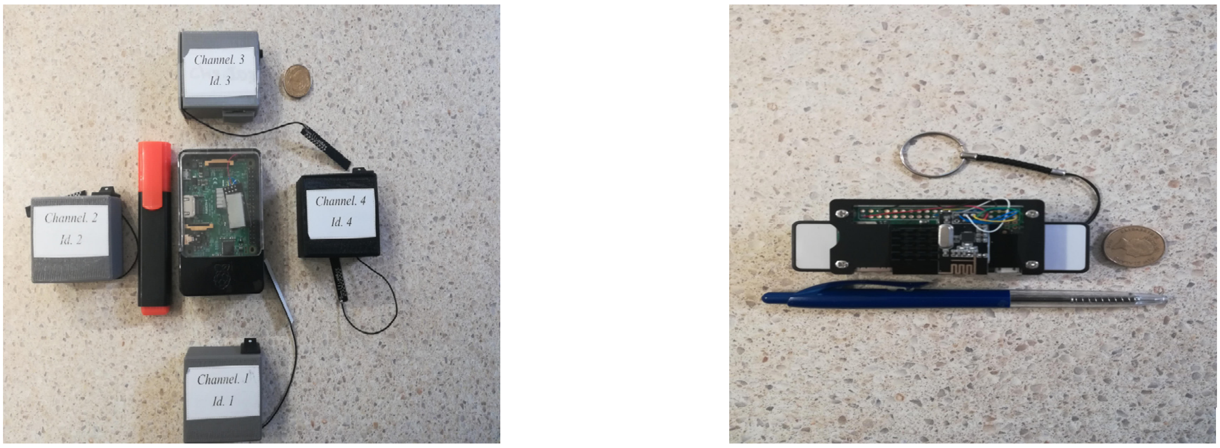


Figure 2. Illustration of the compression and processing of 3D 512 raw (X, Y, Z) data over 4 s window [1].

A key component of the wearable device is the Nordic nrf24 chipset. The Nordic nrf24 chipset is used for the transmission and receipt of data packets. This technology prepares the payload, and along with the WSD node ID generates a date and timestamp for each epoch of data, which is transmitted to the gateway RPi every 4 s.

3.2. Gateway Edge Computing Role in PoPP

One of the most important components of the remote monitoring prehabilitation via the IoT is having a portable, user-friendly internet gateway. In this study, two distinct versions of the Raspberry Pi were used as a gateway to the cloud. These were the Raspberry Pi 3B (RPi3B) in the form of a base station gateway and the more portable single-user RPiZW (Figure 3). In the context of prehabilitation programs, the Raspberry Pi can serve as a gateway for data analysis, allowing for the collection, processing, and transmission of data from various sensors and devices. These characteristics allow the RPi to manage multiple wearable devices simultaneously without any delay. The RPi3B is useful for using WSD on one or multiple users within the same facility, such as a rest home, physiotherapy centre, or gymnasium. Further features offered by RPi3B and RPiZW are the ability to process, organise, and store different data types at the same time.



(**a**) (**b**)

Figure 3. (**a**) RPi3B as a base station gateway, (**b**) RPiZW as a portable gateway.

3.3. Pre-Operative Prehabilitation Program (PoPP) Gateway (RPi) Functionality Role

The gateway (RPi) functionalities are designed and implemented to support a mixed-mode prehabilitation program [11,21]. This program is a hybrid model that uses key components of existing prehabilitation models (e.g., exercise testing and an initial supervised exercise session) but also integrates wearable technology and the IoT to enhance exercise engagement in non-supervised environments. A conceptual IoT system aims to support this model by adopting the boundaries and key elements of a mixed-mode prehabilitation program supported by mathematical formulas for converting physical motion into a numerical code [21]. Therefore, the features of each component of the IoT (WSD, RPi, and cloud) are required to support the pre-operative prehabilitation program requirements.

Several features of the RPi gateway have been designed to support PoPPs. The first RPi-designed feature is the multi-node (ID) receiver. This feature allows the RPi to handle multiple WSDs attached to different users at the same time. The second vital feature is activity recognition. This will be discussed in the next section. Effort calculations are the third important feature, which enable transforming physical activity to numerical values to allow medical staff to easily track the daily and weekly efforts of patients while also providing an overview of the program's progress [11].

The processed data are temporarily stored on the gateway for the duration of the pre-operative prehabilitation program. At the same time, these data can be transferred to the cloud for visualisation, long-term data storage, and further data analysis. Therefore, the gateway is designed to check Internet connectivity every 5 s in order to push the processed data to the cloud. The gateway is also designed to compensate for Internet interruptions when patients are exercising outdoors. When the Internet is down, a comma separated value (CSV) file is opened and all the data are loaded into the queue, along with the original timestamps (Figure 4). This allows the system to retain the timestamps and the order of the data. The system continually checks the Internet status, and once the connectivity is confirmed a basic header of the data is constructed in the form of a string and the main buffer is initialised.

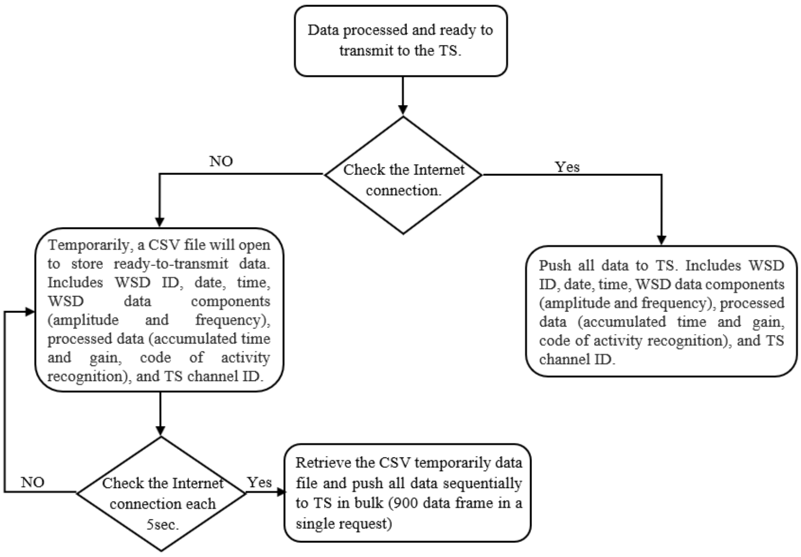


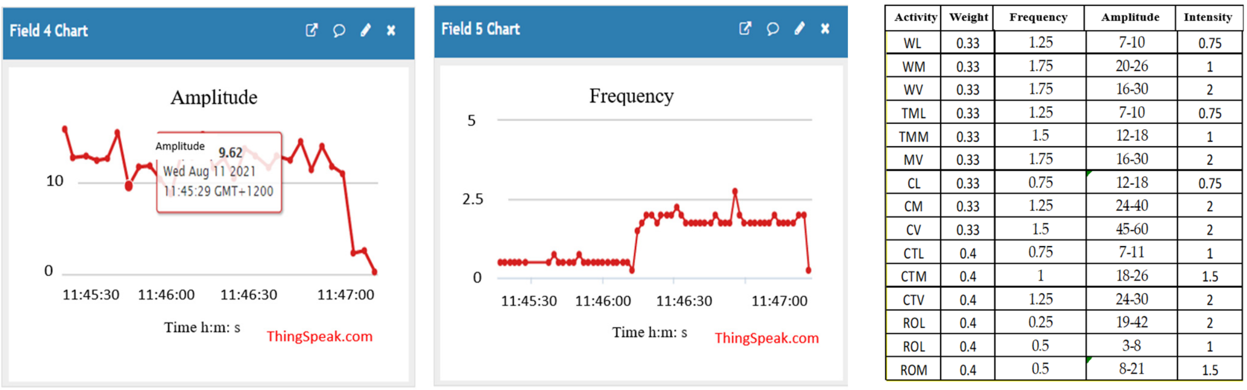
Figure 4. Data storage procedure during the down connection.

While in the queue, the data are gathered from different nodes. The system then sorts the data according to different nodes before sending the data to their respective channels. Once this sorting is complete and the main buffer list is constructed with the data of all nodes, data are then uploaded to ThingSpeak TS for further analysis. The uploaded data are a bulk upload, whereby the system can upload 900 data frames in a single request.

4. Role of the Gateway for Incoming Data Analysis and Activity Recognition

As previously stated, a patient undergoing prehabilitation may be prescribed up to nine different physical activities at light, moderate, or vigorous intensity. During the WSD phase, the raw accelerometer data obtained from the wearable device are subjected to a fast Fourier transform analysis. This analysis is conducted while the participants are engaged in the different physical activities at varying exercise intensities [11,12]. The processed data are then analysed at regular intervals of 4 s to determine the maximum amplitude and dominant frequency. Consequently, every activity exhibits a distinct amplitude and frequency value.

In the initial phase of prehabilitation, patients are required to visit a physical therapy facility to undergo a baseline assessment conducted by healthcare professionals. This initial visit also provides the opportunity to go through programme exercises and establish a preliminary database for individualised activity recognition using the IoT system. Throughout this evaluation, it is imperative that the Internet of Things system is adequately prepared to undertake the analysis, storage, and identification of the primary characteristics of the data obtained from every physical activity. Figure 5a,b show an example of initial session data (amplitude and frequency) from the patient performing physical exercises like walking, treadmill walking, cycling, and rowing activities at low, moderate, and high intensity. The adjacent table (5c) is a database of amplitude and frequency ranges for each activity at the three different intensities.



(**a**) (**b**) (**c**)

Activity	Weight	Frequency	Amplitude	Intensity
WL	0.33	1.25	7-10	0.75
WM	0.33	1.75	20-26	1
WV	0.33	1.75	16-30	2
TML	0.33	1.25	7-10	0.75
TMM	0.33	1.5	12-18	1
MV	0.33	1.75	16-30	2
CL	0.33	0.75	12-18	0.75
CM	0.33	1.25	24-40	2
CV	0.33	1.5	45-60	2
CTL	0.4	0.75	7-11	1
CTM	0.4	1	18-26	1.5
CTV	0.4	1.25	24-30	2
ROL	0.4	0.25	19-42	2
ROL	0.4	0.5	3-8	1
ROM	0.4	0.5	8-21	1.5

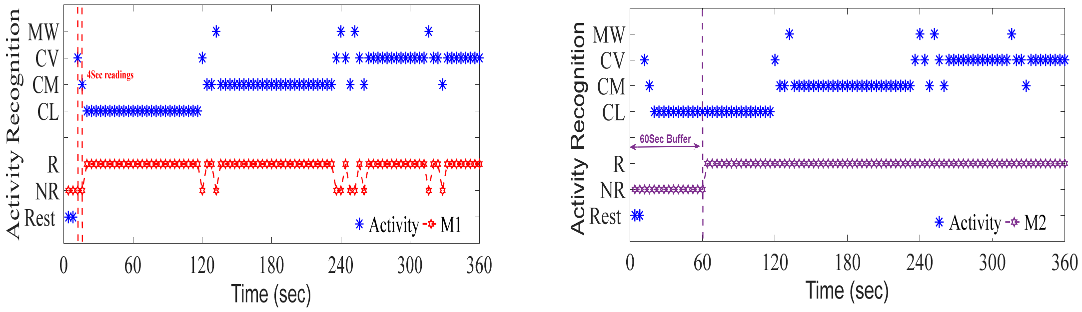
Figure 5. Data collected from WSD during the first visit with amplitude (**a**) and dominant frequency (**b**) values for each physical activity: (**c**) is the list of primary physical activities and their respective frequency and amplitude values. W is walking activity; TM is treadmill walking; C is cycling; CT is cross trainer; and RO is rowing. The letters L, M, and V are light, moderate, and vigorous intensity, respectively.

Throughout a session, various activities exhibit varying degrees of overlap with one another. The presence of this overlap can lead to the inaccurate recognition of certain activities, potentially resulting in miscalculations or the omission of credited efforts. Several studies have utilised machine learning and deep learning methodologies to address this concern [20,21]. The current study used specialised AI techniques (specifically those based on knowledge bases and logical approaches) to improve activity recognition and accurately quantify physical effort. In order to mitigate the issue of power spectrum frequency and amplitude measures overlapping between identified activities, the extracted activities are subjected to analysis using three straightforward logical methods that rely on short-term historical data.

The initial recognition method, referred to as M1, is a direct approach that relies on the preliminary activity recognition data (see the Figure 5c). These data are stored in a distinct table, serving as the foundation for the initial database. In our previous studies [10,11], we have described the process of comparing incoming data (frequency and amplitude) with a relational table that contains activity codes representing average frequency and intensity values for each exercise. This comparison occurs every 4 s. The second method of recognition (M2) detects amplitude and frequency similarities over a short period of time. M2 relies on the assessment of recognition consistency by analysing a brief historical record of the data recognised [11]. The temporal buffer is utilised to store incoming data, which consist of 15 readings, each lasting 4 s and containing recognised outcomes. This buffer is employed to identify the most frequent occurrences of specific activities that have been detected using the initial method. If the proportion of a specific activity exceeds a predetermined threshold (e.g., 80% of the data represents the amplitude and frequency components of that activity), then all the data within that minute will be attributed to the dominant single activity. In the event that the desired level of consistency is not attained, the system will display non-recognised activity (NR).

5. Activity Recognition Outlier Filter

This section provides an analysis of two distinct methodologies employed for the purpose of eliminating omitted movements in diverse physical activities. The integration of the gateway functions involves the incorporation of two logical recognition methods, namely M1 and M2. A series of 6 consecutive minutes of physical movements were randomly chosen as a sample to demonstrate the process of recognising and categorising different activities. Figure 6a,b depict the utilisation of two distinct recognition methods in the identification of cycling activity across a span of 6 min, with the cycling intensities categorised as light (L), moderate (M), and vigorous (V). As previously mentioned, M1 can identify the type of activity and compute the exertion levels every 4 s via amplitude and frequency measures calculated from the fast Fourier transform.



(**a**) (**b**)

Figure 6. Two methods of activity recognition: (**a**) M1; (**b**) M2. R represents 'recognised' and NR represents 'non-recognised activity. CL, CM, and CV represent cycling light, moderate, and vigorous, respectively, and MW represents walking at a moderate intensity.

Figure 6a depicts the observed behaviour of M1 during a 6 min period of physical activity. During the initial minute, M1 demonstrated a recognition accuracy of 73% for the observed activity. The data collected during the transition period from rest to cycling at a light intensity (CL) exhibited inconsistent values for a duration of 16 s. However, after this initial period the output data values stabilised, and the CL was consistently detected. As previously mentioned, the M2 technique relies on the storage of 15 incoming readings within a distinct buffer, and subsequently identifying these readings based on the consistency of the data within the buffer. In this example, a minimum threshold data consistency of 80% is used (i.e., the threshold level is arbitrary and subject to change based on the required level of accuracy). Any level of consistency that falls below this threshold will lead to the rejection of the activity. The M2 system has the disadvantage of not being able to detect activity when the buffer data remain below 80%. Furthermore, there are two main factors contributing to the reduction or increase in recognition rates. These are threshold level and buffer size, which can influence the accuracy of activity recognition. For example, if the threshold level is reduced from 80 to 60%, then the M2 method is able to recognise CL activity during the first minute (Figure 6b). In contrast, if the buffer size is reduced to five readings, then M2 would fail to recognise CL during the first 20 s of the first minute of activity. Accordingly, an optimisation is required between the threshold and buffer size to obtain an optimum recognition result based on the M2 method.

Table 1 presents a summary of the average activity recognition percentages and cumulative gains for each method. The M1 values exhibited higher percentages of activity recognition compared to the M2 method. The M2 method demonstrated the second highest level of accuracy in terms of achieving higher recognition percentages and gain values during the short duration tests of three physical activities. Accordingly, the M1 and M2 techniques can be combined to accurately recognise the nine common physical activities in a simple way and avoid long algorithm techniques using neural network methods.

Table 1. Accumulated gain and average percentage of activity recognition over 6 min.

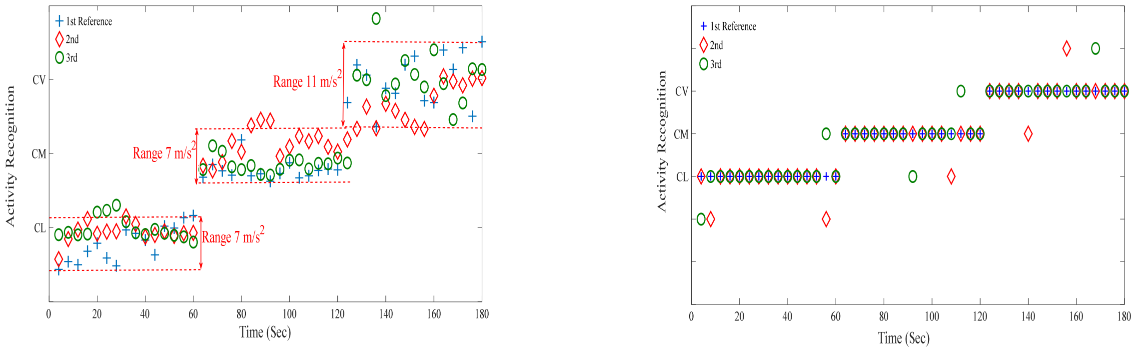
Method	Accumulated Gain	Activity Recognition%
M1	0.129	85
M2	0.126	80

The accumulated gain and history of the activity recognition of each patient can provide a clear picture of the type, intensity, and volume of exercise training occurring during the prehabilitation period for the healthcare provider. They can remotely decide if the patient is performing the prescribed physical activity or not. This has the potential to save time, effort, and cost for both patients and healthcare providers.

6. Database Creation for the PoPP

As mentioned previously, the patient who is undergoing major abdominal surgery must visit the healthcare centre for an initial assessment to involve him or her in a prehabilitation program. The physiotherapist or doctor will prescribe the physical activity based on the patient's fitness level and general health conditions.

Many patients of different ages and genders are involved in cancer prehabilitation programs, but a large percentage of these patients will be over the age of 60 years [1]. In this example, we selected an elderly male patient as a case study. The subject was asked to perform the same activity (cycling, walking, treadmill, and cross-trainer) at light, moderate, and vigorous intensities during three visits to the AUT physiotherapy gymnasium [1]. Data from the first session were used to generate a reference database for activity recognition and effort calculations when he performed the physical activity in the other two sessions. In this example, cycling activity is used to illustrate the development of the reference database, activity recognition, and effort calculations. Figure 7a,b show different intensity levels (low, moderate, and vigorous) of cycling performed by the patient during the three visits. The first visit was considered a reference visit, and the second and third visits were compared to the reference visit. The amplitude ranges for the three distinct intensities of cycling were approximately 7 m/s^2 for low and moderate intensities and 11 m/s^2 for vigorous intensities. In contrast to the amplitude measurements, the frequency measurements presented in Figure 7b exhibited distinct frequency bands for cycling at low, moderate, and high intensities that were consistent across all three visits. This illustrates that by using the IoT technology, a comprehensive personalised database that is able to identify a specific type and intensity of exercise can be created within an initial session for each patient.



(**a**) (**b**)

Figure 7. The CL, CM, and CV physical activity parameter levels based on personalised activity recognition: (**a**) amplitude parameter; (**b**) frequency parameter.

Quantifying Exercise Using Effort Calculations

An important component of remote monitoring of prehabilitation is quantifying cumulative activity and effort in a form that is easily interpreted by patients and clinicians. We developed an effort formula that takes into consideration the type, intensity, and duration of exercise recorded by the WSD. Effort calculations are heavily dependent on physical activity recognition because the mathematical formula is designed based on the physical activity, type, intensity, and time duration [11]. Equation (1) [11] shows the main element of effort (gain) calculations for each activity. The main advantage of this formula is that the gain is translated from physical effort to numerical effort. This is explained in detail in our previous work [11] and based on the equation below.

$$P = W_e \times I \times \left(\frac{D_e}{T}\right) \tag{1}$$

where the components are as follows:

P is the credit gained for the prehabilitation program, independent of the total program duration.

I indicates the exercise intensity level. Here, intensities of 0.75, 1.00, and 2.00 are allocated for light, moderate, and vigorous intensities, respectively. The weighting of the different intensities is based on the relative effect of each intensity on improvements in health and fitness [23–26].

T is the minimum threshold time. This minimum threshold is 10 min of physical activity at a moderate or vigorous intensity [27].

D_e is the duration of exercise, which is proportional to the standard unit of time T.

W_e represents the modality or type of prescribed physical exercise.

The Algorithm 1 shown below illustrates the procedure of gain calculations based on Equation (1). The ability of algorithm to take into account different parameters of exercise (intensity and duration) allows flexibility for the patient to gain points. For example, a patient rowing at a high intensity for 15 min will achieve a similar point gain to performing the same activity at moderate intensity for 30 min.

Algorithm 1 The pseudo-code and the steps used in the gain calculation.

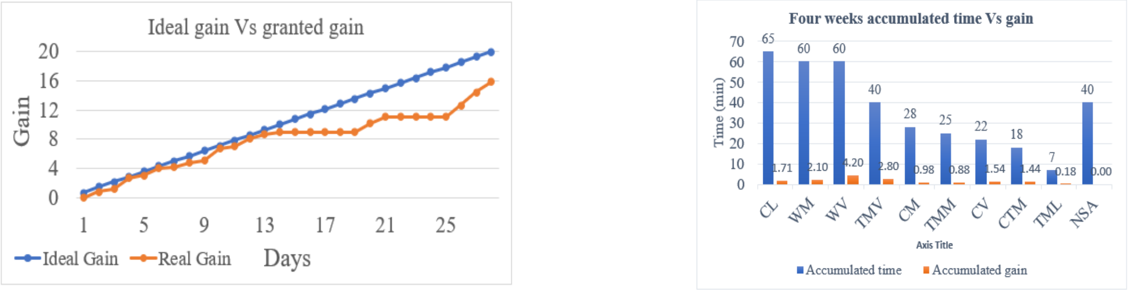
```
// Function to calculate gain (P) based on the equation P=w_e × I × (D_e/T)
    Function calculate gain (w_e, I, D_e, T):
// Calculate gain (P) using the given formula
        P = W_e × I × (D_e/T)
        Return P = P + 1
// Function to read data from a CSV file and process the results
        Function processCSVFile(file_path):
//Read the CSV file and extract the data for each row
      For each row in CSV file:
// Extract values for W_e, I, and D_e from the CSV row
         W_e = row['activity_weight']
         I = row['Intensity_level']
         D_e = row['exercise_time']
// Calculate gain (P) using the function calculated gain
         P = calculategain (W_e, I,D_e,10)// Assuming T is always 10 min
// Output the result or save it in another CSV file, database, etc.
         Print("Gain (P) for the current row:", P)
//Replace 'file_path' with the actual path to your CSV file.
         csv_file_path = "path_to_your_csv_file.csv"
// Call the function to process the CSV file
         ProcessCSVFile(csv_file_path)
```

7. Four-Week Practical Real-World Example of PoPP Supported by an IoT System

We have previously established the use of the IoT for detecting the type and intensity of prehabilitation activities in a gym environment [11]. However, the implementation of remote monitoring in the community has not been established. Here, we provide a case study of a 4-week prehabilitation scenario using the IoT technology and effort gain calculations for an elderly patient participating remotely in a mixed-mode prehabilitation model. The aim was to provide a practical illustration of the calculations involved in various prescribed physical activities. A prerequisite for program completion was achieving an average cumulative gain of 20 points. To achieve this the participant was expected to engage in a minimum of 150 min per week of physical activity at a moderate intensity level or its equivalent. The criterion for the minimal duration of a bout of exercise was at least 10 min of exercise at a moderate intensity level [8]. The cumulative time and gain were determined by the combination of Equation (1) and the recognition techniques M1 and M2 [11].

The accumulated time and gain for each physical activity were recognised and calculated by comparing the sensor data with the stored database developed when the participant had his initial physiotherapy visit, and then the two recognition techniques (M1 and M2) were applied to each incoming data input. Static and any unrecognised activity across the two methods were given zero gain credit. In addition to being sent to TS, the transient CSV file contained real-time activity recognition, accumulated time, and credit.

The patient was given flexibility to choose when and where he performed the prescribed physical activity. The system summarised daily and weekly physical activity with accumulated time and credits. In addition, when there was no activity within a certain number of days or when the credit for physical activity was significantly lower than the target gain, a warning message was sent to both the healthcare staff and the patient. This technique was able to detect more than 78% of the actual patient efforts during the 4-week program, which is a promising result when compared to traditional prehabilitation methods (both supervised and unsupervised). The expected granted gain versus the optimal gain during a 4-week prehabilitation program and the accumulated gain versus time for each physical activity are depicted in Figure 8a,b, respectively. It can be seen that during the first two weeks of prehabilitation real gain was similar to ideal gain. This was followed by two periods where there was a plateau, with a subsequent increase in gain following prompting messages being sent to the participant.



(**a**) (**b**)

Figure 8. (**a**) Granted gain versus number of days for a 4-week mixed-mode prehabilitation program. (**b**) Accumulated time and gain for each physical activity within 4-week prehabilitation program.

8. Conclusions and Future Work

Current research indicates that the gateway can perform multiple tasks simultaneously, including data collection from various WSDs, data analysis, activity recognition, patient monitoring, inactivity prompting, machine learning, and data storage for sorting or long-term storage. Future work such as logical intelligence (LI) could be an intriguing gateway feature. LI is one of the primary factors that could increase the accuracy of physical activity recognition and improve system performance. The incorporation of AI into the system could reduce the need for a healthcare professional or technician intervention to update the database and reduce superfluous health centre visits. Overall, the Raspberry Pi can play a significant role in healthcare IoT prehabilitation systems, as it offers a flexible and robust platform for data analysis, integration, and real-time monitoring. By leveraging the capabilities of the Raspberry Pi and other IoT technologies, prehabilitation programs can be optimised to better meet the requirements of individual patients and improve outcomes. In conclusion, the Raspberry Pi's capabilities, cost, and size make it a valuable instrument for a variety of healthcare applications, including data collection, patient monitoring, telemedicine, and machine learning. This could provide a low-cost option for reducing the load on both healthcare providers and patients.

Author Contributions: Conceptualization, K.A.-N. and A.A.-A.; methodology, K.A.-N.; software, K.A.-N.; validation, K.A.-N., A.A.-A. and G.M.; formal analysis, K.A.-N.; investigation, K.A.-N.; resources, K.A.-N., A.A.-A. and G.M.; data curation, K.A.-N.; writing—original draft preparation, K.A.-N.; writing—review and editing, A.A.-A.; visualization, K.A.-N.; supervision, K.A.-N.; project administration, K.A.-N. and A.A.-A.; funding acquisition, A.A.-A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: This study was approved by the Auckland University of Technology Ethics Committee (AUTEC reference number 19/212).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Al-Naime, K.A.M. *Cyber Physical System for Pre-Operative Patient Prehabilitation*; Auckland University of Technology: Auckland, New Zealand, 2022.
2. Pelosi, A.C.; Rostirola, G.C.; Pereira, J.S.; Silva, K.C.; Fontanari, M.E.R.; Oliveira, M.S.P.; Reis, I.G.M.d.; Messias, L.H.D. Remote and Unsupervised Exercise Strategies for Improving the Physical Activity of Colorectal Cancer Patients: A Meta-Analysis. *Healthcare* **2023**, *11*, 723. [CrossRef] [PubMed]
3. Amru, M.; Mahesh, A.V.N.; Ramesh, P. IoT-based Health Monitoring System with Medicine Remainder using Raspberry Pi. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2020; Volume 981, p. 042081.
4. Soniya, M.G.; Krishnaiah, M.T.R. IoT Based Healthcare Monitoring System using Raspberry Pi. *Ann. Rom. Soc. Cell Biol.* **2021**, *25*, 18308–18317.
5. Roy, S.; Gupta, R. Short range centralized cardiac health monitoring system based on ZigBee communication. In Proceedings of the 2014 IEEE Global Humanitarian Technology Conference-South Asia Satellite (GHTC-SAS), Trivandrum, India, 26–27 September 2014; pp. 177–182.
6. Bora, P.; Kanakaraja, P.; Chiranjeevi, B.; Sai, M.J.S.; Jeswanth, A. Smart real time health monitoring system using Arduino and Raspberry Pi. *Mater. Today Proc.* **2021**, *46*, 3855–3859. [CrossRef]
7. Sangeethalakshmi, K.; Preethi, U.; Pavithra, S. Patient health monitoring system using IoT. *Mater. Today Proc.* **2023**, *80*, 2228–2231.
8. Wiltink, L.M.; White, K.; King, M.; Rutherford, C. Systematic review of clinical practice guidelines for colorectal and anal cancer: The extent of recommendations for managing long-term symptoms and functional impairments. *Support. Care Cancer* **2020**, *28*, 2523–2532. [CrossRef] [PubMed]
9. Jung, Y.; Chung, J.; Son, H. Physical activity interventions for colorectal cancer survivors: A systematic review and meta-analysis of randomized controlled trials. *Cancer Nurs.* **2021**, *44*, E414. [CrossRef] [PubMed]
10. Al-Naime, K.; Al-Anbuky, A.; Mawston, G. Human Movement Monitoring and Analysis for Prehabilitation Process Management. *J. Sens. Actuator Netw.* **2020**, *9*, 9. [CrossRef]
11. Al-Naime, K.; Al-Anbuky, A.; Mawston, G. Remote Monitoring Model for the Preoperative Prehabilitation Program of Patients Requiring Abdominal Surgery. *Future Internet* **2021**, *13*, 104. [CrossRef]
12. Al-Naime, K.; Al-Anbuky, A.; Mawston, G. IoT Based Pre-Operative Prehabilitation Program Monitoring Model: Implementation and Preliminary Evaluation. In Proceedings of the 2022 4th International Conference on Biomedical Engineering (IBIOMED), Yogyakarta, Indonesia, 18–19 October 2022; pp. 24–29.
13. Costilla, R.; Tobias, M.; Blakely, T. The burden of cancer in New Zealand: A comparison of incidence and DALY metrics and its relevance for ethnic disparities. *Aust. N. Z. J. Public Health* **2013**, *37*, 218–225. [CrossRef] [PubMed]
14. Smith, T. A long way from home: Access to cancer care for rural Australians. *Radiography* **2012**, *18*, 38–42. [CrossRef]
15. Jong, K.E.; Smith, D.P.; Yu, X.Q.; O'Connell, D.L.; Goldstein, D.; Armstrong, B.K. Remoteness of residence and survival from cancer in New South Wales. *Med. J. Aust.* **2004**, *180*, 618–622. [CrossRef] [PubMed]

16. Martin, D.; Besson, C.; Pache, B.; Michel, A.; Geinoz, S.; Gremeaux-Bader, V.; Larcinese, A.; Benaim, C.; Kayser, B.; Demartines, N.; et al. Feasibility of a prehabilitation program before major abdominal surgery: A pilot prospective study. *J. Int. Med. Res.* **2021**, *49*, 03000605211060196. [CrossRef] [PubMed]
17. Das, A.; Katha, S.D.; Sadi, M.S. An IoT enabled health monitoring kit using non-invasive health parameters. In Proceedings of the 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, 8–9 July 2021; pp. 1–6.
18. Xu, T.; Wendt, J.B.; Potkonjak, M. Security of IoT systems: Design challenges and opportunities. In Proceedings of the 2014 IEEE/ACM International Conference on Computer-Aided Design (ICCAD), San Jose, CA, USA, 2–6 November 2014; pp. 417–423.
19. Allhoff, F.; Henschke, A. The internet of things: Foundational ethical issues. *Internet Things* **2018**, *1*, 55–66. [CrossRef]
20. Gupta, A.; Al-Naime, K.; Al-Anbuky, A. IoT based Testbed for Human Movement Activity Monitoring and Presentation. In Proceedings of the 6th International Conference on Information and Communication Technologies for Ageing Well and e-Health, Prague, Czech Republic, 3–5 May 2020; pp. 61–68.
21. Al Naime, K.; Al-Anbuky, A.; Mawston, G. IoT for Movement Recognation and Prehabilitation Support System. In Proceedings of the 2022 27th Asia Pacific Conference on Communications (APCC), Jeju Island, Republic of Korea, 19–21 October 2022; pp. 447–452.
22. Gupta, A.; Al-Naime, K.; Al-Anbuky, A. Iot Environment for Monitoring Human Movements: Hip Fracture Rehabilitation Case. In Proceedings of the Information and Communication Technologies for Ageing Well and e-Health: 6th International Conference, ICT4AWE 2020, Prague, Czech Republic, 3–5 May 2020; Springer: Berlin/Heidelberg, Germany, 2021; pp. 44–63.
23. Weggemans, R.M.; Backx, F.J.; Borghouts, L.; Chinapaw, M.; Hopman, M.T.; Koster, A.; Kremers, S.; van Loon, L.J.; May, A.; Mosterd, A. The 2017 Dutch physical activity guidelines. *Int. J. Behav. Nutr. Phys. Act.* **2018**, *15*, 58. [PubMed]
24. Marshall, S.J.; Levy, S.S.; Tudor-Locke, C.E.; Kolkhorst, F.W.; Wooten, K.M.; Ji, M.; Macera, C.A.; Ainsworth, B.E. Translating physical activity recommendations into a pedometer-based step goal: 3000 steps in 30 minutes. *Am. J. Prev. Med.* **2009**, *36*, 410–415. [CrossRef] [PubMed]
25. American College of Sports Medicine. *ACSM's Guidelines for Exercise Testing and Prescription*; Lippincott Williams & Wilkins: Philadelphia, PA, USA, 2013.
26. Whitfield, G.P.; Carlson, S.A.; Ussery, E.N.; Fulton, J.E.; Galuska, D.A.; Petersen, R. Trends in meeting physical activity guidelines among urban and rural dwelling adults—United States, 2008–2017. *Morb. Mortal. Wkly. Rep.* **2019**, *68*, 513.
27. McLellan, A.; Slaght, J.; Craig, C.; Mayo, A.; Sénéchal, M.; Bouchard, D.R. Can older adults improve the identification of moderate intensity using walking cadence? *Aging Clin. Exp. Res.* **2018**, *30*, 89–92. [CrossRef] [PubMed]