An End to End Real-Time Step Counting Algorithm Implementation Using The Wearable RESpeck Monitor

Shuai Shi

4th Year Project Report
Artificial Intelligence
School of Informatics
University of Edinburgh

2022

Abstract

Many studies have demonstrated a strong correlation between daily physical activity levels and health. Walking is the most frequent and basic unit of daily human activity. As people become increasingly concerned about their health, daily steps are used as an indicator to quantify their physical activity levels. As a result, various methods of step counting have been widely investigated. An end-to-end real-time step counting application using a wearable RESpeck monitor has been introduced in this work. This implementation has two steps: first, classifying human activity and capturing the walking category. Then, for different walking activities like running and walking, different step counting algorithms are applied to count the number of steps. In the first step, we present an 3-layer hierarchical deep learning model, while experimenting with different deep learning model architectures and the tuning of hyperparameters. Each layer of the model is assigned a specific responsibility to ensure that their combination is effective. In the second step, data of 5 walking types from 10 volunteers, each with 30 steps. Our step counting algorithm uses this data to get the optimal parameter values for a more accurate step counting. To test the robustness of the whole system, we implemented the algorithm on an Android app and compared the performance with commercial pedometers, such as the Apple Watch. The result from our android application in real-time tests is better than a pedometer app with 12,000 downloads (by 2022.4.7) from the Apple Application Store and close to the apple watch.

Research Ethics Approval

This project obtained approval from the Informatics Research Ethics committee.
Ethics application number: 6359
Date when approval was obtained: 2021-12-17
The participants' information sheet and a consent form are included in the appendix.

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Shuai Shi*)

Acknowledgements

I want to express my gratitude to my supervisor, DK Arvind, for his encouragement and inspiration, as well as Teo for her thorough feedback. Additionally, I want to thank my beloved family for their unconditional support and my personal tutor Paul Jackson for his long-term academic suggestions. Finally, I would like to extend my gratitude to everyone who contributed to the data collection for this study.

Table of Contents

Chapter 1

Introduction

1.1 Motivation for the project

Walking is a fundamental unit of human locomotion. When researchers began to study the relationship between daily physical activity levels and health[8] , the number of steps taken each day became a suitable measurement to quantify the activity level. As steps are objective, intuitive and has strong associations with physical health variables.[37]

Many longitudinal intervention studies have revealed that pedometers motivate wearers to take more steps.[31][21] In a 2007 study, through a randomised controlled trial of 2767 participants, the group using a pedometer had a significant increase in physical activity of 2491 steps compared to the group not using a pedometer. The pedometer group had a 0.38 decrease in body mass index and a 3.8 mm Hg decrease in systolic blood pressure.[11]The results showed that pedometer use was associated with a increase in physical activity and decreased BMI and blood pressure.

1.2 Project objective

This project aims to achieve a high precision pedometer comparable to commercial pedometers. Two important conditions are needed to achieve this goal. The first is to find walking-like activities from other daily human activities. Traditionally, the algorithms used for detection have been based on heuristic strategies. Usually, researchers need to review the data collected from pedometer sensors manually, and they analyse and deconstruct a walking pattern to form a set of heuristic rules to discriminate whether the activity type is walking. Representative approaches are threshold detection[33] and autocorrelation[2], where an algorithm classifies sensor data as walking activity and records steps when it exceeds a threshold of previously observed walking activity. The autocorrelation method discriminates whether the walk is the same type by saving the pattern of previously recorded walks and comparing it with newly received data. However, there are many different types of human activity, even walking, and these classical algorithms are prone to classification errors, leading to false positive step counts.

The second challenge need to overcome is to count steps in real-time. Many studies look for steps in a recorded data segment. They use different filters to smooth out the waveform and count the steps. For example, the zero-crossing algorithm[34], for example, records a step whenever two points cross the 0 points. Without filters, there are many small fluctuations in the data, such as multiple crossing of 0 points in a short period, which would cause the a significant loss in accuracy. When counting steps in real-time, however, to avoid missing steps that span two windows of data, we only count steps after a continuous period of walking. So the length of the walking data is flexible. A fixed filter may make the waveform too smooth or barely work. An algorithm does not require a filter or uses a filter independent of the length of the data is needed.

1.3 Results achieved

Two implementations have been done. One is based on peak detection with minimum peak distance (also known as windowed peak detection as peak detection is claimed the best step counting algorithm [9]), and the other is based on wavelet transform. Results are compared with the Apple watch and Steps (an app for Apple phones). 5 volunteers are asked to follow a set walking routine of 200 steps. The Apple Watch had the maximum accuracy of 95.2%, with peak detection approaching 93.1%. The wavelet transform achieved an accuracy of 88.8%, while Steps achieved an accuracy of 86.9%. It is worth noting that the peak detection algorithm produces false positive and false negative errors. In contrast, wavelet transform has almost only false negative errors. Therefore, the peak detection algorithm is more accurate on a scale of 200 steps. However, they have very similar accuracy in other tests with lower step numbers.

In addition, we have found that the most significant factor affecting the accuracy of the step counting algorithm is the frequency, or speed, of walking. In future studies, deep learning models may applied to measure walking frequency to develop a more precise pedometer directly.

Chapter 2

Background and Related work

2.1 Human activity recognition(HAR)

Human activity recognition(HAR) is a rapidly developing area that emerged from the broader disciplines of ubiquitous computing. Recently, there has been a boom in research into machine learning approaches for HAR challenges. These techniques have shown very efficient at extracting and learning information from activity datasets. The method includes highly derived hand-crafted feature machine learning algorithms and hierarchically self-evolving feature extract deep learning algorithms. HAR is classified into video-based HAR and sensor-based HAR[13]. While video-based HAR analyses films or photos captured by the camera that feature human movements, sensor-based HAR analyses motion data from smart sensors such as an accelerometer or a gyroscope. Due to the rapid advancement of sensor technology and ubiquitous computing, sensor-based HAR is gaining popularity and widespread application while maintaining a high level of privacy protection. As a result, the primary emphasis of this article is on sensor-based HAR. Sensor based HAR has many applications such as smart home activity recognition[41][4][30], functional, and behavioral health assessment[32],Sports analytics[6].

2.1.1 HAR machine learning algorithms

Machine learning approaches have been shown to be more successful in extracting knowledge and discovering, learning, and inferring actions from data than conventional mathematical and statistical procedures.[28]. In shallow learning-based HAR systems, the often employed feature heuristics are heavily reliant on the researcher's domain expertise, and the success of machine learning approaches is strongly dependent on the data representation[7].The commonly used features are time domain features (mean, variance, time sequences;[12]), frequency domain features (Fourier transform, entropy), and other transformations ([19]).

Traditional machine learning approaches depend primarily on feature extraction, with human a priori knowledge determining which characteristics to use. The extraction of features is dependent on one's domain expertise, such as Fourier transforms, wavelet transforms, and entropy. This may result in an approximation of features. This approximates features and often requires numerous training sessions and feature combinations for optimal outcomes. On the other hand, deep learning methods can extract characteristics directly from raw data by performing some nonlinear transformation. We will perform activity classification using a deep learning technique, given the need to develop a real-time pedometer on Android, Code refactoring for feature extraction in java would be very time consuming. The nonlinear transformation determines the type of deep learning network. Deep learning has been popular in the last few years, and numerous works have been done using deep learning in HAR. The popular deep learning techniques in HAR include CNNs, recurrent neural networks (RNN), long-short-term memory (LSTM) and RNN networks. The next section will discuss the rationale behind these models.

2.1.2 Validation of algorithm

Another issue that step counting algorithms encounter is determining the algorithm's validity. In a validation research by Foerster, The accuracy of action classification can reach 95.6 percent when performed under controlled experimental conditions. However, after gathering data from people in their daily lives and identifying it, the accuracy rate decreased dramatically to 66%.[14] Typically, testing are conducted in a quantitative setting in which the tester walks or runs in a prescribed manner for a certain amount of time. Steps, however, are not often restricted to continuous walking or running in daily life, and individuals may make extremely short strides. A well-performing algorithm in a laboratory context may suffer severe performance degradation in a real-world situation. As a result, another aspect of this work was to deploy the suggested algorithm to an Android app and test it in a real setting in order to produce a more practical and robust method for tracking steps.

2.2 Devices

2.2.1 Commercial and experimental devices

As people become increasingly concerned about their physical health, they attempt to quantify the amount of exercise by tracking the amount of walking they do each day. This has encouraged the development of commercial pedometers. For a search on Amazon for pedometers gives 276 results and 13 brands (March 2022). Meanwhile, the market for wearable devices is still growing at a rate of 20% per year and will reach 150 billion euros by 2028. [26] According to Cisco Systems, the wearable industry in the United States looks promising, with the number of linked wearable devices predicted to exceed 439 million in North America by 2022. By 2022, North America is predicted to be the area with the most 5G-connected wearable devices. In 2017, the 439 million connections in North America will surpass the 4G network by 222 million.

Wristbands and smart watches are the most popular products on the commercial market as their portability and integration of additional features[20]. The variety of gadgets employed in research is greater than that of commercially accessible wearable devices.

Figure 2.1: The Apple Watch (left) and the Fitbit (right) are two of the most popular fitness monitoring gadgets available. With a combined market share of approximately 59 percent(2022 Q1) in the north America market for smart wearable devices.[20]

They are worn on different parts of the body for use. For example, on the waist, thighs, ankles, wrists. To acquire more data, some investigations require the user to wear three or more devices and sensors attached to their legs, foot, and knees[22]. To store and interpret the data, users were even needed to carry backpacks weighing up to 5kg[27]. While this method allows for the collection of more data, the equipment is sophisticated, inconvenient to wear, and expensive. Possessing the ability to scale up and acquire additional data is a challenge. Wearable gadgets should therefore be as simple as feasible to use and should be worn in an unobtrusive manner. Additionally, this design will reduce energy usage to maximise user convenience.

2.2.2 Sensors

Accelerometers with three axes are perhaps the most extensively used and effective sensors for determining walking activity[17][18], In these studies, recognition rates for walking were generally greater than 95%, despite differences in methodology. Accelerometers are affordable and consume little electricity[29]. Our research discovered that accelerometers do not perform well at detecting relatively slow motions, such as waddling, because the acceleration changes associated with such movements are insignificant. To address this issue, we adopted gyroscopes, which are sensors that measure angular velocity and are more sensitive than accelerometers, capturing more data and subtle movements. However, because to the gyroscope's significant power consumption, it is only activated when absolutely essential. Numerous studies have examined the influence of acceleration sampling rate on recognition accuracy, concluding that while an increase in sampling rate is advantageous below 20Hz[22], there is a slight further improvement in recognition accuracy above this threshold.

In this work, we use a device called the RESpeck, which described in detail in section 2.2.4.

2.2.3 Respeck

The RESpeck is a non-invasive wearable device developed at the Centre for Speckled Computing at the University of Edinburgh's School of Informatics. It enables simultaneous tracking of activity and respiratory data. All of our data used in this work is collected via RESpeck and the associated Airespeck app. We may either keep the acquired data locally or directly upload it to the cloud. The advantage of this device is its portability. The user can apply it with a plaster on the left side's underside of the last rib. Due to the device's small dimensions (4.4cm x 3.6cm x 0.6cm)2.2, it will not obstruct the wearer's daily activities, and so the data collected will provide a more accurate image of the actual situation. Compared to some more extensive devices, the RESpeck may also be worn daily. In Arvind's research with this device[1], the participant wore the RESpeck except when showering.

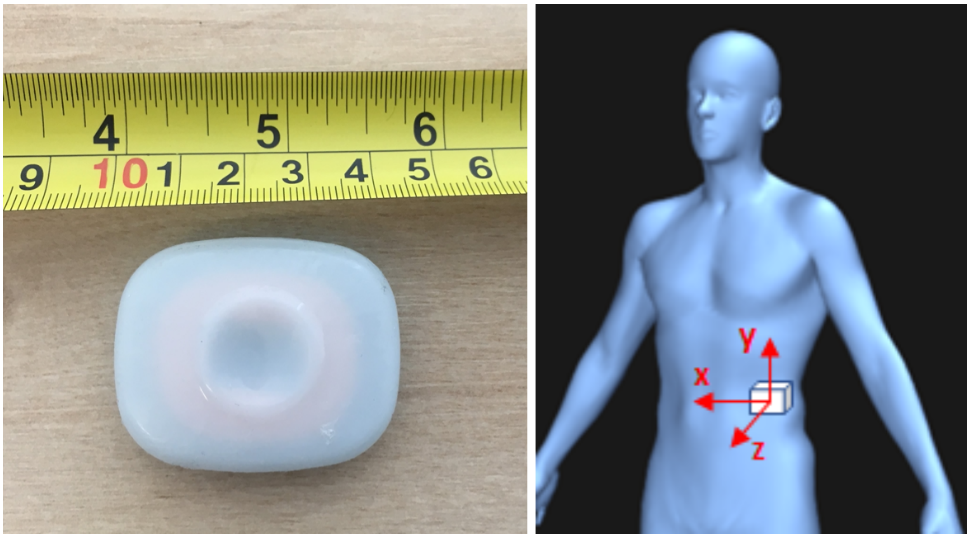

Figure 2.2: Dimensions of RESpeck and Wearing demonstration[35]

The Respeck is composed of a tri-axial accelerometer for measuring non-gravitational accelerations and a gyroscope for determining rotational velocities. Due to the fact that gyroscopes use many orders of magnitude more energy than accelerometers, although we obtained data on acceleration and angular velocity for a variety of activities using a 25Hz sample rate. The data is also downsampled to determine the algorithm's accuracy when just 12.5Hz accelerometer data was used.

RESpeck communicates collected data through Bluetooth to the mobile app; RESpeck does not process or store the data. This enables the RESpeck to operate for an extended period of time, up to six months when only the 12.5Hz sample rate accelerometer is on.

2.3 Step counting algorithms

The most extensively used threshold method counts the instant when a brief, above-threshold acceleration is detected as a step[16][23]. The method performs best in foot pedometers, where a very unique threshold may be obtained due to the extremely high acceleration experienced during stride. The short-term Fourier transform transforms time-domain data into frequency-domain data. However, its resolution is strongly dependent on the window length[5]. As a result, it recognises data that is greater than a specified time period or that is sampled at a high frequency. By continually correlating the mother wavelet with the original signal, wavelet transforms compresses or inflates the original signal[38][40]. They are capable of capturing sudden acceleration changes and are well suited to changes occurring over a short period of time. Certain algorithms use stride (2 steps) as a detection target because to the stride's very unique frequency of roughly 1-2Hz in comparison to other human activities[25]. Agata made a comprehensive comparison of the advantages and disadvantages of various step-counting algorithms, the peak detection has been found with the highest accuracy[10]. So we will use two algorithms in the step counting part, peak detection and wavelet transform.

2.3.1 Definition of a Step

In this project, we define a step as "a movement made by lifting your foot and putting it down in a different place" stated by Merriam-Webster.[37] While Oxford dictionary defines a step as "an act or movement of putting one leg in front of the other in walking or running." This statement means a step needs to retain in a continuous period of walking and running activity. But the real situation is much more complex than that. Other than walking and running, some activities also generate steps such as staging in place, turning around.

Chapter 3

Methodology

3.1 Overview

Step counting is a two step process: firstly, the current activity is classified, and identified as the walking; and, secondly, step counting algorithm is applied for different walking types resulting in the number of steps. The classification uses a hierarchical machine learning model. A discrete wavelet transform-based step counting method is used for both step counting as well as classifying walking and non-walking activities with a good accuracy for different types of walking. Figure 3.1 illustrates the proposed methodology.

3.2 Hierarchical Machine Learning

Figure 3.2 and Figure 3.3 given an overview of the three-layer machine learning model and the model structure. There are three layers which uses a GRU-CNN deep learning model in each layer. Although the structure of the model of each layer is the same, there are differences in the choice of hyper-parameters. The following section describes the machine learning models used in this project and justification of the 3-layer hierarchical architecture.

3.2.1 Recurrent Neural Network (RNN)

Compared with the traditional back-propagation neural network, the cyclic neural network can accept and learn from the sequence information transmitted by other neurons. This is commonly known as the neural network with a specific memory function. Such a neural network algorithm works well on data with time-series changes[36].

In the recurrent neural network, when the current layer neuron outputs data information to the next layer, it will also output a hidden state information for the next layer neuron to learn and use. This circular structure is used to store and learn the past information to realize the learning and memory function of the past information.

Figure 3.4 shows a typical RNN neural network structure. As shown in Figure 3.4, each RNN neural network unit is divided into three layers: input layer, hidden layer and

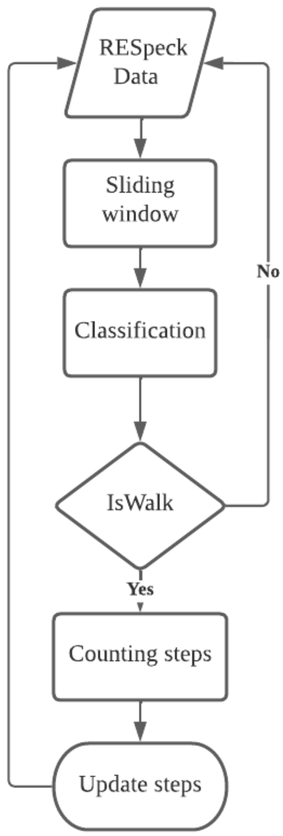

Figure 3.1: Overview of the Step-Counting Methodology

output layer.

Given x_{t-1}, x_t, x_{t+1} as the input time series information from time t to time $t+1$; h_{t-1},h_t and h_{t+1} as the hidden layer information from t to $t+1$; $y_{t-1}y_{t-1}$,y_t and y_{t+1} as the output layer information from t to $t+1$.U,V and W are the neuron weight matrix of input, output and cycle, respectively. As the neurons in each time step are connected in series, the neuron weights of input, output and cycle are shared in the entire RNN, thus improving the learning of the time-series information.

At any time t, the antecedent propagation of the recurrent neural network can be expressed :

$$h_t = f\left(W^* x_t + U^* h_{t-1} + b\right) \tag{3.1}$$

$$y_t = g\left(V^* h_t\right) \tag{3.2}$$

In equations (3.1) and (3.2), f and g are nonlinear activation functions, Where $*$ is the matrix multiplication, W is the weight matrix from the input unit to the hidden unit, U is the connection weight matrix between the hidden units, and V is the weight matrix of the output of the hidden unit, b is the offset vector, x_t is the input, y_t is the output.

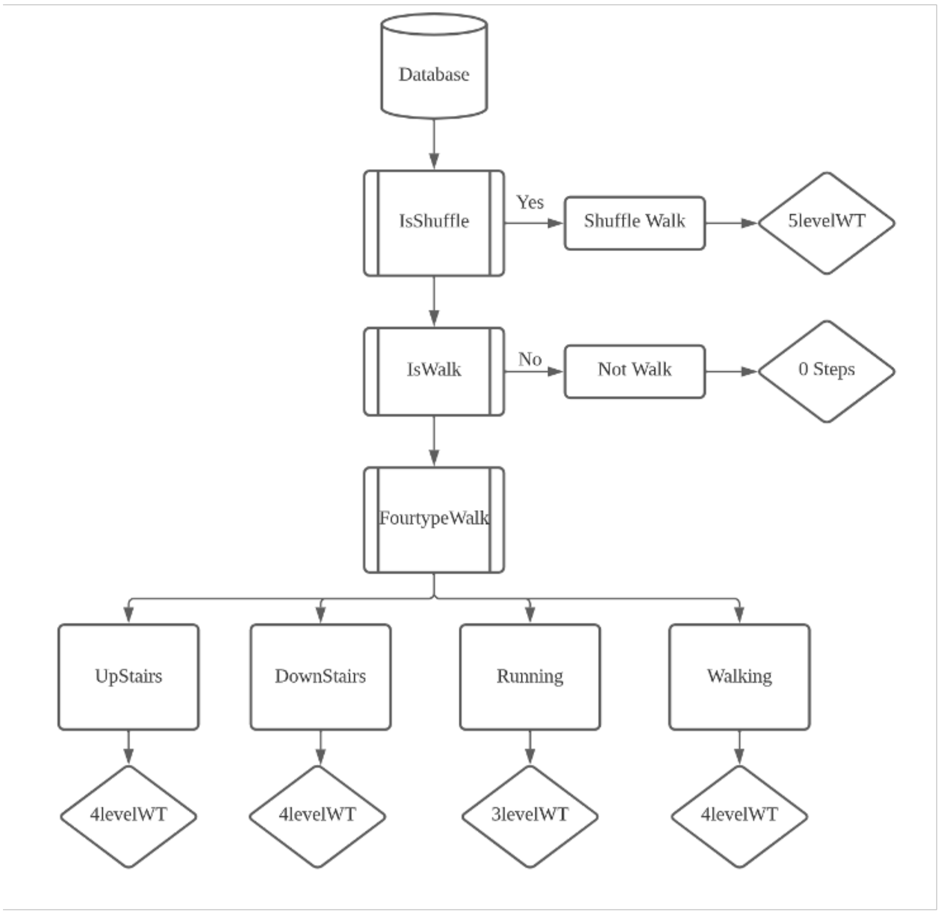

Figure 3.2: Overview of Hierarchical Machine Learning

3.2.2 Long Short-Term Memory (LSTM) neural network

LSTM neural networks can effectively avoid the problems of gradient disappearance and gradient explosion in traditional networks. By adding additional memory units, LSTM can remember past information and store it for a long time. LSTM has strong generalization capability, good learning ability for large and small data sets, and has substantial advantages for dealing with nonlinear problems. The basic unit structure of LSTM is shown in Figure 3.5.

The 'Forgetting' gate f_t based on the status of the last time C_{t-1} decided to discard and retain information. Thex_t values pass passes separately σ And *tanh* functions to determine the value to be updated and generate new candidate values for updating, The updated value is then compared with the forgetting gate f_t update the unit status together. Updated unit status C_t outputs h_t after tanh function and O_t in the output gate. The basic equation of state of LSTM unit is updated.

$$i_t = \sigma\left(W_i\left[h_{t1}, x_t\right] + b_i\right) \tag{3.3}$$

$$a_t = \tanh\left(W_c\left[h_{t1}, x_t\right] + b_c\right) \tag{3.4}$$

$$c_t = f * C_{t1} + i_t * a_t \tag{3.5}$$

$$a_t = \sigma\left(W_o\left[h_{t1}, x_t\right] + b_o\right) \tag{3.6}$$

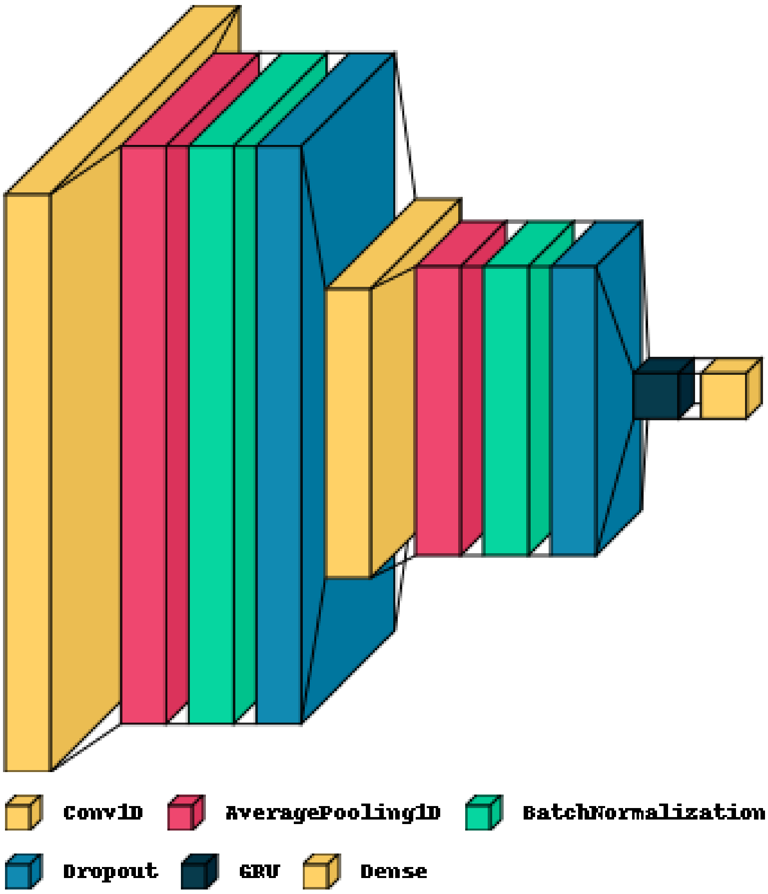

Figure 3.3: Overview of model structure

$$h_t = O_r * \tanh C_t \tag{3.7}$$

Where x_t and h_t represents input vector and output vector respectively, f. i and O represent forgetting gate, input gate and output gate respectively, C_t and C_{t-1} represents the last time and the current unit state respectively, h_{t-1} and h_t represents the output of the last time and the current hidden layer unit respectively, σ Represents sigmoid activation function, tanh represents tangent function, W and b represent the weight matrix and deviation vector.

3.2.3 Gated Recurrent Unit(GRU) network

GRU network is an improved model of long-term and short-term memory network. It optimises the three gate functions of the long-term and short-term memory networks, combines the forgetting gate and input gate into a single update gate, and integrates neuron state and hidden state, effectively alleviating the problem of "gradient disappearance in cyclic neural networks", reducing the number of parameters in the long-term and short-term memory network units, and shortening the model's training time. The basic structure of GRU network is shown in Figure3.6, and the mathematical description is shown in equation below.

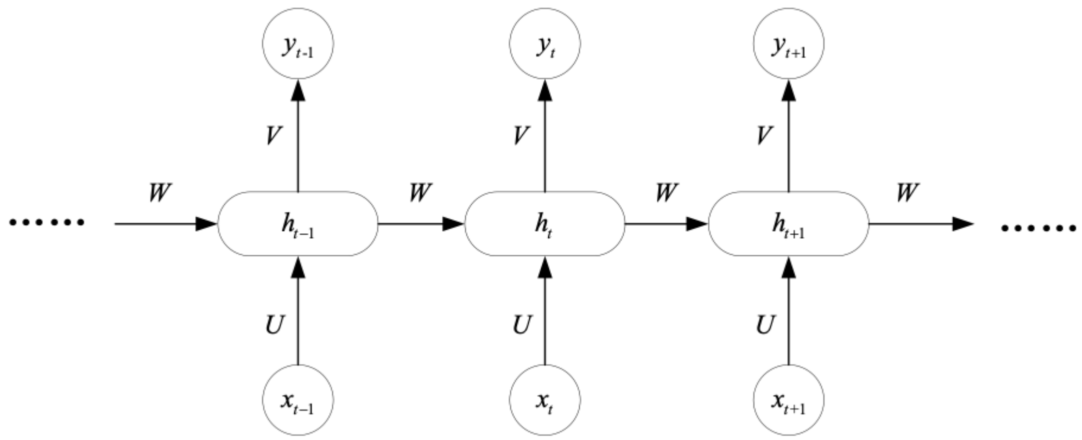

Figure 3.4: RNN neural network structure diagram

$$\begin{cases} r_t = \sigma\left(W_{\mathrm{r}} \cdot [h_{t-1}, x_t]\right) \\ z_t = \sigma\left(W_{\mathrm{z}} \cdot [h_{t-1}, x_t]\right) \\ \widetilde{h}_t = \tanh\left(W_{\widetilde{\mathrm{h}}} \cdot [r_t \times h_{t-1}, x_t]\right) \\ h_t = (\mathbf{I} - z_t) \times h_{t-1} + \mathbf{z}_t \times \widetilde{h}_t \\ y_t = \sigma\left(W_{\mathrm{o}} \cdot h_t\right) \end{cases} \tag{3.8}$$

In equation 3.8, $x_t, h_{t-1}, h_t, r_t, z_t, \widetilde{h}_t, y_t$ are input vectors respectively, The state memory variable of the previous time, the state memory variable of the current time, the state of the update gate, the state of the reset gate, the state of the current candidate set, and the output vector of the current time; $W_{\mathrm{r}}, W_{\mathrm{z}}, W_{\widetilde{\mathrm{h}}}, W_{\mathrm{o}}$ are update gate, reset gate, candidate set, output vector and x_t and h_{t-1} the weight parameters multiplied by the connection matrix, $\mathbf{I}$ represents identity matrix;σ Indicates sigmoid activation function; Tanh is a tangent function.

GRU network takes update gate and reset gate as the core module and inputs variable $\mathbf{x}_t$.The splicing matrix with the state record variable h_{t-1} at the previous time is input of the update gate after sigmoid nonlinear transformation. It determines what extent the state variable at the previous time is brought into the current state. The reset gate controls the amount of information written to the candidate set at the last time. Through $\mathbf{I} - z_t$ times $\mathbf{h}_{t-1}$ storing the information of the last time. The pass $\mathbf{z}_t$ times $\widetilde{\mathbf{h}}_t$ record the information of the current time and add them as the output of the current time.

3.2.4 Convolutional neural network(CNN)

The basic structure of convolutional neural network is shown in Figure 3.7. The overall structure is divided into three parts: input layer, hidden layer and output layer. As the name suggests, the input layer is the interface for inputting data. This layer converts the input data into tensor data mode that can be calculated by neural network.

The hidden layer often contains multiple neural network layers. The effective features in the data are extracted by convolution and pooling. The formula of convolution operation

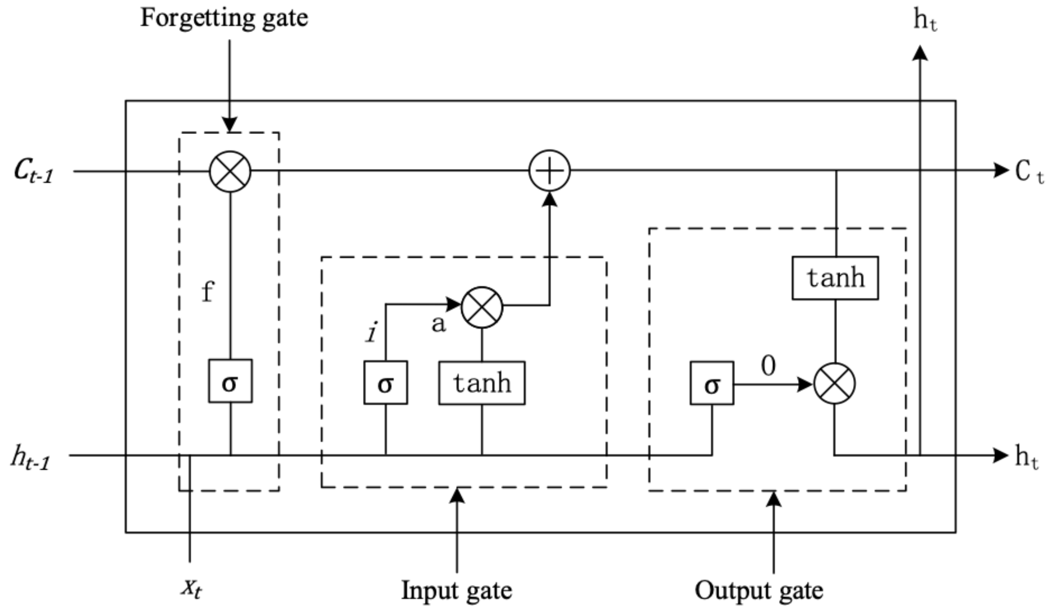

Figure 3.5: LSTM structure diagram

is shown in formula (3.9):

$$x_j = k_j^i * x_{j-1} + b_j^i \tag{3.9}$$

$*$ represents convolution operation. x_{j-1} represents the output data of layer $j-1$. k_j^i represents the ith convolution kernel of layer j. b_j^i is the corresponding offset.

The pooling operation is to compress the feature map after convolution operation. At the same time, pooling operation is also known as down sampling operation, which extracts the secondary features of the output features of convolution layer, so as to reduce the amount of calculation data. There are two common pooling functions: mean pooling and maximum pooling.

(1) Maximum pooling, as shown in formula :

$$p^{l(i,t)} = \max_{(j-1)w+1 \le t \le jw} \left\{ \partial^{l(i,t)} \right\} \tag{3.10}$$

(2) Mean pooling, as shown in formula :

$$p^{l(i,t)} = \frac{1}{w} \sum_{(j-1)^{*}w+1}^{jw} \partial^{l(i,t)} \tag{3.11}$$

$p^{l(i,t)}$ is the output value of the t-th neuron of the ith characteristic map of layer l after passing through the pool layer; $^{l(i,t)}$ is the output value of the t-th neuron of the i-th characteristic diagram of layer L after passing through the activation function.

Finally, the characteristic data that represents the whole data is transformed into one-dimensional. It is inputted into the full connection layer for calculation and finally output the prediction results.

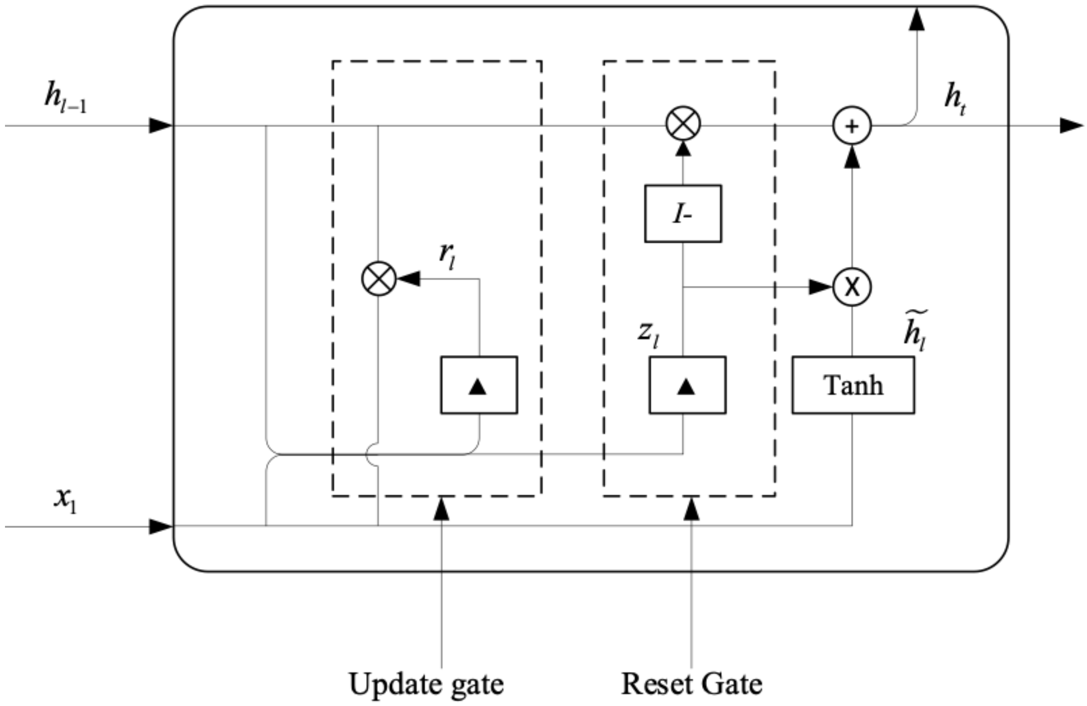

Figure 3.6: GRU structure diagram

3.2.5 Human activity data

The labelled dataset used in "Principles and Design of IoT Systems" course taught at the University of Edinburgh was employed to train the classifier. The labelled dataset of 3-axis accelerometer and gyroscope data sampling at 25 Hz was collected by 48 students wearing the Respeck device for a selection of 18 activity types. The dataset was filtered to retain only walking data together with common everyday activities such as lying down, desk work.

The labelled shuffle walking data was collected from 10 volunteers wearing the Respeck device for the training dataset using the same protocol as in the case of PDIOT dataset. Volunteers were invited to imitate the shuffle walking patterns of older people by leaning with both hands on a wheeled chair and dragging their legs in the process. Figure 3.8 and 3.9 shows images of real shuffle walking and a simulation of shuffle walking, respectively.

Figure 3.10 shows the overview of the training dataset, including all types of activity.

3.2.6 Data prepossessing

3.2.6.1 Sliding window

Sliding window technology has a wide range of applications in human activity recognition[39]. Overlapping sliding windows are applied to segment the data collected by accelerometers and gyroscopes in this work. The data is split into windows of fixed length showed

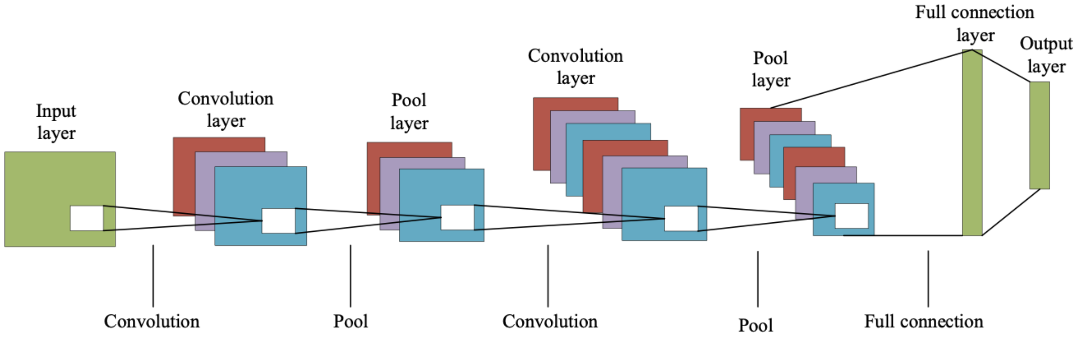

Figure 3.7: CNN structure diagram

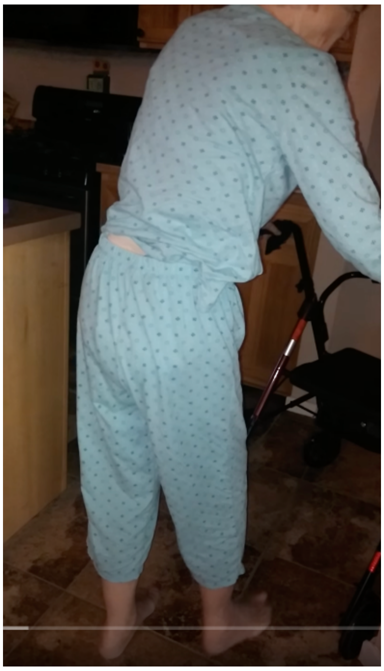

Figure 3.8: Shuffle walking

Figure 3.9: Stimulation of Shuffle walking

in 3.11 and sliding distance (the overlapping part, if the sliding distance is half the length of the window, then each window will have 50% of the data as duplicates). We can think of a sequence of temporal data points as a training data feed to the model with the sliding window. The sliding window size significantly impacts the model's classification accuracy[3].Smaller sliding window sizes allow faster classification. Larger sliding window sizes can be used to identify more complex long duration activities. In our experiments, relation of different window sizes and accuracy of walking class activity recognition are tested. A more detailed description of the experiments and the results are presented in Chapter 4.

3.2.7 Leave one group out validation

To prevent overfitting, data is split by subjectId, also called Leave-one-subject-out cross-validation shown in figure 3.12.

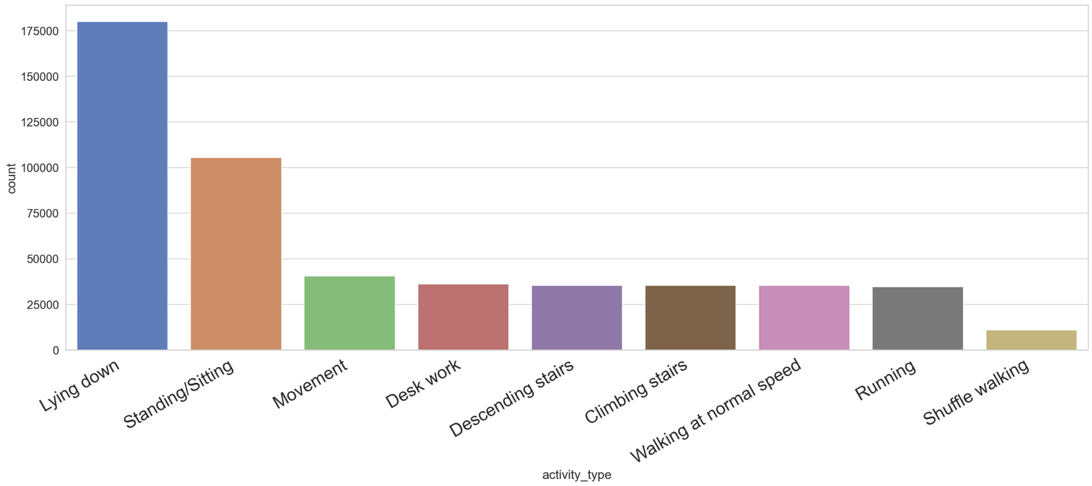

Figure 3.10: Overview of the Training Dataset for classification

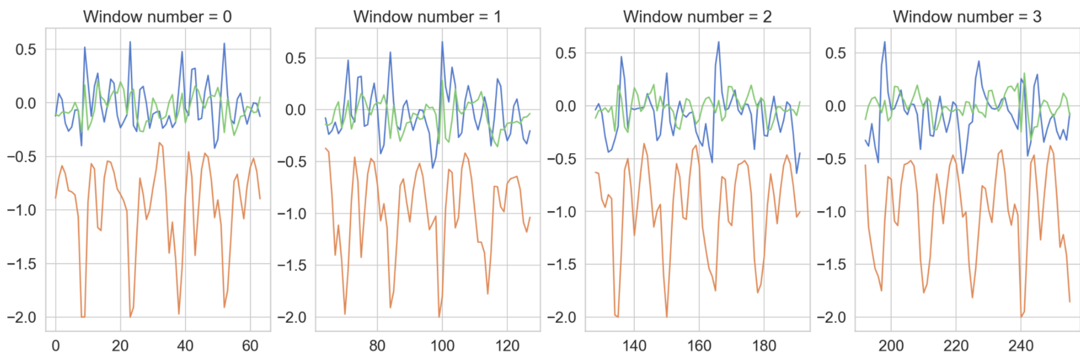

Figure 3.11: Sliding window example

When a subject's data is included in both the training and test sets, the model gains an unfair advantage. Additionally, the results generated by the model will be inflated. Accuracy will drop considerably when the model is tested on an entirely new, unseen subject.

This is why when training a HAR model, a special kind of cross-validation: Leave-One-Subject-Out (LOSOXV), is needed, where we leave one (or more) subject(s) in the testing set at each iteration.

3.2.8 Model structure

3.2.8.1 First Layer - IsShuffle

In the first classification layer, shuffle walking are found. Then non-shuffle walking will be fed into the next classifier.

The shuffle walking is classified first as it is very different from other types of gait. Its accelerometer readings are entirely distinct from other walking types. During data collection, volunteers put their weight on the wheelchair and walked with their feet in a shuffling gait. The fluctuations in the accelerometer are tiny because they do not have a

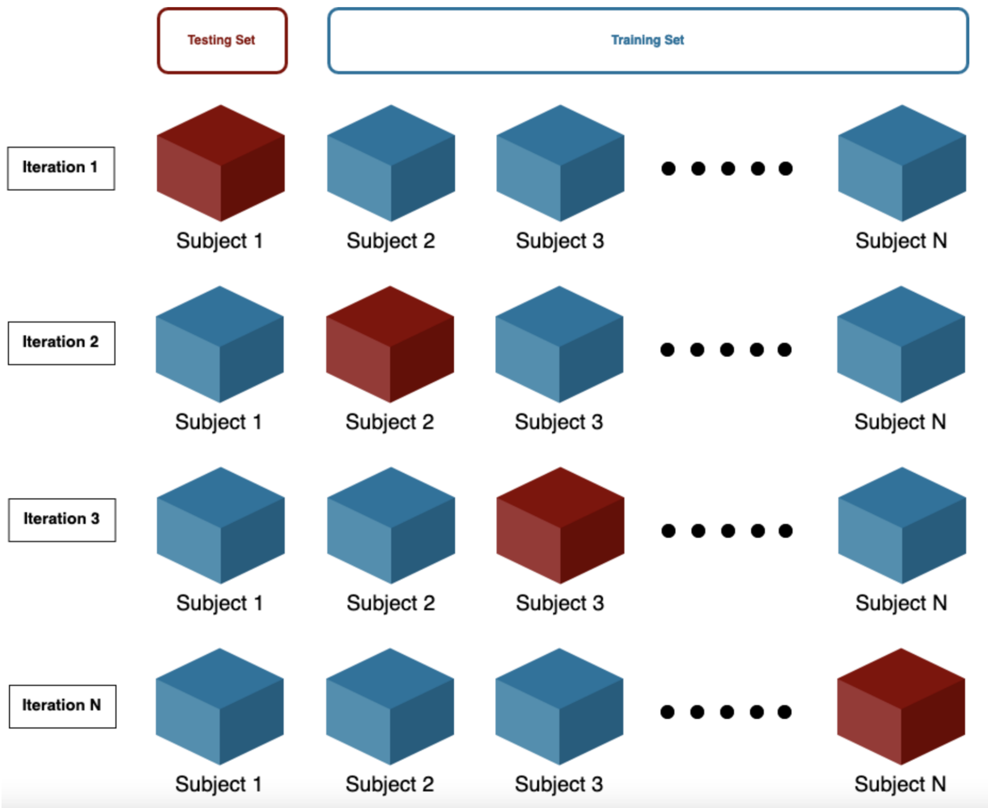

Figure 3.12: Leave-One-Subject-Out[15]

significant movement of raising and lowering the thighs. Figure 3.13 and Figure 3.14 are readings of accelerometer and gyroscope readings of shuffle walking and descending stairs. Shuffle walking readings are smaller in accelerometer readings. Shuffle walking is labelled with other types of walking as one walking label, then dichotomies into walking and non-walking activities. There is a significant decrease in classification accuracy.

Another important reason is the unbalanced distribution of the data set. Due to the small amount of shuffle walking data collected, we adopted multiple classifications to reduce the bias of the model.

3.2.8.2 Second Layer - IsWalk

In the second layer, the classifier finds out the walking activities and the non-walking activities. The deep learning model has the same structure as the previous layer. However, settings of the hyper-parameters are different. For example, the choice of optimiser is Softmax, which is more suitable for binary classification.

Walking is very different from other activities as it has a fixed, repetitive pattern. Usually, a walking activity has two peaks on the accelerometer data(a stride), as a stride usually consists of at least two steps. This layer has the highest classification accuracy when a window length of 64 is chosen, as it including a walking cycle. We investigated the effect of window size in the Evaluation chapter.

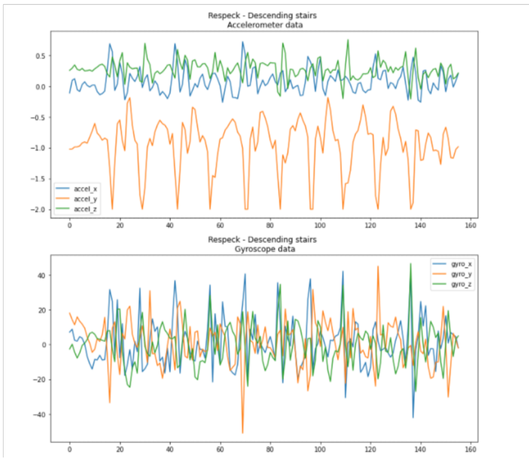

Figure 3.13: Descending stairs readings

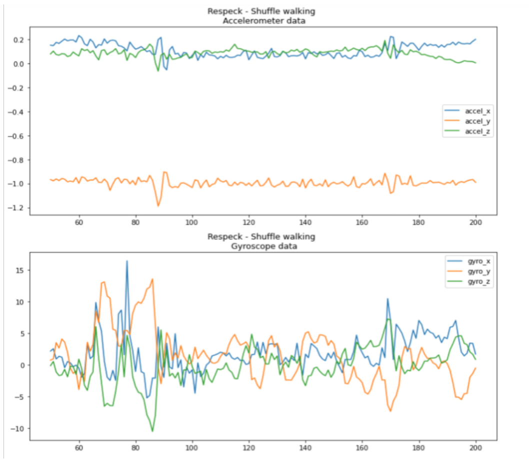

Figure 3.14: Shuffle walking readings

3.2.8.3 Third Layer - FourTypeWalk

The previous layer's output, the walking class, will be divided into four categories in the final layer of classification: going upstairs, going downstairs, walking, and jogging. When the step counting algorithm processes the first three walking activities, it uses the same parameters, so the error in the classification of the first three classes does not affect the accuracy of the final step count. The reason for not using binary classification and still adapting a multi-classification model is twofold. Firstly, it allows for a more balanced data set and higher accuracy. The second is that the model is more scalable and can extend to include other walking activities such as fast running, slow walking.

3.3 Frequency domain step counting method

Walking can be seen as the cyclical, repetitive movement of a person's body parts. A complete gait usually has eight steps as Figure 3.15 shown. There is a specific stage in a cycle where the acceleration peaks. The main idea of our algorithm is to summarise the frequency of peak acceleration or gyroscope data for various walks from the available data. The other frequencies of the original data are then filtered out using wavelet decomposition. Finally, the number of steps is found by peak detection in filtered data.

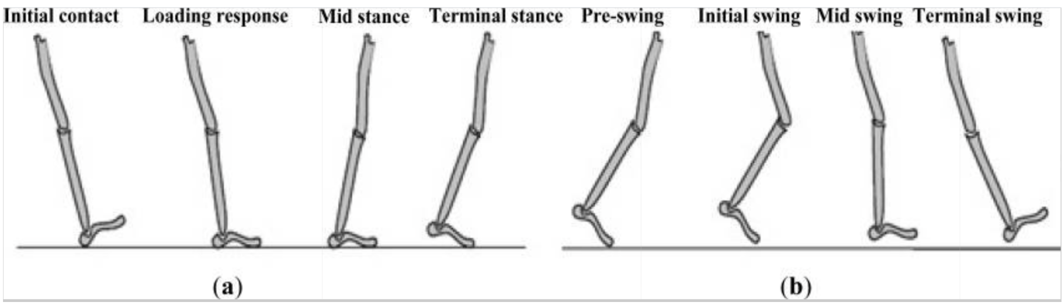

Figure 3.15: gait phases

3.3.1 30 step data

Ten volunteers were asked to walk 30 steps at a straight and even pace using 5 patterns. They are walking, going upstairs, going downstairs, running and shuffle walking. The process for collecting 30 step data is the same as collecting activity data and using the same sensor, accelerometer and gyroscope, 25Hz sampling frequency.

3.3.2 Fast Fourier transform

First, we use the FFT(Fast Fourier transform) to obtain the spectrogram. A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence.Fourier analysis converts the accelerometer data from time domain to the frequency domain. The definition of DFT is

$$X(k) = \sum_{n=0}^{N-1} \omega(n) \left(e^{-j\frac{2\pi}{N}}\right)^{nk} \tag{3.12}$$

where k = 0, 1, . . . , N 1 and $\omega(n)$ is the normalized data. The frequency of the n-th point after transformation, denoted fn, can be calculated as follows:

$$f_n = (n-1) \times \frac{f_x}{N} \tag{3.13}$$

where f_x is the sampling frequency and equals to 25 Hz. By investigating five kinds of walk from 7 subjects to 9 subjects, we get the frequency range of peaks of accelerometer data of each type of walking. Figure below shows the results.

These figures indicates running have the highest frequency around 2.66Hz to 2.99Hz. Walking at normal speed, climbing stairs and downing stairs have the similarly frequency from 1.29Hz to 2.33Hz. Finally, the shuffle walking have the lowest frequency around 0.13Hz to 0.47Hz.

3.3.3 Wavelet decomposition based de-noising

With the FFT, we have determined the frequency range of the various walks. So the signals at other frequencies can be seen as noise. Therefore, we use wavelet decomposition and recombination to filter out the signals at other frequencies.

In wavelet decomposition, the original signal is decomposed into sub-signals of different frequency bands by the scale function $\phi(t)$ and the wavelet function $\psi(t)$-based. The wavelet approximation coefficients $a_0(k)$ and the wavelet detail coefficients $d_j(k)$ of a discrete signal $s(t)$ of length M can be expressed as

$$a_0(k) = \frac{1}{\sqrt{M}} \sum_{M}^{m=1} s(m)\phi_{0,k}(m) \tag{3.14}$$

$$d_j(k) = \frac{1}{\sqrt{M}} \sum_{M}^{m=1} s(m)\psi_{j,k}(m) \tag{3.15}$$

j and k in equations (3.3) and (3.4), which represent the scaling of the subsignal in the frequency domain and the translation in the time domain, respectively.

The original signal can then be reconstructed from the approximation and detail coefficients.

$$s(t) = \frac{1}{\sqrt{M}} \sum_k a_0(k)\phi_{0,k}(t) + \frac{1}{\sqrt{M}} \sum_j \sum_k d_j(k)\psi_{j,k}(t) \tag{3.16}$$

The above process of multi-resolution analysis of the signal using the wavelet transform is the basis for this work's decomposition of the acceleration and gyroscope signal for noise reduction. Many different mother wavelet functions are available when using wavelet analysis to process a signal. The results obtained after the transform vary, so the appropriate mother wavelet function must be chosen for the analysis. After continuous testing and adjustment, the 6-layer Dmey wavelet with the best extraction effect was finally chosen to extract the periodic components. The Figure 3.21 below shows the results of wavelet decomposition of the 3D accelerometer data of Walking at normal speed. The Dmey wavelet is a good approximation of the Meyer wavelet leading to FIR filters that we can use in the discrete wavelet transform. Since it has more obvious spike characteristics, it is easier for us to detect peaks in the next step.

3.3.4 Peak detection

In the last part, we get peaks from different level of wavelet transform according to the frequency range we found in FFT part. The peak detection algorithm is simple: find the local maximum, and because our data is smooth, there is no need to consider the effect of noise. As long as a point is found with two neighbour points smaller than it, it is the local maximum. Then we mark it as a peak.

For example, in Figure 3.19, the frequency range of running is 2.66 to 2.99Hz, then we choose level 3 wavelet transform result with frequency range 0 to 3.12Hz. We will demonstrate the whole process with a running data including 30 steps. From Figure 3.22 we can see the peak of acceleration data in spectrum is (2.4,0.37), then we find peaks on a 3 level wavelet transform with range 0 to 3.12Hz showed in Figure 3.23.We found 30 peaks means there are 30 steps. In Figure 3.24, peaks are projected on the original data.

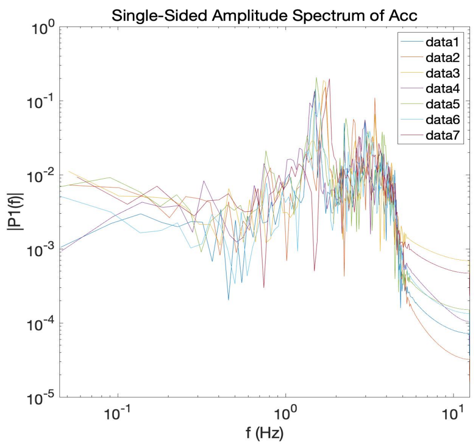

Figure 3.16: spectrum of walking, frequency range[1.32,1.81]Hz

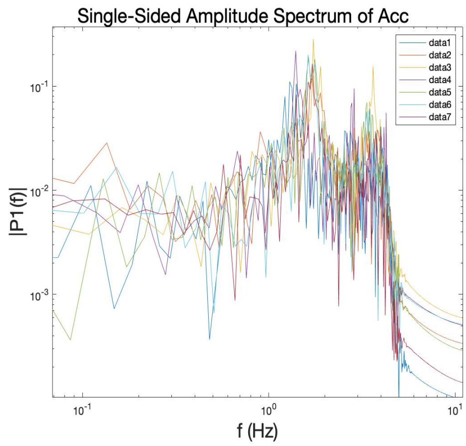

Figure 3.17: spectrum of up stairs, frequency range[1.29,2.04]Hz

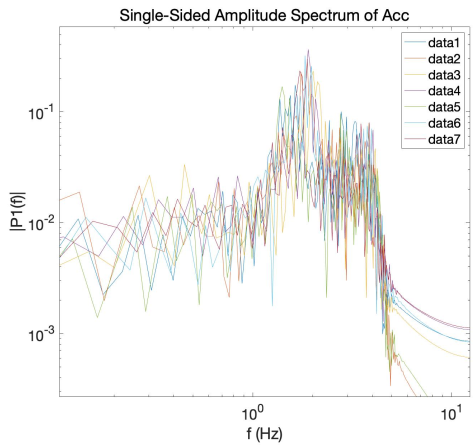

Figure 3.18: spectrum of down stairs, frequency range[1.29,2.33]Hz

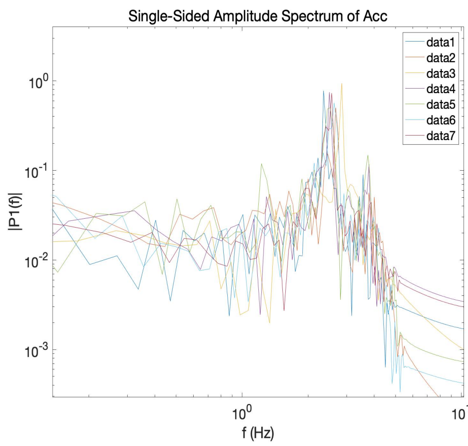

Figure 3.19: spectrum of running, frequency range[2.66,2.99]Hz

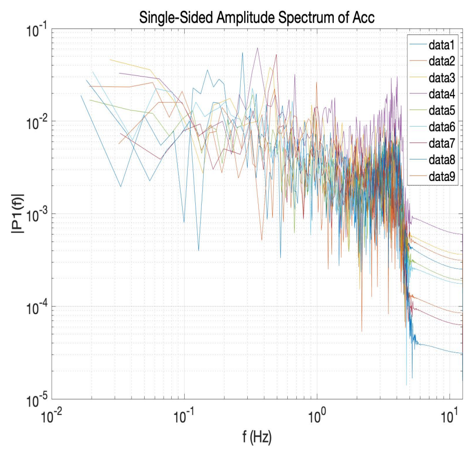

Figure 3.20: spectrum of shuffle walking,
Peak frequency range[0.13,0.47]Hz

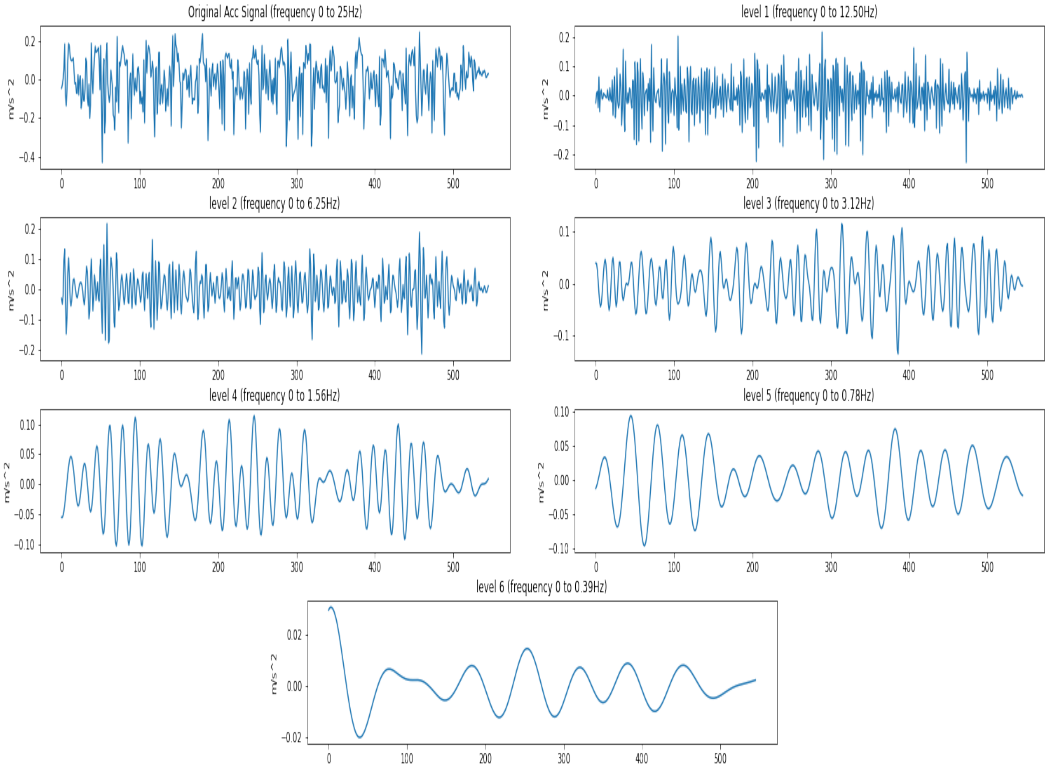

Figure 3.21: Accelerometer data of Walking at normal speed after wavelet transform

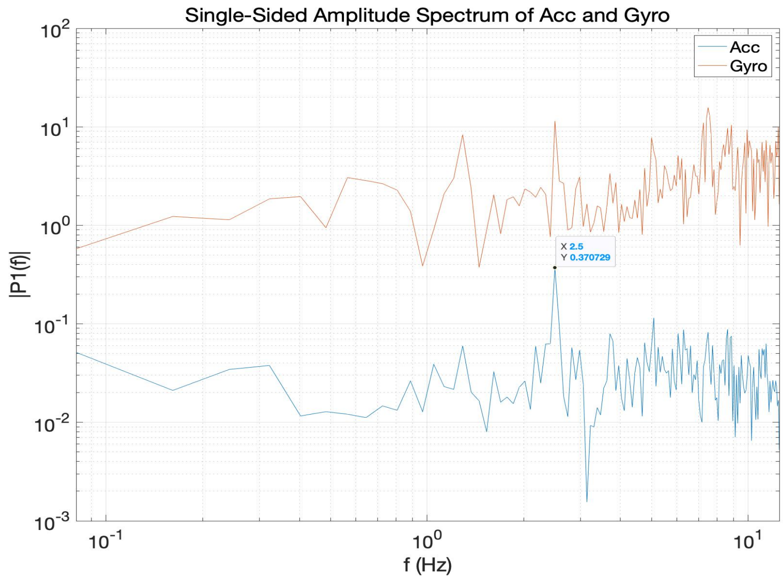

Figure 3.22: Spectrum of Running

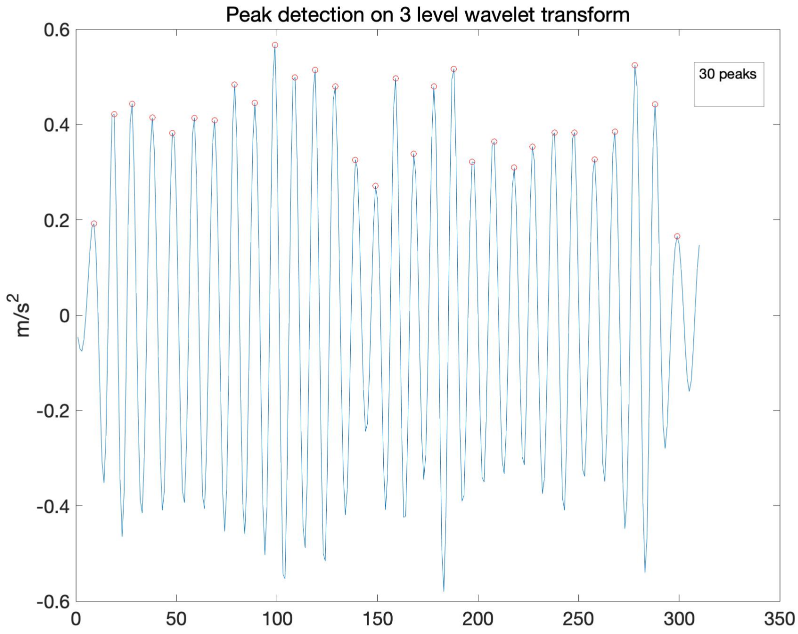

Figure 3.23: Peak detection on 3 level wavelet transform of Running

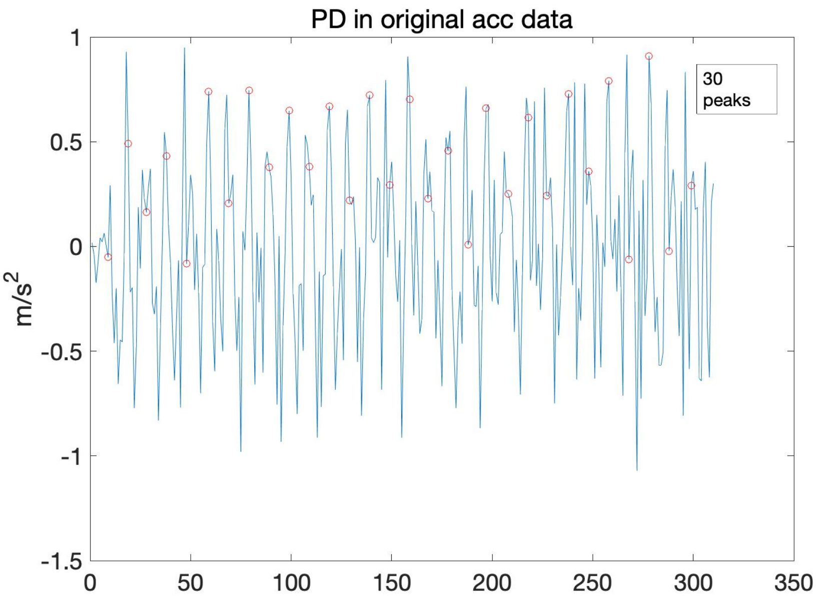

Figure 3.24: Peaks on original Running data

Chapter 4

Evaluation

4.1 Result of hierarchical machine learning model

Two architectures of deep learning models are deployed in this section: a CNN and a CNN+GRU model. The CNN model is the model offered in the Internet of Things course, and it is used as a baseline for comparison in this section.

Additionally, the effect of sampling frequency and sensor type on the model performance are investigated. Three sets of data are compared. To begin, data from the accelerometer and gyroscope were collected at a 25Hz sampling rate, followed by data from the accelerometer at a 25Hz sampling rate and finally data from the accelerometer at a 12.5Hz sampling rate. Because the sample rate and the presence or absence of a gyroscope alter the RESpeck's endurance, we wanted to test if there was a substantial variation in the model outputs between data obtained at low and high power. We can choose whether to activate the gyroscope and sample at a 25Hz rate.

Also, we investigated the effect of window size to the classification accuracy. Three different window size 32,64 in 25Hz data,and half of them in 12.5Hz data are used. Sliding windows with shorter duration, such as 16 in 25Hz or 8 in 12.5Hz, require us to determine the activity state every 0.64 seconds. Numerous human activities last longer than this, and hence shorter window sizes are disregard. Longer sliding windows, such as 128 in 25Hz or 64 in 12.5Hz, require making a decision every 5 seconds, which surpasses the duration of many human activities. Many brief activities occur within 2-3 seconds, and when a window comprises multiple activities, the system's robustness is weakened.

All the models are trained with 100 epochs with a learning rate set to 0.0003 and Adam Optimiser. Leave-one-subject-out method is used as the validation method, and train three times to take the average result.

4.1.1 First layer - IsShuffle

Although a model is trained for nine classes in the first layer, the only concerned one is shuffle walking. Due to the imbalance in the training set, using classification accuracy as a metric for model accuracy would create complications; for example, if the model identified all shuffle walks as walks, the total accuracy would still be about 80% due to the scarcity of shuffle walk data. As a result, the confusion matrix is used to illustrate the classification model's results for this layer. The confusion matrix aggregates and categorises the number of correct and wrong predictions using count values.

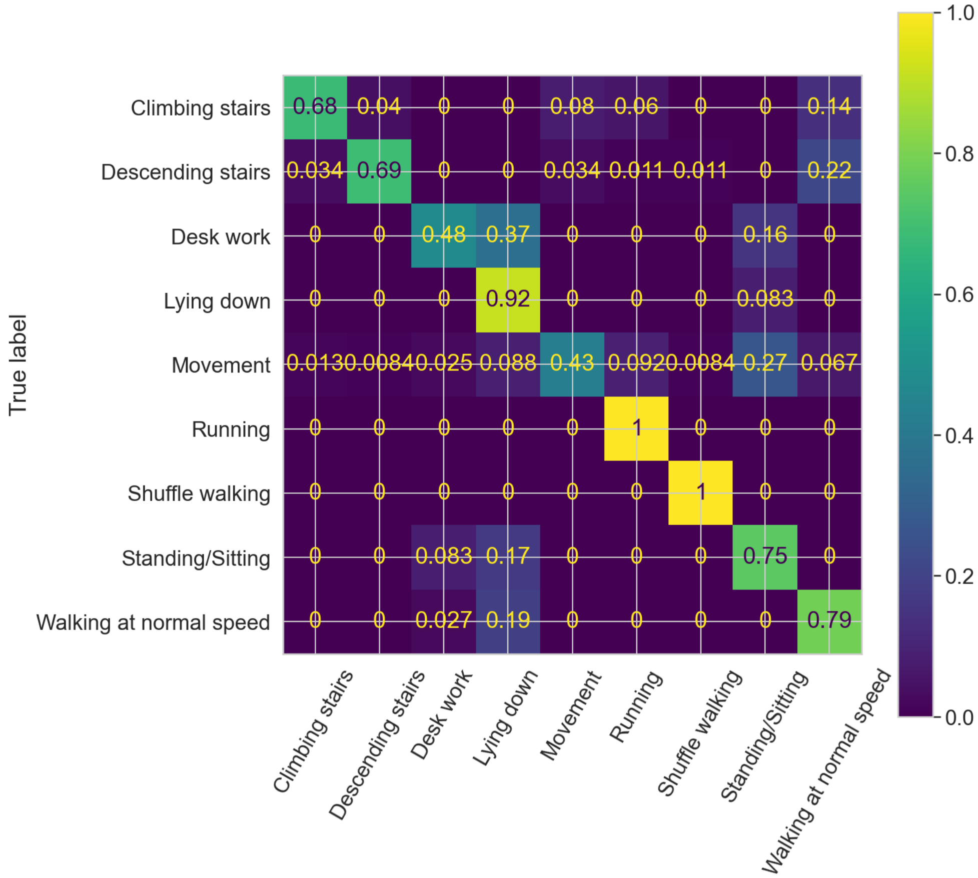

Figure 4.1: IsShuffle confusion matrix using 25Hz Acc and Gyro data

Figure 4.1 and Figure 4.4 are confusion matrix of CNN+GRU structure model trained using 25Hz Acc and Gyro data and only 12.5Hz Acc data respectively. Comparing these figures shows that the gyroscope data is crucial to distinguishing shuffle walking. With the gyroscope, almost all shuffle walks can be accurately classified. When only the 12.5Hz accelerometer data used, there is a surprising drop in accuracy, leaving only 36%. 29% and 33% of the shuffle walks are classified as standing/sitting and Desk work. Therefore we can conclude that because of the shuffle walking movement in which participants are asked to imitate an older adult walking, The pace is slower, and the range of movement is smaller than regular walking. Therefore, the variation in acceleration is also more minor.

Similarly, desk work and standing/sitting are static movements, showing slight variation in acceleration. Therefore, our model cannot differentiate between shuffle walking and desk work, standing/sitting if only accelerometer classification is used. This result is

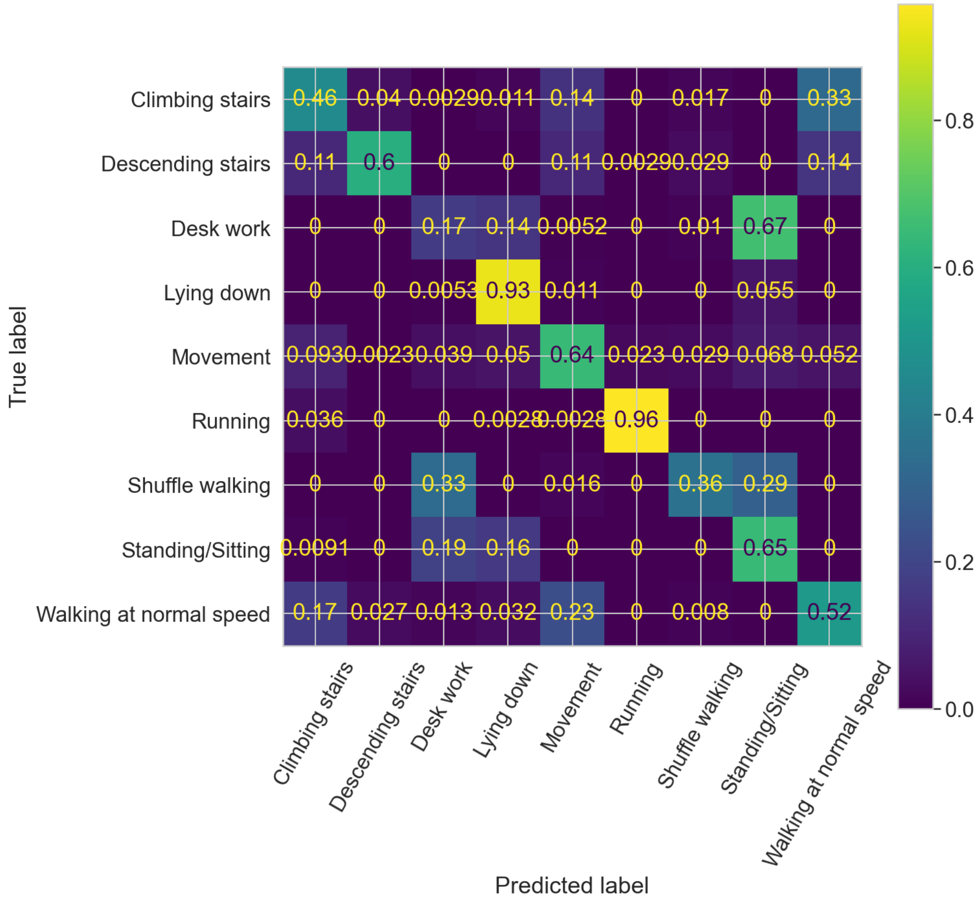

Figure 4.2: IsShuffle confusion matrix using 12.5Hz Acc data

consistent with our visual observations of the shuffle walking accelerometer data.

The best accuracy was achieved with 25Hz Acc+Gyro with window size 64 and the worst classification accuracy was achieved with 12.5Hz Acc with window size 32. The model in the first layer accurately identifies shuffle walking, and if the classification result is non-shuffle walking, then the original data is fed into the model in the second layer.

4.1.2 Second layer - IsWalk

In the second layer, Iswalk, the walking and non-walking states are separated. The walking states include running, regular walking, going up stairs and going down stairs. Walking is distinct from other human activities in that it has a strong periodicity. As a result, our classification accuracy increases when numerous walking cycles are covered inside a window. The experimental results illustrate this, with classification accuracy constantly rising from 32 to 64 window sizes.Since this is a binary classification task, our loss and activation functions are chosen to be more binary-friendly binary crossentropy and sigmoid functions.

Surprisingly, the addition of Gyroscope data resulted in a reduction in the accuracy of the walking classes. This indicates that the gyroscope is not required for walking

Model	Data	Window size	f1-score	Val Loss
CNN	25Hz Acc+Gyro	32	93.23%	0.1398
CNN+GRU	25Hz Acc+Gyro	32	96.66%	0.1229
CNN	25Hz Acc	32	93.37%	0.0655
CNN+GRU	25Hz Acc	32	95.37%	0.1251
CNN	12.5Hz Acc	16	94.43%	0.1258
CNN+GRU	12.5Hz Acc	16	95.00%	0.1322
CNN	25Hz Acc+Gyro	64	96.21%	0.1244
CNN+GRU	25Hz Acc+Gyro	64	97.81%	0.0896
CNN	25Hz Acc	64	97.21%	0.1154
CNN+GRU	**25Hz Acc**	**64**	**98.29%**	**0.0996**
CNN	12.5Hz Acc	32	95.86%	0.0916
CNN+GRU	12.5Hz Acc	32	97.87%	0.0786

Table 4.1: Classification accuracy and loss of each model on second layer

categories other than shuffle walking.

4.1.3 Third layer - FourTypeWalk

A four-class classifier in the final layer is deployed to classify different sorts of walks. It's worth noting that, because our step counting algorithm is identical for walking up and down stairs and for walking normally, the distinction between these three sorts of walks is irrelevant. We need establish a distinction between these three categories and running.

Model	Data	Window size	f1-score	Val Loss
CNN	25Hz Acc+Gyro	32	93.98%	0.1884
CNN+GRU	25Hz Acc+Gyro	32	94.45%	0.1424
CNN	25Hz Acc	32	95.12%	0.1721
CNN+GRU	25Hz Acc	32	95.37%	0.1251
CNN	12.5Hz Acc	16	93.12%	0.2423
CNN+GRU	12.5Hz Acc	16	95.00%	0.1322
CNN	25Hz Acc+Gyro	64	93.30%	0.2030
CNN+GRU	25Hz Acc+Gyro	64	95.65%	0.2820
CNN	25Hz Acc	64	94.95%	0.0952
CNN+GRU	**25Hz Acc**	**64**	**96.65%**	**0.0832**
CNN	12.5Hz Acc	32	94.43%	0.2815
CNN+GRU	12.5Hz Acc	32	95.65%	0.1762

Table 4.2: Classification accuracy and loss of each model on Third layer, CNN+GRU using 25Hz Acc with window size 64 is bolded as it is the best represented model.

Running and the other three kinds of walking are accurately classified, most likely because their frequencies are different.

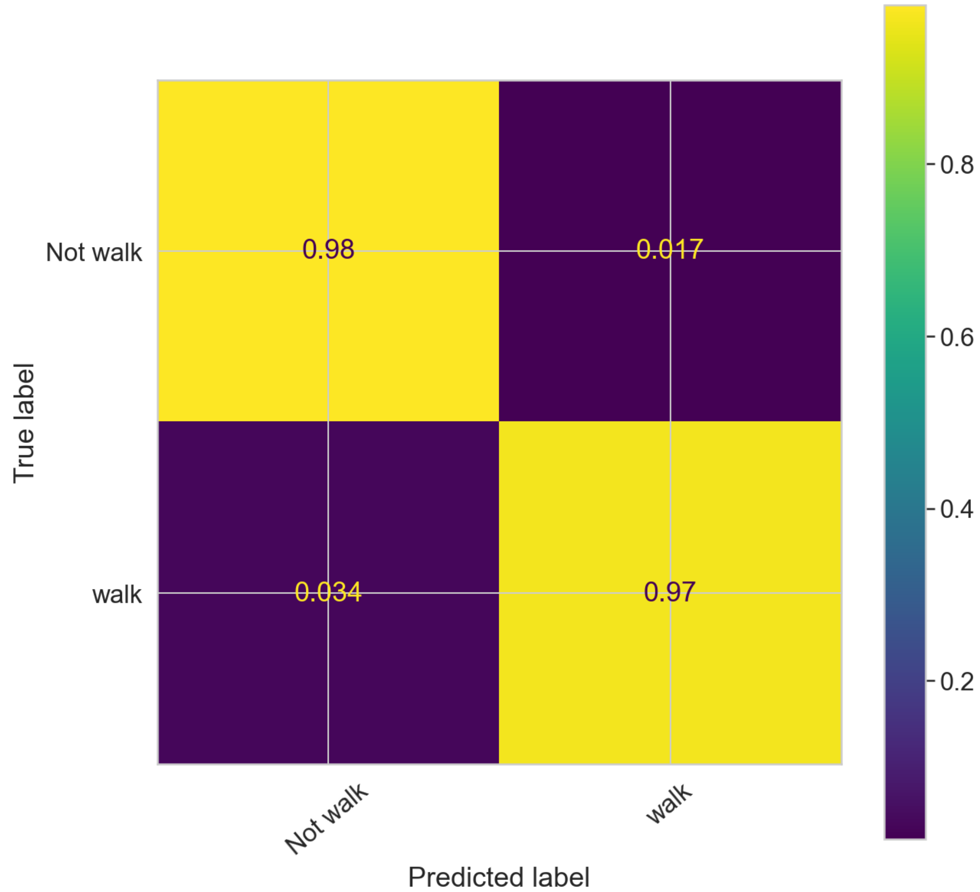

Figure 4.3: IsWalk confusion matrix using 25Hz CNN+GRU data with best performance,CNN+GRU using 25Hz Acc with window size 64 is bolded as it is the best represented model.

4.2 Step counting algorithm performance

4.2.1 Data for evaluating step counting algorithms

For each of the five types of walking, quantitative walking data were collected. Ten volunteers were asked to take 30 steps for each walking type. Data were collected using a 25Hz accelerometer and gyroscope. Again we compared 25Hz acceleration data, 12.5Hz acceleration data and 25Hz gyroscope data.

4.2.2 Results on Walking at normal speed, Climbing and Descending stairs

Firstly the accuracy is calculated by the following formula.

$$Accuracy = 1 - \frac{|Step_{detected} - 30|}{30} \tag{4.1}$$

A peak detection(PD) algorithm is applied and our proposed wavelet transform method(WT) on these 30 steps data. For Walking at normal speed, Climbing and Descending stairs,

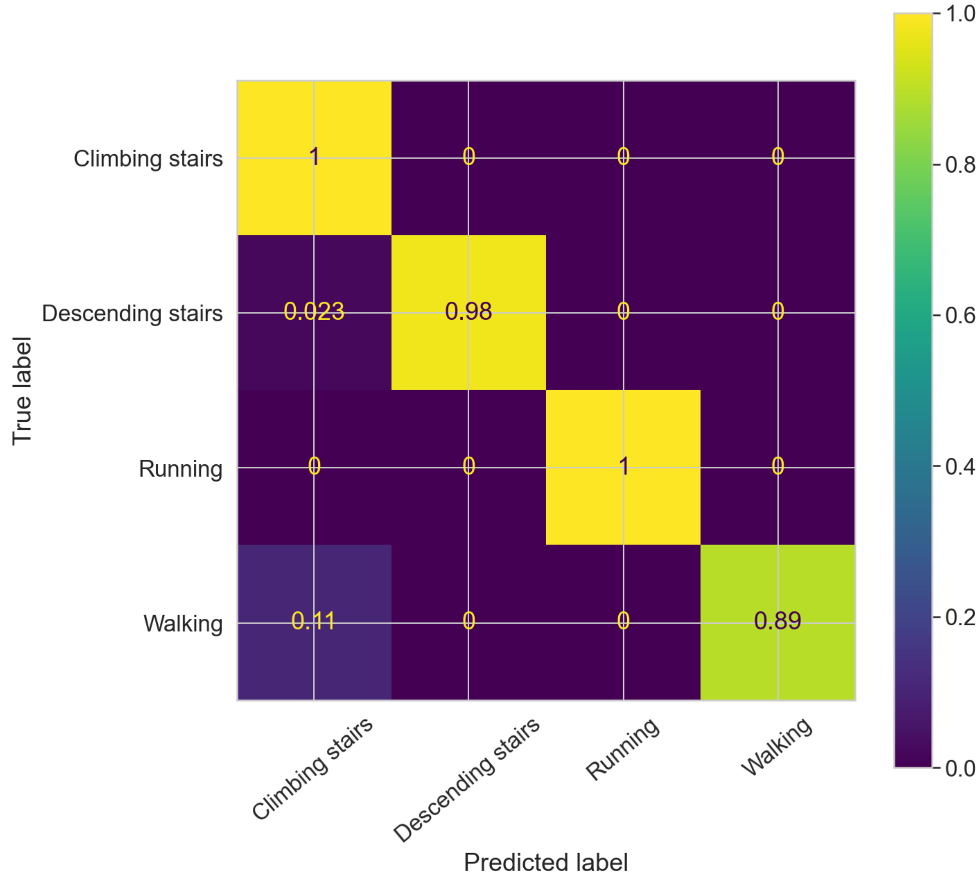

Figure 4.4: FourTypeWalk confusion matrix using 25Hz CNN+GRU data with best performance

PD algorithm has a minimum peak distance 12. This value is imperial and is set by predicting the frequency of the action. WT algorithm us a 4 level wavelet transform, it filters frequencies to a range of 0 to 1.56Hz. Similarly, climbing stairs and descending stairs has the same step counting algorithm parameters. We find that there is no significant difference between the gyroscope data and acceleration data for the two algorithms.

From the three tables, we can observe that our new proposed method, the WT algorithm, has very similar accuracy to the PD algorithm, which misses or overcounts steps. The WT algorithm, on the other hand, tends to undercount steps which means more false negative steps.

Our investigation found that our algorithm tends to count fewer steps when the highest frequency of the walk exceeds the frequency range of the fourth layer wavelet transform, which is 1.56. This means that we may be filtering out the frequencies that are most representative of walking activity.

For subject 2 in table4.3, subjects 7, 8 in table4.4 and subjects 3, 5, and 11 in table4.5, we reused the WT algorithm, using the wavelet transform in three layers (frequency range 0-3.12) and obtain results close to 30 steps.

subject ID	PD on Acc	PD on Gyro	WT on Acc	WT on Gyro
subject1	34	32	31	31
subject2	26	26	21	18
subject3	32	24	26	23
subject4	34	29	27	32
subject5	30	28	26	17
subject6	32	31	31	32
subject7	32	29	31	30
subject8	28	26	25	20
subject9	30	34	30	30
subject10	31	30	30	28
subject11	28	26	29	26
AVG Accuracy	0.9303	0.9121	0.9151	0.8393
STD	0.04595	0.0590	0.0857	0.1542

Table 4.3: Walking at normal speed

subject ID	PD on Acc	PD on Gyro	WT on Acc	WT on Gyro
subject1	28	27	28	23
subject2	34	31	29	25
subject3	31	32	30	26
subject4	37	34	34	32
subject5	34	36	33	31
subject6	32	27	24	20
subject7	26	26	21	24
subject8	27	33	21	28
subject9	31	29	28	20
subject10	34	35	33	34
AVG Accuracy	0.8933	0.8933	0.8933	0.8466
STD	0.04595	0.0573	0.0512	0.0956

Table 4.4: Climbing stairs

4.2.3 Results on Running

For Running, PD algorithm has a minimum peak distance 6. This value is imperial and is set by predicting the frequency of the action. WT algorithm us a 3 level wavelet transform, it filters frequencies to a range of 0 to 3.12Hz.

There is no significant difference between the gyroscope data and acceleration data for the two algorithms. In running, the WT algorithm has a higher accuracy than the PD algorithm. The high accuracy of the WT algorithm for the runs is that the ten running data we collected had the highest frequency points in the range of 2.66 to 2.99Hz, all in the frequency interval 0-3.12 Hz of the third layer wavelet transform. Therefore the WT algorithm can filter the noise sufficiently and retain the critical frequencies.

subject ID	PD on Acc	PD on Gyro	WT on Acc	WT on Gyro
subject1	29	28	26	19
subject2	25	26	27	26
subject3	27	27	21	21
subject4	32	29	24	26
subject5	23	21	23	20
subject6	33	30	27	28
subject7	30	31	30	29
subject8	32	31	29	33
subject9	34	32	30	29
subject10	34	35	32	30
subject11	31	30	23	25
AVG Accuracy	0.9030	0.9151	0.8727	0.8484
STD	0.0642	0.0845	0.0972	0.1217

Table 4.5: Descending stairs

subject ID	PD on Acc	PD on Gyro	WT on Acc	WT on Gyro
subject1	34	32	32	32
subject2	34	35	32	31
subject3	29	18	31	25
subject4	36	34	32	31
subject5	33	31	31	32
subject6	29	28	31	31
subject7	31	27	31	30
subject8	32	31	30	31
subject9	32	30	30	27
subject10	31	31	30	29
subject11	33	33	30	28
AVG Accuracy	0.9151	0.8969	0.9696	0.9151
STD	0.0519	0.1048	0.0264	0.0422

Table 4.6: Running

4.2.4 Results on Shuffle walking

For Shuffle walking, PD algorithm has a minimum peak distance 15. This value is imperial and is set by predicting the frequency of the action. WT algorithm us a 5 level wavelet transform, it filters frequencies to a range of 0 to 0.78Hz.WT's gyroscope data has the highest accuracy in shuffle walking, close to 80%. We can observe that WT has good results for shuffle walks where the highest frequencies are 0-0.78Hz. However, subjects 1, 2, 5 and 9 all have frequencies above 0.78Hz at the highest point, reaching around 1Hz. We performed a four-level wavelet transform frequency range of 0-1.56Hz on these data and obtained results for about 30 steps.

subject ID	PD on Acc	PD on Gyro	WT on Acc	WT on Gyro
subject1	26	26	19	20
subject2	28	28	17	19
subject3	41	46	32	32
subject4	47	48	34	35
subject5	29	28	15	18
subject6	51	50	34	34
subject7	35	38	29	30
subject8	42	38	30	31
subject9	21	28	14	15
subject10	39	39	32	32
AVG Accuracy	0.6966	0.7033	0.7733	0.7933
STD	0.2040	0.2172	0.1970	0.1685

Table 4.7: Shuffle walking

4.2.5 Conclusions of step counting algorithms result

The data above was originally tested at 25Hz, but we retested it at 12.5Hz. The outcomes were nearly comparable. The frequency with which data is sampled has little effect on either algorithm. It's worth mentioning that the PD algorithm's minimum peak distance has been halved, while the level of WT algorithm has been increased by one while testing.

Since the data collection process varies considerably in terms of the start pace and final pace subjects take, their patterns are not the same as those of the intermediate paces, which may cause bias. Also, as subjects press the start record button themselves during the data collection, some data may be long or short, including data from unrelated walks or end the recording early. For these reasons, the overall accuracy of our algorithm may be slightly lower than it is.

The critical data for step counting is the frequency of the data, which can alternatively be characterised as the walk's speed; the type of walk is irrelevant. Both PD and WT can be thought of as indirect methods for determining the final number of steps by frequency; PD uses the empirical minimum wave distance, whereas WT uses an FFT to obtain the highest frequency. Unfortunately, the FFT requires approximately 300 sampling points to determine the most representative frequency. As a result, we cannot conduct this in real-time step counting to calculate the walk's frequency.

The machine learning model's determination of the kind of walk is more akin to a forecast of the true frequency associated with the type of walk based on prior experience.

4.3 Practical results using Android App

To validate the system's practicality, we deployed the app for Android and compared the results to those obtained from commercial pedometers. TensorFlow exports our model to the Tflite format, which Kotlin can read. For faster development, we also use Python code in Android Studio via the Chaquopy package.

The chosen classifier was a CNN+GRU model that used accelerometer and gyroscope data and a 64-window length. Although the accuracy of using the accelerometer alone was higher in the two layers for recognizing walking, it was not significantly higher. In order not to increase the complexity of the system, we chose to use the gyroscope and accelerometer together. We get data from RESpeck and initiate categorization whenever a window is filled with data. We employed a half-overlapping window to reduce classification time, retaining the last 32 bits of the window after each classification, reducing classification time from 2.56 seconds to 1.28 seconds.

Following classification, we determine the appropriate step counting algorithm settings based on the classification results, which are different wavelet transform levels for the WT algorithm and different minimum peak distance for the PD algorithm.

Although categorization occurs every 1.28 seconds, we did not want our step counting method to run so frequently. Because if the user took ten steps continuously, separating it into a 1.28-second window would prevent us from capturing the total number of steps taken across both windows. Additionally, an excessive number of breakpoints would have an effect on our PD algorithm, leading it to count less steps.

As a result, we preserved both the present and prior activity states. If the categorization result indicated that the walk was always the same kind, we stored the data until the state changed. After the status change, we count the number of steps and empty the list where the walk data is stored.

In Algorithm 1 we show this process in pseudo-code.

When the pedometer function is enabled, the current step count is displayed prominently in the user interface. To facilitate testing, we have added a ’clear’ button that resets the counter to zero showed in figure4.5.

4.3.1 Comparison to consumer device

The accuracy is calculated by the following formula

$$Accuracy = 1 - \frac{|Step_{detected} - 200|}{200} \tag{4.2}$$

Performance should be compared to regular consumer pedometers. This section compares results of PD , WT, apple watch and health app. To be clear, we can only assess the run count accuracy RCA which only interested in the total number of steps counted, not in false positive or false negative since consumer pedometer algorithms are confidential.

The subjects were instructed to walk two hundred steps, walk 40 steps,run 40 steps, and shuffle walk 40 steps. They were also instructed to go upstairs, downstairs four times, ten steps each time. To ensure the classification algorithm’s robustness, the activity data from the subjects in this experiment were omitted from the training set.The Apple Watch is worn on the left wrist, while the phone is kept in the left trouser pocket. All participants were between the ages of 18 and 22, with three males and two females.

As can be seen from the experimental findings, Apple watch achieves the greatest results, while WT’s results on the 30-step data tend to count less steps. This is because,

Algorithm 1 Step counting using live data

```
Data: (xAcc, yAcc, zAcc, xGyro, yGyro, zGyro) ▷ *3 axis data send from RESpeck's
      acclermeter and gyroscope through Bluetooth
'window'                          ▷ *64*6 floatArray stores 3 axis data
'windowIndex' = 0                 ▷ *index of window
'WalkData'                        ▷ * floatArray stores walk data
Result: Counted steps             ▷ * Steps of a single continuous walking activaty
while Step counting function on do
    if windowIndex <= 378 then
        append (xAcc, yAcc, zAcc, xGyro, yGyro, zGyro) to window
        windowIndex += 6
    else
        currentState = HierarchicalClassification(window)
        if currentState != "Not walk" and lastState == "Not walk" then
            append window to WalkData
        end
        if currentState != "Not walk" and currentState == lastState then
            drop last 32 data of WalkData
            append window to WalkData
        end
        if currenState != "Not walk" and currentState != lastState and lastState !=
        "Not walk" then
            steps += countStepbystate(lastState,WalkData)
            WalkData.clear()
            append window to WalkData
            drop last 32 data of WalkData
        end
        if currentState == "Not walk" and lastState != "Not walk" then
            steps += CountStepbystate(lastState,WalkData)
            WalkData.clear()
        end
        lastState = currentState
        remove front half part in window
        move remain last half part in window to front
    end
end
```

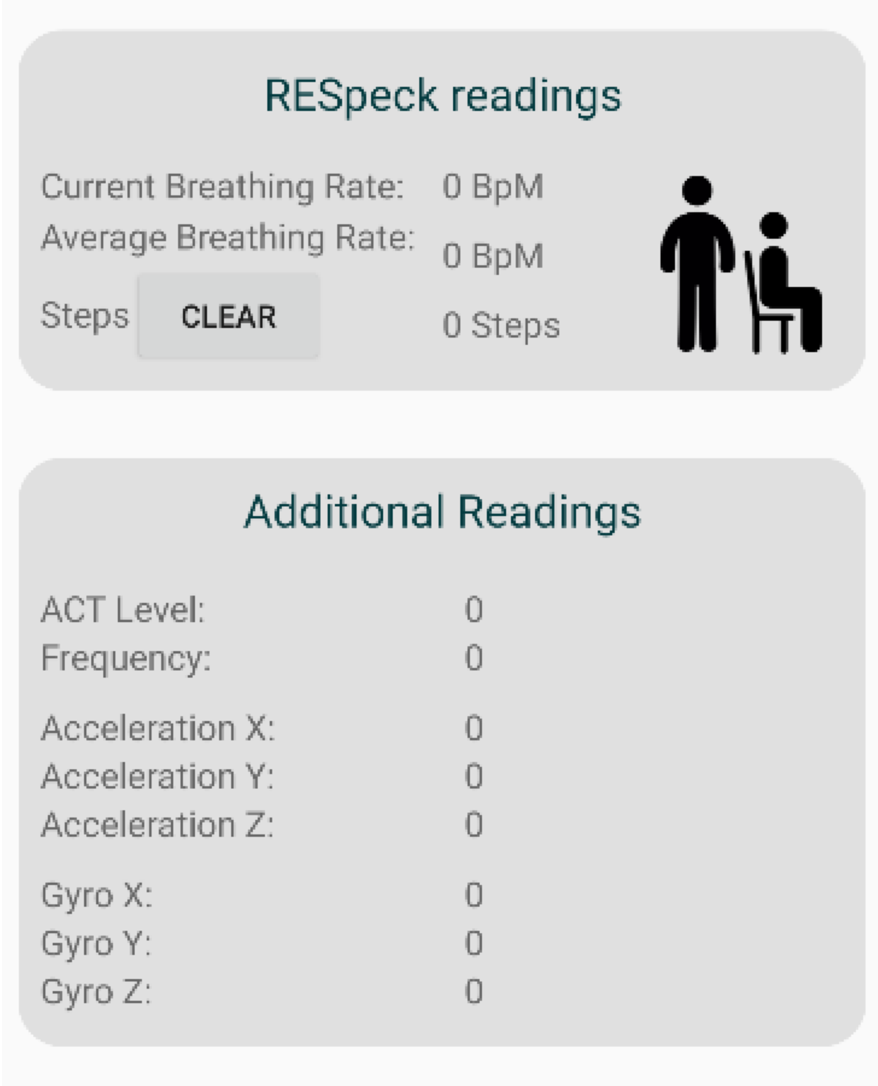

Figure 4.5: User interface

while the classification system can recognise activity as normal walking, walking at varying speeds and frequencies can result in step undercounting.

PD has an accuracy rate of 93.1 percent, which is quite good. Although our proposed WT is not as accurate as PD, we know from our study of frequency that frequency, and probably speed, is the most important component affecting step counting accuracy. This will aid us in our further research.

It's worth noting that while PD and WT show comparable accuracy on 30-step data, with WT being slightly more accurate, WT is 5% less accurate on 200-step data than PD. This is because PD counts fewer steps when walking quickly and more steps when walking slowly. Thus, when we reach 200, the false positive and false negative steps cancel out; as a result, the PD has a high accuracy rate. However, if the walking frequency is within the frequency range of a certain wavelet transformation level, WT will produce a very accurate result. When the walking frequency exceeds the specified range of wavelet transform layers, however, WT returns a smaller number of steps.

subject ID	PD on Android	WT on Android	Apple watch	Steps app
subject1	211	169	201	233
subject2	197	188	194	231
subject3	194	166	192	222
subject4	218	172	222	223
subject5	231	179	211	221
AVG Accuracy	0.9310	0.8879	0.9520	0.8699
STD	0.0542	0.0541	0.0350	0.0248

Table 4.8: Comparison to Consumer Device

Thus, PD is more accurate when the overall number of steps is considered rather than the precision of each individual step.

Chapter 5

Conclusions

5.1 Discussion

We constructed an end to end pedometer system and compared the accuracy of various step counting algorithms in this work. Our system comprises two components: the first is a walk classification method, and the second is a step counting algorithm. Our initial, intuitive solution was to apply step counting algorithms with different thresholds for different types of walking. However, we discovered through experimentation that the specific kind of walk does not affect the step counting problem or that the type of walk is merely an expression of walking frequency. A high-frequency walk is referred to as a run, a moderate frequency walk is referred to as walking, going up and downstairs, and a low-frequency walk is referred to as shuffle walking. Calculating the number of steps accurately is highly dependent on the frequency of walking. Therefore, to keep better track of steps, we should classify walking activities according to their frequency rather than simply using literal expressions. As a result, we can distinguish only between walking and non-walking activities. Machine learning approaches can then be used to predict the frequency.

For a better generalization ability, a complete research should take into account a wide number of participants with varying genders, ages, heights, weights, and health status. This is to ensure that new users may be supported without the requirement for extra training data collection. However, for a variety of objective reasons, the data for this work is mostly collected from the age range of 19 to 23 years. Although they were instructed to mimic an elderly person's walking pattern, the outcome may still vary from the real scenario. Therefore, to further improve the system's robustness, it is essential to gather more data from diverse age, height, weight, and gender groups. At the same time, dataset should maintain a balance in the quantity of data collected for each group to avoid deep learning model from producing bias.

We observe that our newly proposed approach for computing wave crests following wavelet transform has a high accuracy while its frequency is in the n-th level wavelet transform range. However, because each person's walking patterns vary, even for the same type of walking, their frequency domain peaks may be in two levels of the wavelet decomposition. If we apply a higher level wavelet transformation on a frequency lower than its peak, our algorithm will calculate fewer steps. Therefore, in future work, we might convert the classification results of deep learning classifiers to regression models to determine walking frequencies.

5.2 Future work

In essence, shuffle walking, walking, and running are all variations in speed, proportional to frequency. As the frequency domain peaks for ascending and descending stairs and walking are identical, we can utilise the same level in the wavelet decomposition. Given that our ultimate goal is to get steps, accurately classifying walking styles is not the primary objective. As a result, once the second layer of the model has identified the state as walking, the third layer can no longer focus on the specific type of walking. Instead, training a regression model to estimate the walking frequency and thus choose the appropriate number of wavelet transform levels to achieve accurate step counting. We may perform an FFT on all the walk data and use the frequency domain peak as the model's y-value.

Another idea is to acquire step counts using deep learning models. Lin's approach involved collecting walking data and labelling a timeline based on recorded movies, denoting when each foot touched the ground as a step[24]. He and his team manually labelled 60,820 actual steps in their work and achieved an accuracy of 86 percent. This approach was initially adopted, but it was too time-consuming to track the number of steps, and the deep learning model required excessive data to train, so the approach is abandoned. However, we can now utilise the proposed method to automatically mark the number of steps, eliminating the time spent manually recording the data.

Bibliography

[1] D. K. Arvind, D. J. Fischer, C. A. Bates, and Sanjay Kinra. Characterisation of breathing and physical activity patterns in the general population using the wearable respeck monitor. In *BODYNETS*, 2019.

[2] Sikha Bagui, Xingang Fang, Subhash Bagui, Jeremy Wyatt, Patrick Houghton, Joe Nguyen, John Schneider, and Tyler Guthrie. An improved step counting algorithm using classification and double autocorrelation. *International Journal of Computers and Applications*, pages 1–10, 2020.

[3] Oresti Banos, Juan-Manuel Galvez, Miguel Damas, Hector Pomares, and Ignacio Rojas. Window size impact in human activity recognition. *Sensors*, 14(4):6474–6499, 2014.

[4] Oresti Banos, Rafael Garcia, Juan A Holgado-Terriza, Miguel Damas, Hector Pomares, Ignacio Rojas, Alejandro Saez, and Claudia Villalonga. mhealthdroid: a novel framework for agile development of mobile health applications. In *International workshop on ambient assisted living*, pages 91–98. Springer, 2014.

[5] Pierre Barralon, Nicolas Vuillerme, and Norbert Noury. Walk detection with a kinematic sensor: Frequency and wavelet comparison. In *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 1711–1714. IEEE, 2006.

[6] Billur Barshan and Murat Cihan Yüksek. Recognizing daily and sports activities in two open source machine learning environments using body-worn sensor units. *The Computer Journal*, 57(11):1649–1667, 2014.

[7] Yoshua Bengio. Deep learning of representations: Looking forward. In *International conference on statistical language and speech processing*, pages 1–37. Springer, 2013.

[8] Claude Bouchard, Steven N Blair, and William L Haskell. *Physical activity and health*. Human Kinetics, 2012.

[9] Agata Brajdic and Robert Harle. Walk detection and step counting on unconstrained smartphones. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 225–234, 2013.

[10] Agata Brajdic and Robert Harle. Walk detection and step counting on unconstrained smartphones. In *Proceedings of the 2013 ACM International Joint Con-*

ference on Pervasive and Ubiquitous Computing, UbiComp '13, page 225–234, New York, NY, USA, 2013. Association for Computing Machinery.

[11] Dena M. Bravata, Crystal Smith-Spangler, Vandana Sundaram, Allison L. Gienger, Nancy Lin, Robyn Lewis, Christopher D. Stave, Ingram Olkin, and John R. Sirard. Using Pedometers to Increase Physical Activity and Improve HealthA Systematic Review. *JAMA*, 298(19):2296–2304, 11 2007.

[12] Andreas Bulling, Ulf Blanke, and Bernt Schiele. A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys (CSUR)*, 46(3):1–33, 2014.

[13] Diane Cook, Kyle D Feuz, and Narayanan C Krishnan. Transfer learning for activity recognition: A survey. *Knowledge and information systems*, 36(3):537–556, 2013.

[14] F Foerster, M Smeja, and J Fahrenberg. Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring. *Computers in Human Behavior*, 15(5):571–583, 1999.

[15] Teodora Georgescu. Project title. https://github.com/specknet/pdiot-practical/blob/master/Labs/Week%201%20Lab.md, 2013.

[16] Pragun Goyal, Vinay J Ribeiro, Huzur Saran, and Anshul Kumar. Strap-down pedestrian dead-reckoning system. In *2011 international conference on indoor positioning and indoor navigation*, pages 1–7. IEEE, 2011.

[17] Yuya Hanai, Jun Nishimura, and Tadahiro Kuroda. Haar-like filtering for human activity recognition using 3d accelerometer. In *2009 IEEE 13th digital signal processing workshop and 5th IEEE signal processing education workshop*, pages 675–678. IEEE, 2009.

[18] Zhen-Yu He and Lian-Wen Jin. Activity recognition from acceleration data using ar model representation and svm. In *2008 international conference on machine learning and cybernetics*, volume 4, pages 2245–2250. IEEE, 2008.

[19] Tâm Huynh and Bernt Schiele. Analyzing features for activity recognition. In *Proceedings of the 2005 joint conference on Smart objects and ambient intelligence: innovative context-aware services: usages and technologies*, pages 159–163, 2005.

[20] Mordor Intelligence. North america smart watch market: 2022 - 27: Industry share, size, growth - mordor intelligence.

[21] Minsoo Kang, Simon J Marshall, Tiago V Barreira, and Jin-Oh Lee. Effect of pedometer-based physical activity interventions: a meta-analysis. *Research quarterly for exercise and sport*, 80(3):648–655, 2009.

[22] Tzu-Ping Kao, Che-Wei Lin, and Jeen-Shing Wang. Development of a portable activity detector for daily activity recognition. In *2009 ieee international symposium on industrial electronics*, pages 115–120. IEEE, 2009.

[23] Justin J Kavanagh and Hylton B Menz. Accelerometry: a technique for quantifying movement patterns during walking. *Gait & posture*, 28(1):1–15, 2008.

[24] Basil Lin. Machine learning and pedometers: An integration-based convolutional neural network for step counting and detection.

[25] Jani Mantyjarvi, Mikko Lindholm, Elena Vildjiounaite, S-M Makela, and HA Ailisto. Identifying users of portable devices from gait pattern with accelerometers. In *Proceedings.(ICASSP'05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005.*, volume 2, pages ii–973. IEEE, 2005.

[26] Aleksandr Ometov, Viktoriia Shubina, Lucie Klus, Justyna Skibińska, Salwa Saafi, Pavel Pascacio, Laura Flueratoru, Darwin Quezada Gaibor, Nadezhda Chukhno, Olga Chukhno, Asad Ali, Asma Channa, Ekaterina Svertoka, Waleed Bin Qaim, Raúl Casanova-Marqués, Sylvia Holcer, Joaquín Torres-Sospedra, Sven Casteleyn, Giuseppe Ruggeri, Giuseppe Araniti, Radim Burget, Jiri Hosek, and Elena Simona Lohan. A survey on wearable technology: History, state-of-the-art and current challenges. *Computer Networks*, 193:108074, 2021.

[27] Juha Parkka, Miikka Ermes, Panu Korpipaa, Jani Mantyjarvi, Johannes Peltola, and Ilkka Korhonen. Activity classification using realistic data from wearable sensors. *IEEE Transactions on information technology in biomedicine*, 10(1):119–128, 2006.

[28] Sreenivasan Ramasamy Ramamurthy and Nirmalya Roy. Recent trends in machine learning for human activity recognition—a survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(4):e1254, 2018.

[29] Sasank Reddy, Min Mun, Jeff Burke, Deborah Estrin, Mark Hansen, and Mani Srivastava. Using mobile phones to determine transportation modes. *ACM Transactions on Sensor Networks (TOSN)*, 6(2):1–27, 2010.

[30] Attila Reiss and Didier Stricker. Introducing a new benchmarked dataset for activity monitoring. In *2012 16th international symposium on wearable computers*, pages 108–109. IEEE, 2012.

[31] Caroline R Richardson, Tiffany L Newton, Jobby J Abraham, Ananda Sen, Masahito Jimbo, and Ann M Swartz. A meta-analysis of pedometer-based walking interventions and weight loss. *The Annals of Family Medicine*, 6(1):69–77, 2008.

[32] Daniel Roggen, Kilian Forster, Alberto Calatroni, Thomas Holleczek, Yu Fang, Gerhard Troster, Alois Ferscha, Clemens Holzmann, Andreas Riener, Paul Lukowicz, et al. Opportunity: Towards opportunistic activity and context recognition systems. In *2009 IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks & Workshops*, pages 1–6. IEEE, 2009.

[33] UkJae Ryu, Kyungho Ahn, Entae Kim, Munhae Kim, Boyeon Kim, Sunghun Woo, and Yunseok Chang. Adaptive step detection algorithm for wireless smart step counter. In *2013 International Conference on Information Science and Applications (ICISA)*, pages 1–4. IEEE, 2013.

[34] Jungryul Seo, Yutsai Chiang, Teemu H Laine, and Adil M Khan. Step counting on smartphones using advanced zero-crossing and linear regression. In *Proceedings*

of the 9th International Conference on Ubiquitous Information Management and Communication, pages 1–7, 2015.

[35] Jordi Sorribas. *Gait Analysis using the wearable Respeck monitor*. 2019.

[36] Alper Tokgöz and Gözde Ünal. A rnn based time series approach for forecasting turkish electricity load. In *2018 26th Signal Processing and Communications Applications Conference (SIU)*, pages 1–4. IEEE, 2018.

[37] Warren W Tryon. *Activity measurement in psychology and medicine*. Springer Science & Business Media, 2013.

[38] Martin Vetterli and Jelena Kovacevic. *Wavelets and subband coding*. Number BOOK. Prentice-hall, 1995.

[39] Gaojing Wang, Qingquan Li, Lei Wang, Wei Wang, Mengqi Wu, and Tao Liu. Impact of sliding window length in indoor human motion modes and pose pattern recognition based on smartphone sensors. *Sensors*, 18(6):1965, 2018.

[40] Jian-Hua Wang, Jian-Jiun Ding, Yu Chen, and Hsin-Hui Chen. Real time accelerometer-based gait recognition using adaptive windowed wavelet transforms. In *2012 ieee asia pacific conference on circuits and systems*, pages 591–594. IEEE, 2012.

[41] Mi Zhang and Alexander A Sawchuk. Usc-had: a daily activity dataset for ubiquitous activity recognition using wearable sensors. In *Proceedings of the 2012 ACM conference on ubiquitous computing*, pages 1036–1043, 2012.

Appendix A

Data Compliance and documentation

A.1 Data complicance

All the data that it is used in this project has been collected with the RESpeck device. Given that this work involves data recorded with the RESpeck developed in the Centre for Spleckled Computing a Non-Disclose Agreement (NDA) was needed. The NDA was signed between the recipient (me) and the discloser (Professor DK K Arvind) on the 22th of February of 2021. The template of the NDA can be found next. The Participants' information sheet and Participants' consent form are listed below too.

Non-Disclosure Agreement for sharing of programs and data-sets

Date: **22 February 2021**

Parties:

Name:

Address:

(the Recipient)

and

Professor D K Arvind, Centre for Speckled Computing, School of Informatics, University of Edinburgh, Scotland, U.K.

(the Discloser)

1. The Discloser intends to disclose information in the form of electronic programs and datasets (the Confidential Information) to the Recipient for the purpose of undertaking work as part of their Masters project (the Purpose).

2. The Recipient undertakes not to use the Confidential Information for any purpose except the Purpose, without first obtaining the written agreement of the Discloser.

3. The Recipient undertakes to keep the Confidential Information secure and not to disclose it to any third party, who know they owe a duty of confidence to the Discloser and who are bound by obligations equivalent to those in clause 2 above and this clause 3.

4. The undertakings in clauses 2 and 3 above apply to all of the information disclosed by the Discloser to the Recipient, regardless of the way or form in which it is disclosed or recorded but they do not apply to:

   a) any information which is or in future comes into the public domain (unless as a result of the breach of this Agreement); or

b) any information which is already known to the Recipient and which was not subject to any obligation of confidence before it was disclosed to the Recipient by the Discloser.

5. Nothing in this Agreement will prevent the Recipient from making any disclosure of the Confidential Information required by law or by any competent authority.

6. The Recipient will, on request from the Discloser, return all copies and records of the Confidential Information to the Discloser and will not retain any copies or records of the Confidential Information.

7. Neither this Agreement nor the supply of any information grants the Recipient any licence, interest or right in respect of any intellectual property rights of the Discloser except the right to copy the Confidential Information solely for the Purpose.

8. The undertakings in clauses 2 and 3 will continue in force indefinitely.

9. This Agreement is governed by, and is to be construed in accordance with, Scottish law. The Scottish courts will have non-exclusive jurisdiction to deal with any dispute which has arisen or may arise out of, or in connection with, this Agreement.

Signed and Delivered as a Deed by:

Name:

Shuai Shi

____
Signature

in the presence of:

____
Signature of witness

____
Name of witness

Participant Information Sheet

Project title:	Classification of Physical Activities and Social Signals using a wearable Respeck monitor
Principal investigator:	D.K. Arvind
Researcher collecting data:	Celina Dong/ Stylianos Charalampous/ Shuai Shi Teodora Georgescu

This study was certified according to the Informatics Research Ethics Process, RT number 2019/27996. Please take time to read the following information carefully. You should keep this document for your records.

Who are the researchers?

The three students, Celina Dong, Stylianos Charalampous and Shuai Shi, will collect data as part of their undergraduate projects. They are all 4th/5th year Masters in Informatics students at the School of Informatics, University of Edinburgh.

The main researcher is Teodora Georgescu, a Research Associate at the School of Informatics, University of Edinburgh. Other researchers involved in the project include Andrew Bates and Sharan Maiya who will provide technical support during data collection. The project is being supervised by Professor D K Arvind as the Principal Investigator, under the aegis of the Centre for Speckled Computing, University of Edinburgh.

What is the purpose of the study?

The aim of the project is to identify physical activity and social signals in people by analysing data from the Respeck monitor worn as a plaster on their chest. Examples include walking, running and climbing stairs for physical activities, and social signals such as coughing, speaking and swallowing (due to eating or drinking). You will be invited to wear the Respeck device as a plaster on the chest and perform instances of the examples listed previously. You will be filmed during one part of the data collection for the purpose of correct data labelling – in the post-processing part of your data we will use the video as a guide to correctly label the data with the appropriate activities you performed. Your data will be collected and added to a mix of similar data collected from other volunteers which will be analysed to classify accurately the different activities. The labelled data collected will be used to train machine learning models trained to distinguish accurately between them.

Why have I been asked to take part?

You have been invited to take part in this study because you are either a student at the University of Edinburgh, or because you belong to an age group that our research is interested in.

Do I have to take part?

No – participation in this study is entirely up to you. You can withdraw from the study at any time without giving a reason. After this point, personal data will be deleted and anonymised data will be combined such that it is impossible to remove individual information from the analysis. Your rights will not be affected. If you wish to withdraw, contact the PI. We will keep copies of your original consent, and of your withdrawal request.

What will happen if I decide to take part?

You will be invited to wear the Respeck device encased in a small disposable bag with the blue, flat surface against the skin just below your ribcage and secured to your chest with the medical tape provided.

Please ensure the device is the right way up, i.e. you can read the text on the flat side of the device.

A mobile phone with a specially designed application will automatically collect data from the Respeck device.

You will be asked to perform a series of gentle activities as listed below. The optional activities will be only be administered for the students,

Physical activities:

- Sitting down (straight, bent forward, bent backward)
- Standing up
- Lying down (back, front, left, right)
- Walking at three different speeds (slow, medium and fast)

- Ascend/Descend a set of stairs
- (Optional) Wear when travelling in a bus/car/train
- (Optional) Riding a bike
- Moving your body at the waist from left to right and repeat 5 times.
- Swinging your body to the front and back and repeat 5 times
- Running

Social signals:

- Coughing
- Talking
- Eating/Drinking
- Singing
- Laughing
- Breathing normally
- Hyperventilating

You might be asked to perform some of these activities at the same time, such as coughing when you are lying down. The intensity of these activities will be adjusted to your comfort level. Each activity and social signal will be recorded for at least 30 seconds, and tiring activities, such as forced coughing, will be divided into shorter segments of 10-15 seconds of continuous coughing.

For the second part of the data collection, you will be asked to perform a sequence of activities, uninterrupted, in order to simulate the real data we might be getting from Respeck wearers. During this time you will also be filmed using a simple phone camera operated by the data collector. We ask for your permission to film you so that, in the post-processing phase of the collection, we can accurately label the actions you performed.

At any point in time, if you feel that you do not wish to continue with the study, then please feel free to let me know and the study will be stopped immediately.

Are there any risks associated with taking part?

You'll be invited to wear the Respeck device which has undergone the necessary safety tests. Participants with known plaster/plastic allergy will be excluded. The device is enclosed in a disposable plastic bag and is not in direct contact with the skin. The Respeck device is cleaned and sterilised once returned. There are no significant risks associated with participation. The researchers will maintain at least 2m social distance and will wear masks and safety visor.

Are there any benefits associated with taking part?

No.

What will happen to the results of this study?

The results of this study may be summarised in published articles, reports and presentations. Quotes or key findings will always be anonymous. With your consent, information can also be used for future research. Your data may be archived for a minimum of 5 years.

With your consent, the research team might share the fully anonymised data of this study with other researchers outside of the University of Edinburgh as part of publications.

Data protection and confidentiality.

Your sensor data will be processed in accordance with Data Protection Law. All information collected about you will be kept strictly confidential. Your data will be referred to by a unique participant number rather than by name.

Your sensor data will only be viewed by the research team: Teodora Georgescu, Andrew Bates and Professor D K Arvind for this project. Your anonymised data may be used in other ethically approved research projects supervised by Professor D K Arvind or be made available to other researchers outside of the University of Edinburgh as part of publications. By signing the consent form, you agree to such usage.

Summaries of the anonymised sensor data is stored on the University's secure encrypted cloud storage services *datasync* (https://www.ed.ac.uk/information-services/computing/desktop-personal/datasync), for which the research team has writing access and MInf and Year 4 project students supervised by Professor Arvind will have reading access. We only store summaries of accelerometer data, and not personal information such as name, age or address.

Your consent information will be kept separately from your responses in order to minimise risk.

What are my data protection rights?

The University of Edinburgh is a Data Controller for the information you provide. You have the right to access information held about you. Your right of access can be exercised in accordance Data Protection Law. You also have other rights including rights of correction, erasure and objection. For more details, including the right to lodge a complaint with the Information Commissioner's Office, please visit www.ico.org.uk. Questions, comments and requests about your personal data can also be sent to the University Data Protection Officer at dpo@ed.ac.uk.

Who can I contact?

If you have any further questions about the study, please contact Teodora Georgescu (tgeorges@ed.ac.uk).

If you wish to make a complaint about the study, please contact:
Professor D K Arvind (dka@inf.ed.ac.uk) or the Informatics Ethics Panel (inf-ethics@inf.ed.ac.uk).

When you contact us, please provide the study title and detail the nature of your complaint.

Updated information.

If the research project changes in any way, an updated Participant Information Sheets will be made available on request from Teodora Georgescu (tgeorges@ed.ac.uk).

Alternative formats.

To request this document in an alternative format, such as large print or on coloured paper, please contact Teodora Georgescu (tgeorges@ed.ac.uk).

General information.

For general information about how we use your data, go to: edin.ac/privacy-research

Participant number:______________________

Participant Consent Form

Project title:	Classification of Physical Activities and Social Signals using a wearable Respeck monitor
Principal investigator (PI):	D.K. Arvind
Researcher:	Celina Dong/ Stylianos Charalampous/Shuai Shi/ Teodora Georgescu
PI contact details:	dka@inf.ed.ac.uk

By participating in the study you agree that:

- I have read and understood the Participant Information Sheet for the above study, that I have had the opportunity to ask questions, and that any questions I had were answered to my satisfaction.
- My participation is voluntary, and that I can withdraw at any time without giving a reason. Withdrawing will not affect any of my rights.
- I consent to my anonymised data being used in academic publications and presentations.
- I understand that my anonymised data will be stored for the duration outlined in the Participant Information Sheet.

Please tick yes or no for each of these statements.

1. I agree to my physical activity being recorded using the Respeck monitor.

Yes **No**

2. I agree to being video recorded.

Yes **No**

3. I allow my data to be used in future ethically approved research.

Yes **No**

4. I agree to take part in this study.

Yes **No**

Name of person giving consent	Date dd/mm/yy	Signature

Name of person taking consent	Date dd/mm/yy	Signature

THE UNIVERSITY *of* EDINBURGH informatics