WearRF: Hybrid Sensing for Fatigue Detection Using Wearables and RF

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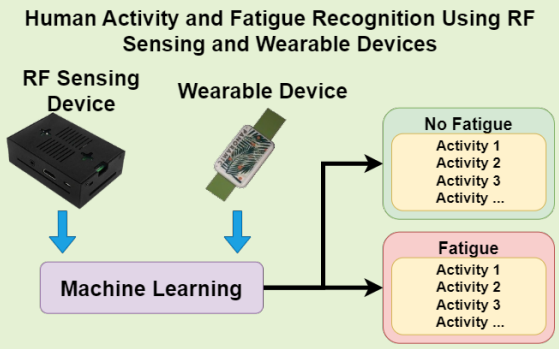
***Abstract*—In the field of smart healthcare, wearable and sensing devices are connected to the Internet of Things (IoT) to assess patients within their own homes. Fatigue is a multidimensional experience that can be characterised by exhaustion and reduced physical performance. Monitoring people within their homes to detect slower pace could be a promising method to objectively measure aspects of human fatigue. This paper makes use of both a wearable bracelet and Radio Frequency (RF) sensing to detect simulated fatigue from human activity monitoring. Different activities are collected at a normal pace to represent no fatigue and then repeated at a slower pace to represent fatigue. Artificial intelligence (AI) is used to detect if there is fatigue present or not regardless of activity taking place as well as identifying which activity took place and if fatigue is present in said activity. When using the data from both the bracelet and RF sensing, Random Forest and ResNet algorithms achieved 100 % in detecting fatigue as opposed to non-fatigue using algorithms. When using only the bracelet, only the Random Forest algorithm was able to achieve 100 % accuracy. Using only RF data, 94.80 % accuracy was achieved with a Convolutional Neural Network (CNN). When detecting individual activities with fatigue and no fatigue, the Random Forest algorithm achieved an accuracy score of 97.40 % using both the bracelet and RF sensing and with only the bracelet data. CNN was again the best algorithm for RF sensing only with an accuracy score of 89.84 %.**



***Index Terms*—Smart healthcare, Fatigue Detection, RF Sensing, Wearables, Artificial intelligence,**

I. Introduction

The implementation of the Internet of Things (IoT) has become more widespread due to improvements in sensor technology, wireless communications, and data analysis. Smart healthcare is the concept of using IoT devices for remote patient healthcare within the home [1]. IoT has provided effective diagnostic testing and patient monitoring within the healthcare sector [2]. IoT devices such as smart watches can provide monitoring of fatigue. Fatigue is a multidimensional symptom which is under-researched and poorly defined [3]. One common working definition of fatigue is an "overwhelming feeling of sustained exhaustion that is debilitating and interferes with an individual's ability to function and perform activities" [4]. Cognitive and subjective experiences of fatigue are typically measured by self-report. Measuring the initiation and sustainability of voluntary activities can also be useful in characterising physical manifestations of fatigue. Despite its prevalence, clinical treatments for fatigue are lacking, and management is often by trial and error. Digital sensors could add value in clinical trials of investigational medicines [5]. Self-management strategies for fatigue often involve "pacing" or carefully managing activity levels to conserve energy [6]. Being able to identify and monitor patterns of activities could inform self-management strategies. Fatigue also has a strong correlation with the risk of falls particularly with older individuals [7]. IoT-enabled smart healthcare can be used for the detection of falling events [8]. Falling has a mortality risk, therefore there is value in fall prevention techniques. Artificial intelligence (AI) can be regarded as the main underlying component of IoT sensing [9]. The information from the sensors must be interpreted so that decisions can be made on what type of activity has occurred [10]. This paper looks at using sensors with AI to detect several activities and if fatigue is present in these activities. This paper makes use of a traditional wearable device that contains multiple sensors that reflect the movements of the individual wearing the device and compares the data to a contactless monitoring system. Wearable devices have the advantage of being very accurate in detecting motion however they do have some disadvan-

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tages such as battery life and related to the healthcare of older individuals is potential preexisting issues with memory resulting in the individual forgetting to wear the device [11, 12]. Contactless sensing removes the need for devices to be charged and worn. Contactless sensing however suffers from lower accuracy than wearable devices due to a disconnect from the body and more emphasis on sensing the environmental changes caused by human motion [12]. The wearable device used in this paper is the Panoramic Digital Health activity bracelet [13]. Low Power (LP) accelerometer; High Energy (HE) accelerometer, Gyroscope, Magnetometer, and Pressure sensors are contained within the bracelet. While collecting data using the bracelet, the contactless sensing method is run in parallel. For contactless sensing, this paper implements Radio Frequency (RF) sensing. RF sensing works on the concept that as a wireless signal is travelling from the transmitter device to the receiver device, any movement occurring in between the signal will affect how that signal propagates through the wireless medium [14]. The information on how the RF signal travels from the transmitter to the receiver is described in the Channel State Information (CSI) [15]. The CSI contains the amplitude and the phase of a received RF signal [16]. This paper will make use of the amplitude of the RF signal as this shows prominent changes when movement occurs between the transmitter and receiver. An example of RF sensing is making use of ambient Wi-Fi traffic which is already present in many homes to perform a sensing function by observing the CSI of the received Wi-Fi signal [17]. This paper will use 2.4 GHz Wi-Fi to perform the RF sensing. AI can be used to train models to classify unseen testing data. This paper aims to compare the wearable and RF sensing activity detection methods to detect fatigue in a person. Data is collected for 7 activities namely ”Walking”, ”Stand from Chair”, ”Sit on Chair”, ”Stand from Bed”, ”Sit on Bed”, ”Get out of Bed” and ”Get into Bed”. These activities were collected while performing normally and then performed slowly to mimic fatigue. All activities were collected by a single healthy subject. Experimentation of this data will show if AI models can identify different activities and between fatigue and non-fatigue from the multiple sensor data.

II. Related Work

There have been many previous works looking at the use of wearable technology and contactless technology to detect human movements. This section looks at works which are related to this paper.

The work of [18] made use of an identification and sensing platform to read data from a triaxial accelerometer wearable sensor. The dataset consisted of 14 volunteers performing four activities. The four activities were collected in a single room and consisted of sitting on a bed, lying, walking and sitting on a chair. These activities are also used in the experiments of this paper. A Convolutional Neural Network (CNN) was used to classify the dataset and it produced an accuracy result of 98.37 %. In the work of [19], Inertial Measurement Unit (IMU) sensors were used to detect fatigue in 24 participants using a treadmill. There were 4 levels of fatigue measured. Creating four labels of low, medium, high and very high fatigue. To create fatigue the treadmill was set to a speed which caused the participant to display higher levels of effort thus slowing down their running speed. Similar to the work of this paper where activities are performed at a slower pace to simulate fatigue. The Random Forest algorithm was used to classify the IMU data and reached an accuracy score of 94 %. Fatigue can be observed by looking at motion, electroencephalogram (EEG), electrocardiogram (ECG) and respiratory data [20]. The work of [21] looks at observing the ECG and facial features to detect fatigue using a contactless system. The contactless system is an off-the-shelf radar system with ECG and a camera used for ground truth. The experiment had 3 labels consisting of alert, minor fatigue and severe fatigue. The results of the paper achieved an accuracy of 81.4 % by using the Support Vector Machine (SVM) machine learning algorithm. The work of [22] made use of a purpose-built Emerald system which works similarly to a low-power radar. The device was used to detect Parkinson’s disease from gait speed over long-term monitoring There have been many publications on using CSI to detect human movements [23, 24] and breathing rates [25, 26]. CSI has been used to detect fatigue in the application of driver fatigue. The paper [27] system works by detecting human activities within a car environment with activities such as repeated yawning, head itching, face scratching, and head nodding as indicators of fatigue. CSI has also been used to detect movements during sleep which would indicate rhythmic movement disorder which can cause daytime fatigue [28]. This paper seeks to address a gap in the literature when related to fatigue detection within a home environment and to see if there is a gradual decline in human motion. This paper also compares RF sensing results to results achieved when using a wearable device.

III. Methodology

The methodology is divided into three stages, data collection, data processing and data classification. The data collection stage details how the data was collected using the wearable Panoramic Digital Health bracelet and the RF sensing system. The data processing stage details how the collected data is prepared into datasets for AI classification. The classification stage will detail the AI methods used to perform data classification.

A. Data Collection

1) Devices: The wearable bracelet used was the Panoramic Digital Health bracelet, which includes 2 three-axis accelerometers, a three-axis gyroscope, a three-axis magnetometer, a barometric pressure sensor and a Bluetooth sensor. It also includes a Bluetooth low-energy beacon that is used to activate the device from a mobile phone app, receive signals from optional environment beacons, and transmit data to a mobile phone app. The environmental beacons are used for the localisation of individuals. This paper does not make use of environment beacons as all activities take place in a single environment. When the bracelet is activated by the mobile phone app, a configuration file is downloaded to the bracelet

Fig. 1: Panoramic Digital Health Bracelet Worn on the Wrist

to specify the sensors to be used and the data rates. For this project, data was collected at 50Hz from the low-power accelerometer, 52Hz from the high-energy accelerometer and gyroscope, 20Hz from the magnetometer and 25Hz from the pressure sensor. Raw data is stored encrypted on the bracelet in 1 GB Flash memory for retrieval by USB. Figure 1 shows the Panoramic Digital Health bracelet worn on the wrist.

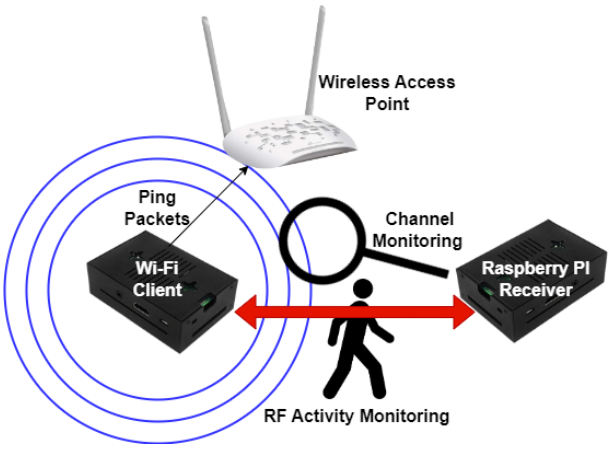

Fig. 2: Topology of the Proposed RF Sensing System

The RF sensing method of this paper makes use of the publicly available Nexmon Channel State Information Extractor project [29, 30] to extract the CSI from a Raspberry Pi Model 3B+ onboard Wi-Fi chip. The Raspberry PI serves as the receiver in the proposed RF sensing system. The proposed RF system consists of a simple Wi-Fi network setup for data collection. In the Wi-Fi network, there is a wireless access point, a Wi-Fi client and the Raspberry PI receiver. The Wi-Fi client device is an additional Raspberry Pi for simplicity. The Wi-Fi client then sends ping packets over the wireless medium to the wireless access point. This allows the Wi-Fi client to serve as the transmitter in the proposed RF sensing system. The sample rate is configured on the Wi-Fi client by setting the rate at which ping packets are sent to the wireless access point. The IPERF tool is used to send UDP ping packets at the rate of 5 Mbits/second. The Raspberry PI receiver is set to monitor the traffic on the network. Additionally, it is set to filter traffic based on the Medium Access Control (MAC) address of only the Wi-Fi client. This allows for controlled placement of the devices to ensure human activity can be effectively captured. Figure 2 shows how the RF sensing system works concerning the Wi-Fi client (transmitter) and the Raspberry PI receiver devices in the data collection Wi-Fi network. Human activity can then take place between the Wi-Fi client and the Raspberry PI receiver. As the Wi-Fi client is consistently transmitting wireless packets into the environment, when the packets are received at the Raspberry PI receiver side, human movements have affected the propagation path of the packets. Therefore when the CSI data is stored on the Raspberry PI receiver, it contains patterns in the signal that have been caused by the human movements. This data can then be further processed.

TABLE I: Breakdown of Collected Activities

Activities		No. Samples
1	Normal Walk	20
	Slow Walk	21
2	Normal Stand from a Chair	41
	Slow Stand from a Chair	22
3	Normal Sit on a Chair	41
	Slow Sit on a Chair	22
4	Normal Stand from Bed	44
	Slow Stand from Bed	21
5	Normal Sit on the Bed	44
	Slow Sit on the Bed	21
6	Normal get out of Bed	21
	Slow get out of Bed	23
7	Normal get into Bed	20
	Slow get into Bed	22

2) Experimental Setup: Data is collected in a small bedroom environment. The bedroom has an office desk with a chair and a bed. This space allows for the collection of walking, sitting, standing and getting in and out of bed activities. The activities collected for this paper are Walking, Sitting/Standing from a chair, Sitting/Standing from a bed, and Getting in/ Out of bed. Each activity is collected using a normal speed to mimic non-fatigue and a slow speed to mimic fatigue. The complete breakdown of all activities is shown in Table I. These activities are selected as they represent daily activities that people would likely do every day within their homes. These activities are likely to show if there is fatigue as it is expected that the pace of completion of these activities is likely to slow down when fatigue is present. Through long-term monitoring of these activities, it is likely to notice any changes in human performance that could indicate the presence of fatigue. The human subject wears the bracelet on their right wrist. The RF devices are placed in opposite corners of the room. This allows RF traffic from the transmitter to be received from the full diagonal length of the room. Thus any human activity within the room will affect the received signal at the Raspberry PI receiver side. Figure 3 shows the placement of devices in the room and where each activity takes place. The Wi-Fi client (transmitter) is placed on the window sill next to the bed. The

Raspberry Pi receiver is placed on a small table in the opposite corner of the Wi-Fi client (transmitter). This gives coverage to all positions of activities shown in Figure 3 as blue circles.

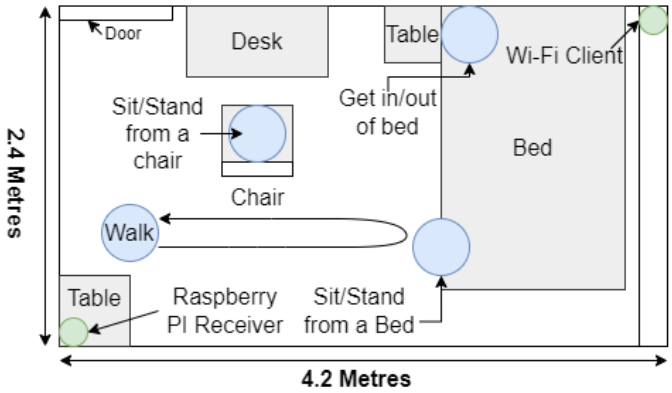

Fig. 3: Floor Plan of the Experimental Setup

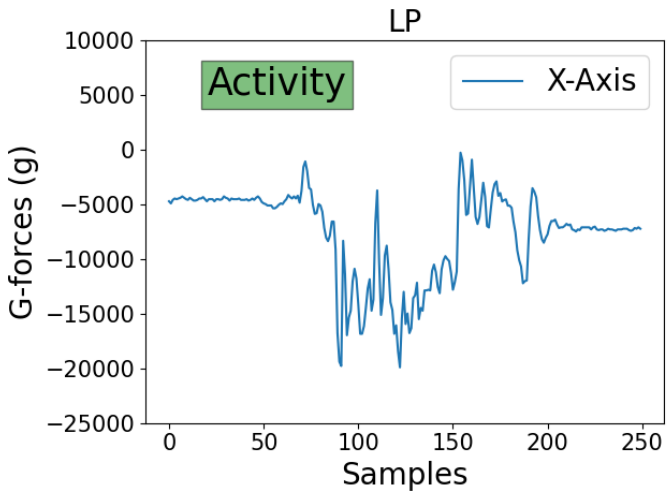

Fig. 4: Activity Detected by the LP Sensor

3) Collection Process: Data is collected from a single healthy subject. Who performs activities at their normal healthy pace to represent no fatigue and then performs the same activities at a slower pace to simulate fatigue. The current study was approved by the University of Glasgow's ethics board. All experiments were performed in accordance with relevant guidelines and regulations and informed consent was sought from the participant before conducting the experiments. To collect the data both the Panoramic Digital Health bracelet and the RF sensing system need to be run in parallel. To run the Panoramic Digital Health bracelet, it is activated from the mobile application. this clears the data on the bracelet and new data begins to be collected. The RF system works by capturing incoming packets on the receiver device. This is achieved by using the preinstalled tcpdump packet sniffer program which can store captured network packets to a file. From tcpdump, we can set the number of packets to capture before stopping. In this paper, the number of packets to capture is set to 200,000. This number of packets is received in approximately 8 minutes due to the sample rate being approximately 400 samples per second. The Panoramic Digital Health bracelet is set up to start collecting data first. Then a bash script is run on the Raspberry Pi receiver device to run tcpdump to collect 200,000 CSI packets after a short delay to allow the subject to move to the start position of the activity to be performed. A background timer is used to perform beeps every 10 seconds to indicate when the subject should perform the activity. The first beep is ignored. This is to allow a space in the bracelet data between setting up the data collection and actual data collection. This means that the initial movement seen in the bracelet sensor data can be dismissed. Except for walking, each activity consists of the subject performing one activity and then another. For example in the activities get out of bed and get into bed are collected together. The subject will get into bed on the first movement. Then when the timer indicates they should perform they will get out of bed and then this is repeated for the duration of the data collection run. The 10-second interval between movements allows for clear identification of when activities occurred and what activity was occurring when labelling the data for AI classification.

B. Data Processing

The data collected in both the Panoramic Digital Health bracelet and the RF sensing system is time series data. The data that is extracted from the Panoramic Digital Health bracelet is in the form of DAT files. These DAT files can be read by using a Java Jar file provided by Panoramic Digital Health. The JAR file allows for the data from each sensor to be exported into CSV format. These CSV files contain the timestamps and the sensor data. The RF sensing system data is in the format of Packet Capture (PCAP) files. These PCAP files are retrieved from the Raspberry PI device via a shared folder with the processing PC. The PCAP files contain the network packets. These network packets contain the CSI in the format of complex numbers. The received signal contains 64 subcarriers. The guard subcarriers are removed as they do not contain useful information [31]. Then the remaining subcarriers are divided by the sum of the absolute values of the subcarriers to remove the effects of Automatic Gain Control (AGC) which is present in the Raspberry Pi onboard Wi-Fi chip. AGC causes pulse-like noise in the CSI data which is not ideal when using the CSI to detect motion [32]. This paper makes use of the amplitude of the signal which is obtained by calculating the absolute value of the processed complex numbers. The mean value of all the remaining subcarriers is then used to reduce the CSI into 1-dimensional time series data. The mean amplitude of the received signal is then stored in CSV format. The packets captured in the tcpdump also contain the Unix timestamps of when packets were received. This information is also extracted and stored in the CSV.

C. Data Classification

1) Data Labelling: To identify the movements of interest across all of the bracelet sensors and the RF sensing system, the Low Power accelerometer is selected to find the timestamps of the movements. This is achieved by dividing the full

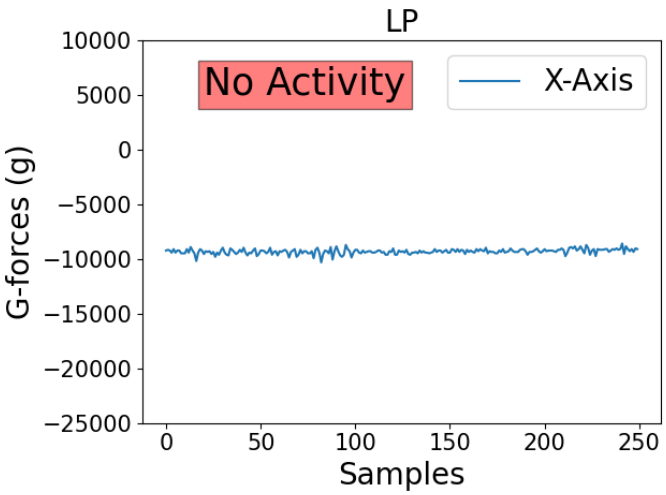

Fig. 5: No Activity Detected by the LP Sensor

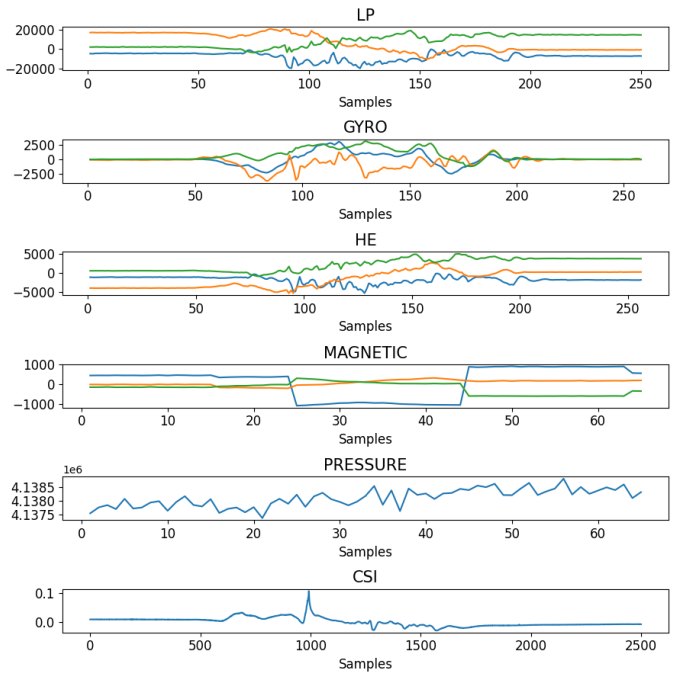

Fig. 6: Panoramic Digital Health Bracelet and Channel State information for the First Instance of the Getting into Bed Activity

low-power accelerometer CSV into sliding windows. From these individual windows, it is clear when a movement has occurred as there is a change in the G-forces (g). Figure 4 shows the difference in G-forces (g) when movement occurs and Figure 5 shows no movement occurring on the LP sensor of the bracelet.

When the movement occurs in the centre of the sliding window, the number of the sliding window is stored in a spreadsheet. A Python script is then run which reads the sliding window timestamps and then compares these timestamps to the timestamps on the other sensors and the RF sensing methods. Then all of the data is concatenated into a single CSV file and stored as an extracted movement. Extracted movements are placed in the appropriate folders in regards to the label as seen in Table I. Figure 6 shows an example of all the data from the bracelet sensors and RF sensing system for the first instance of the getting into bed activity.

2) Dataset Creation: Three datasets are created for classification. The first dataset is comprised of only the data collected from the Panoramic Digital Health bracelet. The various sensors of the bracelet are flattened into a single dimension to allow all sensor data to be fed into 1 dimensional AI algorithms. The second dataset is comprised of only the data collected using the proposed RF sensing system. This data is in the format of 1-dimensional time series data as described in section III-B. The final dataset is comprised of all the data collected from all devices. This concatenates the data from the first and second datasets. This allows for a comparison of results from the individual sensing methods and how the sensing methods complement each other when used together. Python scripts are used to locate the CSV files from the appropriate folders and then concatenate them together into a dataset with appropriate labels for supervised learning.

3) Artificial Intelligence: The Artificial Intelligence used in this paper includes decision trees, clustering and support vector machines, which are considered Machine Learning techniques. A subset of Machine Learning is Deep learning which has a stronger focus on neural networks. To achieve Machine Learning on the datasets, Sklearn and PyTorch libraries are used. Sklearn contains many machine learning algorithms. This paper uses some common classification algorithms to test the data. The chosen algorithms are Random Forest, K-Nearest-Neighbour and Support Vector Machine. Sklearn makes the implementation of these algorithms very easy and simplistic. The PyTorch library allows the implementation of Deep Learning algorithms to be used and allows for much greater customisation of building model layers. This paper makes use of Convolutional Neural Network (CNN) and Residual Network (ResNet) architectures.

CNN is one of the most implemented neural networks within Deep Learning. CNNs are successful due to using layers to perform convolution operations that extract features from the input data [33]. Extracted features found in the training data can be compared to extracted features in the testing data to find matches and thus allow classification. CNN is used mostly in the field of image recognition. Where 2-dimensional data is used as the input [34]. However 1-dimensional CNNs are available which can work well with time series data [35]. The dimension of CNN is dependent on the type of input data. This paper makes use of time series data so 1-dimensional is most appropriate. Figure 7 show the CNN network architecture used in this paper. The ResNet model of this paper makes use of convolutional architecture to recognise features of the input data [36]. The residual connections in the ResNet architecture provide an increase in the performance of training in a neural network [37]. This is achieved by using shortcuts to skip specific layers to simplify training [38]. This enables the network to grasp the residual, which is the distinction between the input and the output of

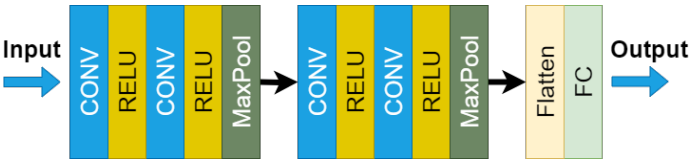

Fig. 7: CNN Model Architecture

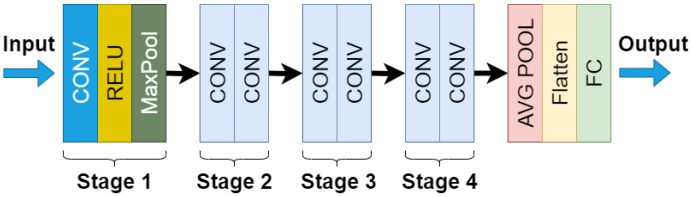

Fig. 8: ResNet Network Architecture

the layers that are bypassed [39]. Figure 8 show the ResNet network architectures used in this paper. The accuracy of each algorithm will be presented in the results section. The mathematical equation to calculate the accuracy is shown in Equation 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \quad (1)$$

The datasets are divided into training and testing data with an 80 % split for training data and a 20 % split for testing data. The algorithm is only trained on the testing data. The results section presents the algorithm classification for only the testing data. This serves as the validation data for each trained algorithm. The datasets are also shuffled to mix up the labels across the training and testing data. A random seed is used to ensure the data is shuffled the same way on each run. The datasets contain 14 labels. Namely the 7 activities for both normal and slow speeds. These 14 labels present a multiclass problem where the algorithms will try to identify what activity occurs and if fatigue is present. Binary classification is also tested with the algorithms where only fatigue and non-fatigue states are tested regardless of what activity is being performed.

IV. Results and Discussion

The results section will be divided into two subsections to represent the results of the binary classification and to represent the results of the multiclass classification.

A. Binary Classification

The results of the binary classification are to demonstrate that the algorithms can distinguish between the speeds at which the activities are being performed. Applications would include detecting a decline in performance to carry out activities that would indicate potential fatigue. The two classes in these results are normal pace and slow pace. Figure 9 shows the obtained accuracy results in bar chart format and Table II shows the exact accuracy values for each algorithm.

The Random Forest and ResNet algorithms performed the best by both achieving 100 % accuracy when using all the available data. The Random Forest algorithm was also able to achieve 100 % accuracy with data only received from the

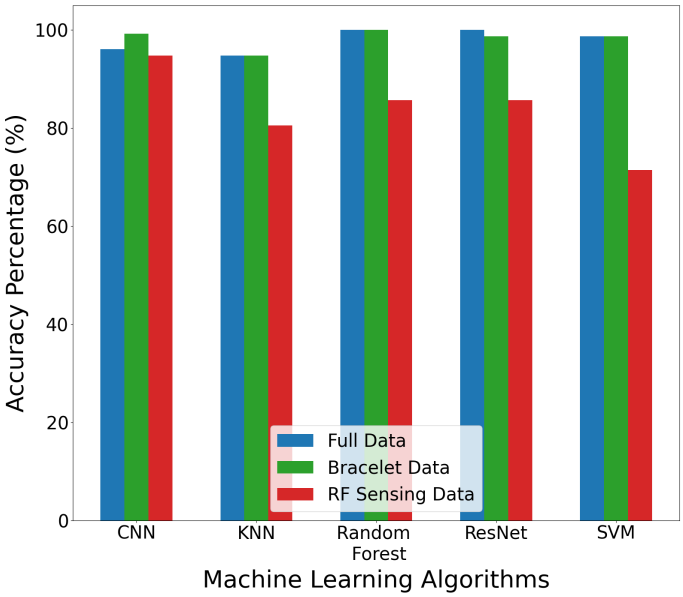

Fig. 9: Machine Learning Results of Binary Classification

bracelet. All the algorithms performed well when using the data from the bracelet. The accuracy of the algorithms dropped slightly when using only the RF sensing method. These results show that fatigue is more likely to be detected when using a wearable device but still possible with RF sensing. The CNN algorithm was able to detect fatigue with an accuracy of 94.80 % when using only the RF sensing data. All of the algorithms however were able to detect the majority of classes in the RF sensing testing data correctly.

TABLE II: Binary Classification Accuracy Values for Each Algorithm

	Full Data	**Bracelet Data**	**RF Sensing Data**
CNN	96.09 %	99.21 %	94.81 %
KNN	94.80 %	94.80 %	80.51 %
Random Forest	100 %	100 %	85.71 %
ResNet	100 %	98.70 %	85.71 %
SVM	98.70 %	98.70 %	71.42 %

B. Multiclass Classification

The results of the multiclass classification present how the tested algorithms performed when they were tasked to identify 7 activities performed at two different speeds, normal pace and slow pace. Symbolising fatigue and non-fatigue. This provides a total of 14 classes. From these results, it can be seen how well the algorithms can detect different classes with the different sensors used in this experiment. Figure 10 shows the obtained accuracy results in bar chart format and Table III shows the exact accuracy values for each algorithm.

These results again show that the wearable bracelet device is more accurate than the RF-sensing device. The multiple labels have greatly highlighted this from the previous binary results. This is likely due to the wearable device being directly placed on the human body and the multiple sensors installed

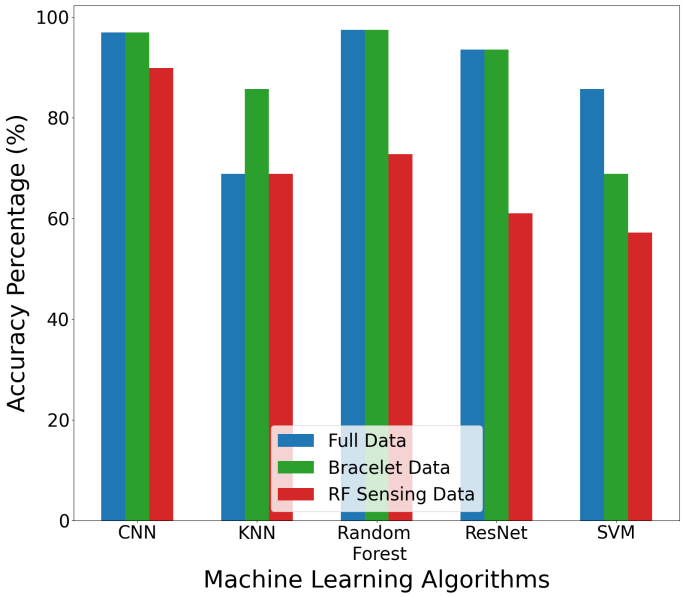

Fig. 10: Machine Learning Results of Multiclass Classification

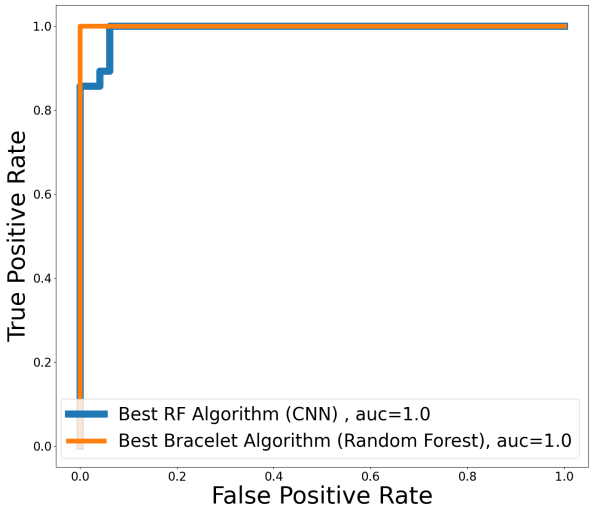

Fig. 11: ROC Curve and AUC for Best-Performing Algorithms for the Bracelet Data and RF Sensing Data

on the bracelet. The Random Forest algorithm performed the best overall with results of 97.40 % accuracy. The Random Forest algorithm also performed the same when using the full data and the bracelet-only data. So it was unaffected by the addition of the RF sensing data. The CNN algorithm was still the best-performing algorithm when using only the RF sensing data with an accuracy result of 89.84 %. which is around a 5 % accuracy decrease from the binary results. The only algorithm which showed a benefit to using both bracelet and RF sensing data was the SVM algorithm as results for the SVM algorithm were poor for both bracelet only and RF sensing only.

TABLE III: Multiclass Classification Accuracy Values for Each Algorithm

	Full Data	**Bracelet Data**	**RF Sensing Data**
CNN	96.87 %	96.87 %	89.84 %
KNN	68.83 %	85.71 %	68.83 %
Random Forest	97.40 %	97.40 %	72.72 %
ResNet	93.50 %	93.50 %	61.03 %
SVM	85.71 %	68.83 %	57.14 %

C. Discussion

The results of this experiment have shown that the tested devices can detect a slower rate of human movements which could indicate an important manifestation of physical fatigue. When using all available devices the results show that there is a high accuracy in identifying simulated fatigue and also the different activities taking place. Additionally, the results have shown that the wearable bracelet was more accurate in both binary and multiclass experiments than the RF sensing system. This can be attributed to the wearable device having multiple sensors, and being placed on the human subject which reduces overall noise. The RF sensing method is more susceptible to noise as it is dependent on reflections of RF signals which can be affected by the environment in addition to the human subject. The results are as expected when comparing wearable and non-wearable sensing devices. As shown in the related works of [18, 19] which made use of wearable devices compared to [20] which used radar technology. Figure 11 shows the Receiver Operating Characteristic (ROC) curve with the Area under the ROC Curve (AUC) for the best-performing algorithms for the bracelet data and RF sensing data. The ROC curve is an important metric for measuring the performance of a diagnostic test [40]. The ROC is a probability curve that the algorithms will correctly classify between classes. The AUC is a value between 0 and 1, the higher the AUC the more capable the model is for distinguishing between classes in this case Normal and Slow movements [41]. It is shown in this experiment that both the bracelet and the RF sensing techniques have an AUC of 1. The RF sensing ROC has slightly less probability than the bracelet ROC as expected with a slightly lower accuracy compared to the 100 % accuracy for the bracelet using the Random Forest algorithm and 94.80 % accuracy for the RF sensing data using the CNN algorithm. The results have showcased the accuracy that can be achieved by the Panoramic Digital Health bracelet. Although the RF sensing method is less accurate, it has still seen 94.80 % accuracy with binary classification. These results could be seen as acceptable when taking into account the other benefits of RF sensing just as the lack of reliance on battery power and removing the need for individuals to wear devices.

V. Conclusion

Technologies can be used to help with healthcare starting at home. IoT devices can monitor individuals within their own homes, collecting valuable information which can be used to help healthcare professionals to diagnose illnesses and conditions. This can allow for longer periods of monitoring

which can be beneficial in identifying more inconspicuous symptoms. Signs of fatigue within individuals, particularly elderly individuals can be indicative of underlying health conditions or illnesses. Therefore there are great benefits for monitoring technologies to be able to recognise fatigue from human movements. In this paper, we have shown a good sensitivity of both a wearable bracelet and an RF sensing method to detect changes in the speed of movement which may be associated with fatigue. Fatigue symptoms are multi-faceted, and we acknowledge that slowing rate of movement is only one of the implications of fatigue and that other symptoms such as a change in sleep pattern, brain fog, and post-exertional malaise were not assessed in this study. There is potential for the sensors in this study to be used to capture other aspects of human movement that may give additional insights into the fatigue experience, such as sleep monitoring.

The innovation of this paper is the utilisation of IoT devices to detect simulated fatigue, collection of a dataset with machine learning classification, and analysis of sensor technologies. The Panoramic bracelet data was collected in the presence of an environment beacon, so that data analysis can be restricted to data collected in the bedroom, excluding for example movement outside the home which might otherwise confound the assessment of change in speed of movement associated with fatigue. A range of Machine Learning algorithms are used to test the accuracy of the combined sensors and each sensor individually. It was found that the wearable device was more accurate than the RF sensing method. The wearable device was able to achieve an accuracy score of 97.40 % to classify 14 different classes. The RF sensing method was able to classify 14 different classes with an accuracy score of 89.84 %. The wearable device is expected to have higher accuracy due to its direct connection to the human body. Environmental conditions have a minimum impact on wearable devices whereas environmental conditions have a large impact on RF sensing methods. Despite the lower accuracy, RF sensing has the advantage of removing the need to wear a device and a non-reliance on battery power.

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