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A WHEELCHAIR SITTING POSTURE DETECTION SYSTEM USING PRESSURE SENSORS

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ABSTRACT: The usage of machine learning in the healthcare system, especially in monitoring those who are using a wheelchair for their mobility has also helped to improve their quality of life in preventing any serious life-time risk, such as the development of pressure ulcers due to the prolonged sitting on the wheelchair. To date, the amount of research on the sitting posture detection on wheelchairs is very small. Thus, this study aimed to develop a sitting posture detection system that predominantly focuses on monitoring and detecting the sitting posture of a wheelchair user by using pressure sensors to avoid any possible discomfort and musculoskeletal disease resulting from prolonged sitting on the wheelchair. Five healthy subjects participated in this research. Five typical sitting postures by the wheelchair user, including the posture that applies a force on the backrest plate, were identified and classified. There were four pressure sensors attached to the seat plate of the wheelchair and two pressure sensors attached to the back rest. Three classification algorithms based on the supervised learning of machine learning, such as support vector machine (SVM), random forest (RF), and decision tree (DT) were used to classify the postures which produced an accuracy of 95.44%, 98.72%, and 98.80%, respectively. All the classification algorithms were evaluated by using the k-fold cross validation method. A graphical-user interface (GUI) based application was developed using the algorithm with the highest accuracy, DT classifier, to illustrate the result of the posture classification to the wheelchair user for any posture correction to be made in case of improper sitting posture detected.

ABSTRAK: Penggunaan pembelajaran mesin dalam sistem penjagaan kesihatan terutama dalam mengawasi pergerakan pengguna kerusi roda dapat membantu meningkatkan kualiti hidup bagi mengelak sebarang risiko serius seperti ulser disebabkan tekanan duduk terlalu lama di kerusi roda. Sehingga kini, kajian tentang pengesanan postur ketika duduk di kerusi roda adalah sangat kurang. Oleh itu, kajian ini bertujuan bagi membina sistem pengesan postur khususnya bagi mengawasi dan mengesan postur duduk pengguna kerusi roda dengan menggunakan pengesan tekanan bagi mengelak sebarang kemungkinan ketidakselesaan dan penyakit otot akibat duduk terlalu lama. Lima pengguna kerusi roda yang sihat telah dijadikan subjek bagi kajian ini. Terdapat lima postur duduk oleh pengguna kerusi roda termasuk postur yang memberikan tekanan pada bahagian belakang telah di kenalpasti dan dikelaskan. Terdapat empat pengesan tekanan dilekatkan pada bahagian tempat duduk kerusi roda dan dua pengesan tekanan dilekatkan pada bahagian belakang. Tiga algoritma pengelasan berdasarkan pembelajaran terarah melalui pembelajaran mesin seperti Sokongan Vektor Mesin (SVM), Hutan Rawak (RF) dan Pokok Keputusan (DT) telah digunakan bagi pengelasan postur di mana masing-masing memberikan ketepatan 95.44%, 98.72% dan 98.80%. Semua algoritma pengelasan telah dinilai menggunakan kaedah *k*-lipatan pengesahan bersilang. Sebuah aplikasi grafik antara muka (GUI) telah dibina menggunakan algoritma dengan ketepatan paling tinggi, iaitu pengelasan DT bagi memaparkan keputusan pengelasan postur untuk pengguna kerusi roda bagi membantu pembetulan postur jika postur salah dikesan.

KEYWORDS: *posture detection; smart wheelchair; pressure sensor; machine learning; classification*

1. INTRODUCTION

A sitting posture detection system (SPDS), also known as sitting posture recognition system (SPRS), is a system used to differentiate between the proper and improper sitting posture possessed by a human on a chair. In the medical field, the system has been widely used to assist medical practitioners in monitoring patients who are confined to a wheelchair due to injuries in the legs, spine, or spinal cord that will limit their body movement as compared to an average person. The main objective of the system is to ensure the wheelchair user leads a better quality of life and prevents them from developing any possible discomforts that may adversely affect their daily activities, such as development of pressure ulcers due to the prolonged sitting on the wheelchair.

Over the years, posture detection systems have been tremendously improved in terms of accuracy, in line with the advancement of technology. Typically, the system consists of three main stages, namely the data acquisition, data processing, and data transmission. Data acquisition is focused on how to acquire data from the user with various types of components, such as pressure sensors, Kinect sensors, force sensors, accelerometers, etc. whereas data processing is involved in classifying the data acquired to differentiate between the proper and improper sitting posture. Most researchers have developed their own systems with the assistance of machine learning techniques in processing their acquired data. Finally, data transmission is the stage where the processed data that has been evaluated is shown to the user for posture correction if necessary.

In defining the improper sitting posture, it is crucial to understand the sitting behavior for every wheelchair user. Research has been conducted on how in-seat movement and weight-shiftings (WSs) (30% - 90% off loading of at least side of the buttocks for at least 15 seconds) behavior of full-time wheelchair users will result in a lifetime risk of developing pressure ulcers [1]. Other than WSs, participants also performed other maneuvers, such as pressure reliefs (PRs) (90% off-loading of the entire buttocks for at least 15 seconds) in order to reduce the pressure, hence increasing the blood flow to the buttock tissues. Based on the analysis performed, it was found that the participants performed WSs much more frequently as compared to PRs. In fact, the WSs were performed nearly two times per hour for many of the subjects' days. At the same time, it is noted that by doing intermediate leans, which are the same as the WSs, may reduce the pressure between 29% and 46% [1].

Nowadays, the development of a sitting posture detection system that mainly focuses on wheelchair users is still rare compared to its development for general purpose sitting posture. Many research papers that are related to the sitting posture detection system are more focused on detecting sitting posture on a chair for a general purpose, such as during work or driving. In Malaysia, 548,186 disabled persons were registered with the Jabatan Kebajikan Masyarakat (Community Welfare Department) and 36.0% of them are physically impaired that mostly are in need to commute using a wheelchair, especially the elderly for easy to commute [2]. To date, the amount of research on sitting posture detection on wheelchairs is limited.

Therefore, this paper aimed to develop a sitting posture detection system that predominantly focused on monitoring and detecting the sitting posture of a wheelchair user by using pressure sensors to avoid any possible discomfort and musculoskeletal disease resulting in prolonged sitting on the wheelchair.

1.1 Sensor Selection

The usage of sensors is paramount in ensuring the sitting posture detection system is unobtrusive and will not give any discomfort to the user, especially the wheelchair user. Many of the previous works in this field have opted to use pressure sensors or force sensitive resistors (FSR) in detecting the sitting posture. Ma et al. [3] used a cushion equipped with the pressure sensors. Similarly, Zemp et al. [4] also used a number of pressure sensors (FSR406) in developing the posture recognition system. In recent years, Matuska et al. [5] developed a sitting posture detection system using force sensors that were accessible by mobile applications, which is one of the outcomes of the IoT. The authors used the six single-zone force-sensing resistors FSR402 to obtain the force by measuring the resistance values based on the data acquired from the sensors embedded in the smart wheelchair.

In addition, Fragkiadakis et al. [6] also developed a sitting posture recognition system by using piezoresistive pressure sensors for detecting the distribution of pressure from one sitting posture to another. The reason for choosing the piezoresistive sensor was that this type of sensor has tolerance to temperature changes and a lifespan of three million charging cycles. Additionally, Rosero-Montalvo et al. [7] also developed an identification system for a wheelchair user's posture using pressure sensors. In spite of that, Wan et al. [8] designed their latest posture recognition system by considering the hip position for the sake of posture analysis.

In contrast, recent work on position detection documented the use of a variety of sensors other than pressure or FSR sensors. Another type of sensor used for the sitting posture detection system is the load cell sensor which was developed by Roh et al. [9]. Min et al. [10] developed a scene recognition and semantic analysis in detecting unhealthy sitting posture amongst office workers using Microsoft Kinect Sensor. In addition, Chin et al. [11] also developed a posture recognition system using Kinect Sensor in differentiating between a good and bad sitting posture. Last but not least, Qian et al. [12] had proposed the usage of nanocomposite sensors in identifying human posture.

To sum up, the authors used various types of sensors, and this has been the norm for a long period of time in the posture recognition field. Furthermore, since the release of Kinect Sensor by Microsoft in 2010, it has been famously known to be used in the posture recognition field as it is mainly invented for human sensing purposes. However, in the case of posture recognition for wheelchair users, it is more efficient to use a pressure sensor than a Kinect sensor for its unobtrusiveness for wheelchair users.

1.2 Data Classification Technique

One of the biggest data analytic techniques that has been widely used across multiple disciplines is machine learning techniques. In terms of posture detection, the type of machine learning techniques that has been used in most of the developed systems is supervised learning of classification techniques. Most researchers have come out with predetermined postures that might be possessed by the user on the chair or wheelchair and have verified it with the medical experts for distinguishing the proper and improper sitting posture. For instance, Zemp et al. [4] proposed seven different postures that are typical for seated people, while Roh et al. [9] suggested six different postures to be performed by the subjects as the training data. The selection of subjects also played an important role in acquiring classifiers with high accuracy. Ma et al. [3] chose the subjects with the age range of 22 to 36 years old and the BMI range of

16 to 34 in order to avoid any error in recognizing the sitting postures by the users. The summary of the past sensors and classifications used are shown in Table 1.

Table 1: Summary of the Past Sensors and Classification Used

Authors	Types of Chairs	Types of Sensors	Placement of Sensors	Classification Algorithm	Classification Accuracy
Ma et al. [3]	Wheelchair	Pressure Sensor	7 on the seat, 4 on the backrest	J48 Decision Tree (DT)	99.48%
Roh et al. [9]	Office Chair	Load Cell Sensor	4 on the seat plate	SVM using RBF Kernel	97.20%
Min et al. [10]	Office Chair	Kinect Sensor	N/A	Faster R-CNN, Gaussian Mixture	95.60%
Zemp et al. [4]	Office Chair	Pressure Sensor	10 on the seat, 4 on the backrest, 2 on the armrest	Random Forest	90.90%
Matuska et al. [5]	Office Chair	Force Sensor	4 on the seat, 2 on the backrest	Random Forest	97.00%
Rosero-Montalvo et al. [7]	Wheelchair	Pressure Sensor	3 on the seat	k-NN	>75%
Qian et al. [12]	Office Chair	Nanocomposite Sensor	Wearable on the back	ANN	98.76%
Fragkiadakis et al. [6]	Chair	Pressure Sensor	8 on the seat, 5 on the backrest	WG30NN	98.33%
Chin et al. [11]	Office Chair	Pressure Sensor Array	Cushion on the seat	SVM with Linear Kernel	97.10%
Wan et al. [8]	Office Chair	Kinect Sensor	N/A	SVM with Polynomial Kernel	89.60%

Based on the literature review, the objectives of this paper are: (a) to investigate improper sitting postures in a wheelchair, (b) to identify and classify the improper sitting posture in a wheelchair using pressure sensors and machine learning, and (c) to develop a sitting posture detection system in a wheelchair. This paper is organized as follows. Section 2 explains the predefined sitting postures selection, sensor deployment, experimental setup and classification of sitting postures and the graphical user interface (GUI) with machine learning model development. The results of classifying the sitting postures with three classifiers and the developed GUI system are presented in Section 3. Finally, the conclusion of the results obtained, and future work are described in Section 4.

2. METHODOLOGY

2.1 Predefined Sitting Postures Selection

Usually, the predefined sitting postures are selected based on the targeted user's typical postures. Rosero-Montalvo et al. [7] chose the predefined sitting posture based on the typical sitting postures on a wheelchair and related it to the conventional taxonomy recommended by the physician and physiotherapist experts. The typical postures subsequently were classified into two types, namely recommended proper sitting posture and improper sitting postures.

In this project, the predefined proper sitting postures were selected based on previous papers and recommendation by medical experts [3,5,7,9]. On the other hand, the selection of predefined improper sitting postures will be based on the possible harmful effects on the backbone of the user. Therefore, in this project, the predefined sitting posture with their possible harmful effects is described in Table 2. Figure 1 shows the illustration of predefined sitting postures that were used in this project.

Table 2: Wheelchair Users Postures of Interest

Types of Sitting Posture	Possible Health Problems
Proper Posture	No harm
Lean Right Posture	Respiratory issues, muscle imbalance stress on liver, stomach, and right kidney
Lean Left Posture	Respiratory issues, muscle imbalance stress on spleen and left kidney
Lean Forward Posture	Knee issues, back pain, and stress on abdomen
Lean Backward Posture	Back pain and weaken abdominal muscle

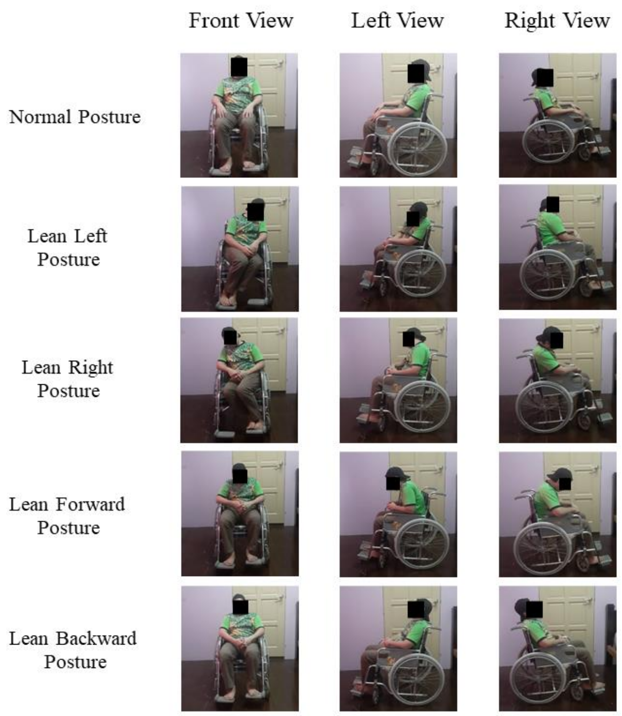

Fig. 1: The predefined sitting postures in this project.

2.2 Sensor Deployment

The selection of the sensor position is determined based on the body mass distribution and pressure points on the wheelchair seat. At the same time, the position of the sensor is also determined using the possible pressure points that need to be considered when the predefined sitting postures are possessed by the subject during the experiment. Ma et al. [3] mentioned that sensor deployment on the seat is sufficient to detect sitting posture. However, sensor deployment on the backrest will be supplementary for comprehensively detecting the sitting postures.

Assuming a conventional size for the seat and backrest of a wheelchair is 45 cm x 40 cm, the seat and the backrest are split into 4 square zones that are horizontally and vertically symmetrical with respect to the center point. For the wheelchair seat, one pressure sensor (FSR) was placed at the center of each square zone to represent the body mass distribution regions located on the left and right buttock zone and the front contact zone between thighs and seats. Additionally, one pressure sensor (FSR) was placed at each lower square zone of the backrest. Correspondingly, all the pressure signals were marked as FSR1, FSR2, FSR3, FSR4, FSR5 and FSR6 and the obtained instance vector was FPR = [FSR1, FSR2, FSR3, FSR4, FSR5, FSR6]. The sensor deployment configuration for this project is shown in Fig. 2.

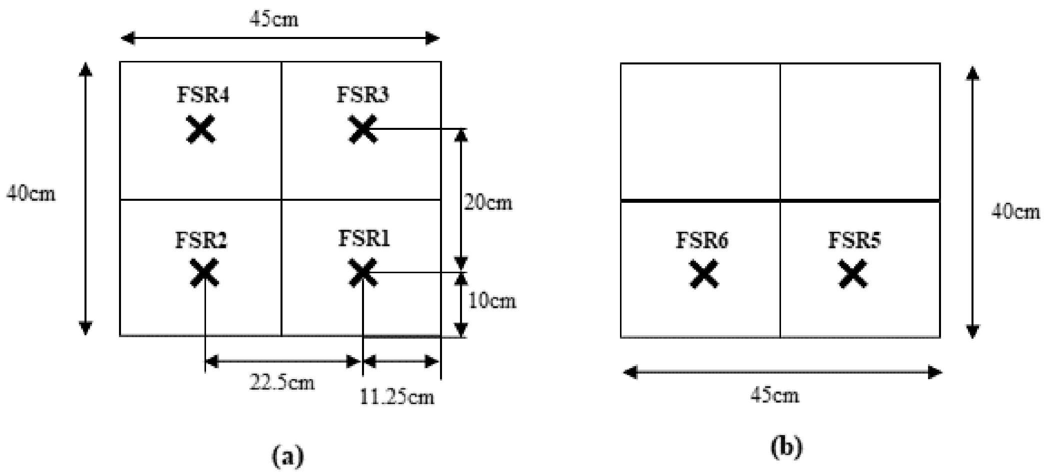

Fig. 2: Schematic diagram for sensor deployment: (a) On the seat plate, (b) On the backrest.

2.3 Data Collection

The age and BMI of the subjects had to be in the range of 18 to 40 years old and 16 to 35, respectively. There were 5 subjects (3 males, 2 females; 22.8±0.4 years old; BMI=22.9±2.6) volunteered in this study. This study was approved by the International Islamic University Malaysia research ethics committee (IREC). Before the data recording session began, all the subjects had the details of the process explained to them. The subjects were also required to read all the information sheets provided prior to starting the experiment. The information included predefined sitting postures that were required to be performed by the subject and the procedure of data recording. Then, the consent form was filled in and signed by the subject to ensure the confidentiality of their data and recording.

2.4 Experimental Setup

During the experimental test, the subjects were asked to sit in the wheelchair and perform all the predefined postures that were selected in the previous stage. For each posture, they were required to keep the posture for three minutes for the data to be collected. However, the subjects were allowed to adjust their posture for the first 30 seconds before starting each new data collection. Each subject repeated 3 trials per posture in order to obtain more reliable samples. The FSR sensors, marked as FSR1, FSR2, FSR3, FSR4, FSR5, and FSR6 were sampled with a sampling rate of 1 sample per second as it is sufficient to capture posture transitions. The microcontroller (Arduino Mega 2560) that was used in this project had a low energy consumption property. The deployment of the FSR sensors is displayed in Fig. 3.

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Fig. 3: Sensors deployed on a real wheelchair.

2.5 Classification of Sitting Postures

Three classifiers were used to determine the best one for the classification. The selection of the classifiers was based on the accuracy and frequency of use in previous papers on sitting posture recognition, namely support vector machine (SVM), decision tree, and random forest (RF). Furthermore, a cross-validation method was used in order to evaluate the classifiers' performance.

This method is also known as k-fold cross-validation, whereby it is used to estimate a machine learning algorithm performance while generating predictions on data that was not utilized during the model training. The process included only one parameter, k, which specified the number of groups into which a given data sample should be divided. In this particular work, the training and test sets were separated using a 10-fold cross-validation in order to provide a low bias in the estimation of model performance. At the same time, the classifiers were also evaluated by looking into a few more parameters namely, confusion matrix, precision score, recall score, and F-score accuracy. The process flow of the classification work in this project is illustrated in Fig. 4.

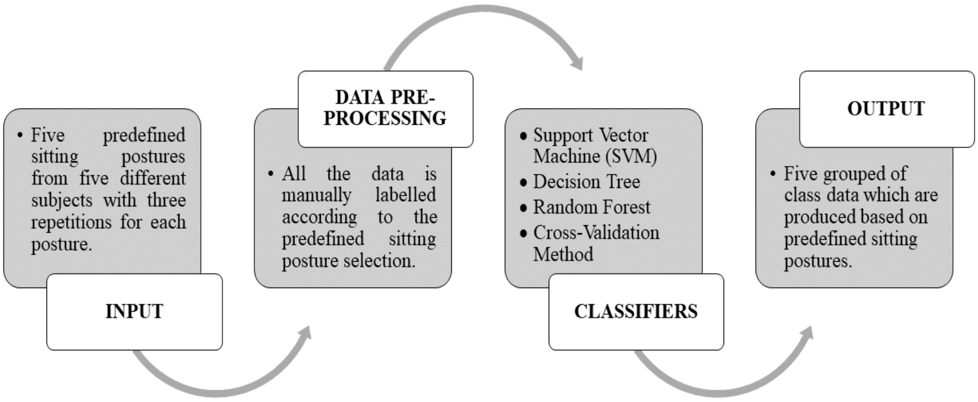

Fig. 4: Process flow of the classification.

On the other hand, the F-measure accuracy (overall accuracy) of the test data was computed to assess recognition performance. F-measure represents the combination of precision and recall, defined, respectively, as follows:

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$$precision = \frac{TP}{TP+FP} \quad (1)$$

$$recall = \frac{TP}{TP+FN} \quad (2)$$

$$F - measure = \frac{2(recall)(precision)}{recall+precision} \quad (3)$$

where *TP* is true positive, *TN* is true negative, *FP* is false positive, and *FN* is false negative.

2.6 Graphical User Interface (GUI) with Machine Learning Model Development

The final stage of this project is to develop a graphical user interface (GUI) mobile application with embedded machine learning model with the highest value of accuracy. Upon completion of the development of the machine learning model, a smart device mobile application was built using MIT App Inventor. The smart device consists of a mobile application that uses the GUI concept for the user to interact with the electronic device for their well-being while sitting on the wheelchair. In this mobile application, the sensor data will be transferred over the Bluetooth serial connection from the Arduino Microcontroller to the mobile application of the user's smart device. Prior to the data transmission, the sensor data will be analyzed by the trained classifier model that is embedded into the Arduino Microcontroller and subsequently classified the type of posture possessed by the user in real time.

3. RESULTS AND ANALYSIS

3.1 Experiments

During the experimental test, the number of samples taken for each predefined posture is shown in Table 3. The FSR sensor readings are displayed in Fig. 5 below.

Table 3: Number of samples taken for each predefined sitting postures

Types of Sitting Posture	Description	Number of Samples
Recommended Proper Sitting Posture	User seated correctly on the wheelchair	2,700
Lean Left	User seated leaning to the left	2,700
Lean Right	User seated leaning to the right	2,700
Lean Forward	User seated leaning forward	2,700
Lean Backward	User seated leaning backward	2,700

Based on Fig. 5, the FSR sensor values on both buttocks (FSR3, FSR4) were nearly equivalent illustrating that the body weight on the buttocks was evenly distributed during the posture made. Even though, the FSR sensors value on the knees (FSR1, FSR2) produced a slightly bigger range as compared to the FSR sensors value on the buttocks (FSR3, FSR4). In addition, the FSR sensors value on the backrest which were practically similar supplementing the recorded data for the recommended proper sitting posture.

On the other hand, Fig. 6 depicts the value of FSR3 (located on the left buttock) was higher than FSR4 (located on the right buttock). In addition, the value of FSR sensor on the left knee (FSR1) was significantly higher than the FSR sensor on the right knee (FSR2) and similarly to the value of the FSR sensor on the left part of the backrest (FSR5) which is also leading the value of the FSR sensor on right side of the backrest (FSR6). Therefore, it can be

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said that all the values for the FSR sensors located on the left side of the wheelchair were higher in comparison to the values of the FSR sensors which located on the right side of the wheelchair.

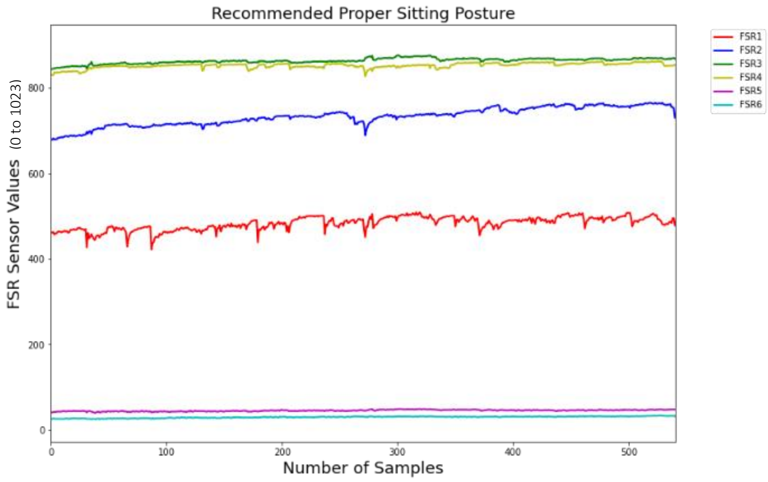

Fig. 5: Pressure sensor data during recommended proper sitting posture.

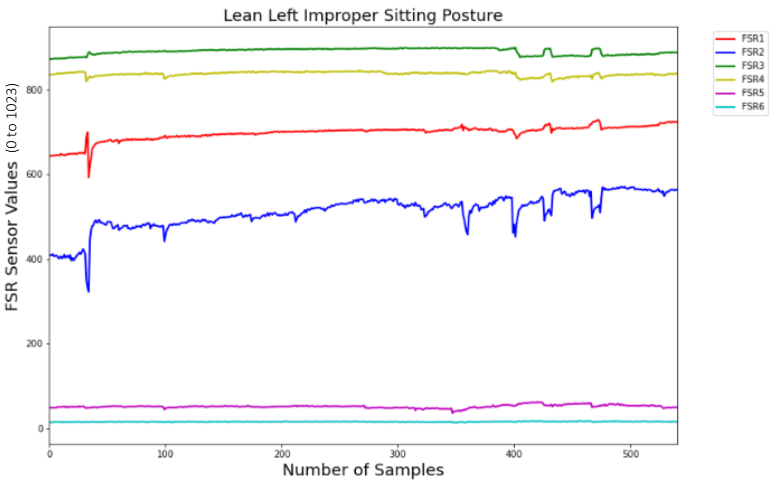

Fig. 6: Pressure sensor data during lean left posture.

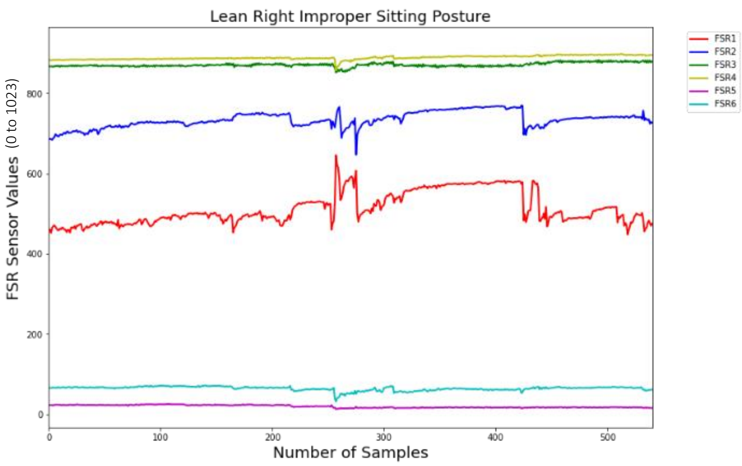

Fig. 7: Pressure sensor data during lean right posture.

In contrast to the previous sitting posture, the readings for FSR sensors on the left side of the wheelchair were greater than the values for FSR sensors on the right side of the wheelchair. It can clearly be seen from the graph that the FSR sensors which located on the right (FSR2, FSR4, FSR6) produced a higher reading in comparison to the FSR sensors which located on the left (FSR1, FSR3, FSR5). This was because the subject was asked to simulate a sitting posture that gave a higher pressure on the right which made the overall body weight of the subject not evenly distributed.

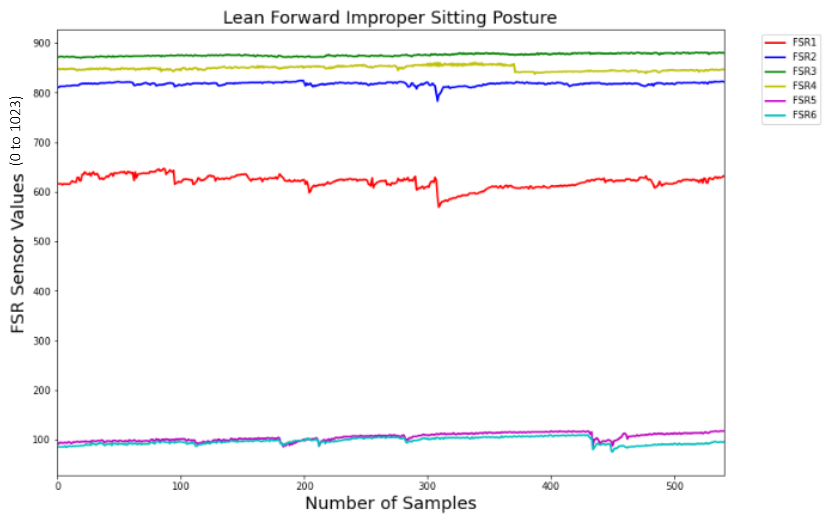

Fig. 8: Pressure sensor data during lean forward posture.

As observed from the plot, the readings of the FSR sensors located on the seat (FSR1, FSR2, FSR3, FSR4) were nearly equivalent for all the sensors. However, the value of FSR1 was slightly lower as compared to the other three FSR sensors.

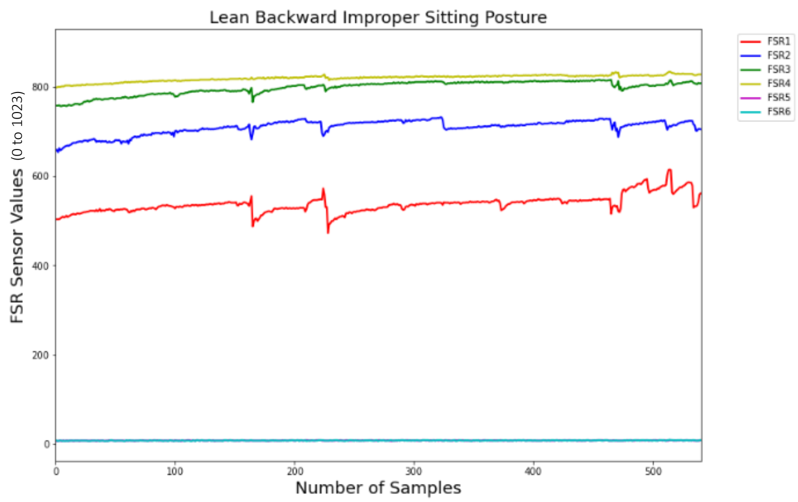

Fig. 9: Pressure sensor data during lean backward posture.

Based on the graph, the reading of the FSR sensors on the seat (FSR1, FSR2, FSR3, FSR4) were approximately comparable to each other, just as they were in the lean forward improper sitting posture. The main difference in this sitting position was that the readings of FSR sensors on the backrest were almost zero, in contrast to the previous sitting posture, in which the reading FSR sensors on the backrest were amongst the highest of all the predefined

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sitting postures in this project. This was due to the subject's buttocks creeping forward, resulting in the subject's back barely touching the FSR sensors on the backrest.

3.2 Classification of Sitting Postures

In this study, three classification algorithms (support vector machine, random forest, and decision tree) were used to classify each predefined sitting posture. All the datasets were trained, tested, and validated by each of the algorithms prior to deploying as the finalized machine learning model. Since the classification algorithms were so dependent on the nature of the datasets, the number of datasets used to train, test, and validate the classifier was the same for each posture. For each posture, the number of samples were obtained by measuring the data for 3 min for each of the five subjects with three repetitions (180 s x 3 times x 5 subjects) which resulted in 2,700 samples per posture.

The performance of all the classifiers were evaluated by looking into their accuracy, precision score, recall score, and F1-score. These parameters will act as contributing factor in choosing the best classifier for building the machine learning model. At the same time, a confusion matrix was also used to analyze the robustness of the classifier in classifying each of the predefined sitting postures. The confusion matrix is a practical tool in visualizing and summarizing the performance of the classification algorithms.

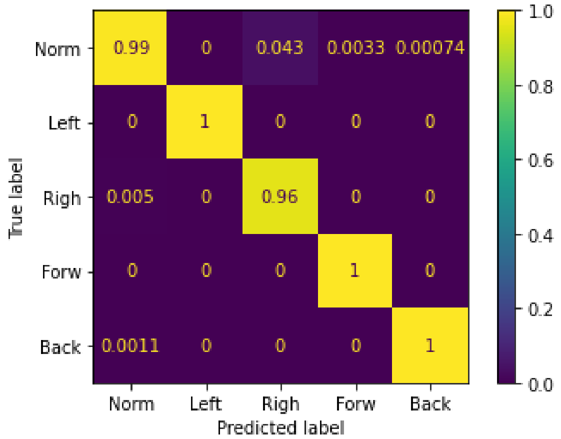


Fig. 10: Confusion matrix for the support vector machine classifier.

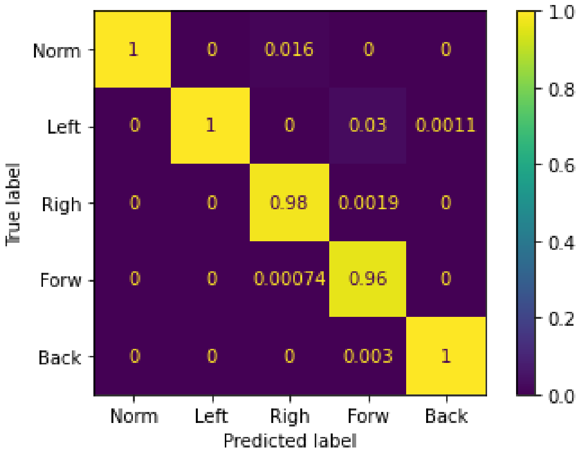


Fig. 11: Confusion matrix for the random forest classifier.

In this work, the predefined sitting postures were classified using the SVM with radial basis function (RBF) as the kernel type. The accuracy obtained from the SVM was 95.44% which was the lowest accuracy obtained in this project. Furthermore, the F1-score of this classifier was 0.9799 which computed with a precision and recall score of 0.9811 and 0.9798, respectively. The confusion matrix of the model showed that the model managed to correctly classify the recommended proper sitting posture with a probability of 0.99. However, the model produced the lowest probability of 0.96 when predicting the lean right improper sitting posture.

Random forest classifiers obtained the second highest value of accuracy which was 98.72% overall. This classifier's precision and recall scores were 0.9887 and 0.9884, respectively, resulting in an F1-score of 0.9884. Since this classifier recall score was higher than the SVM classifier recall score, the F1-score was also higher than the previous classifier. In addition, the confusion matrix of the model showed that the random forest classifier managed to classify all 2,700 samples of the recommended proper sitting posture correctly, giving a probability of 1. However, the posture that was misclassified the most was "lean forward" in which 0.04 out of 2,700 samples were misclassified.

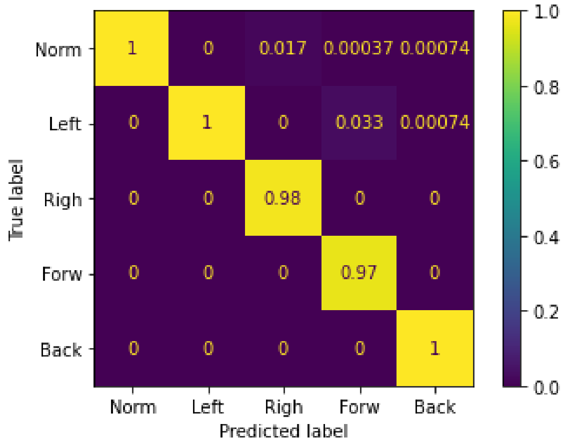


Fig. 12: Confusion matrix for the decision tree classifier.

Apart from that, the decision tree classifier recorded the highest accuracy amongst all the classifiers that were used in this project with an accuracy of 98.8%. In addition, because of the better precision and recall scores of 0.9898 and 0.9896, respectively, this model's F1-score was also the highest of the three, at 0.9896. Like the random forest classifier, the decision tree classifier also managed to successfully classify all the recommended proper sitting posture correctly. However, as compared to the random forest classifier, this classifier was able to improve the probability of correctly recognizing the lean forward improper sitting posture by 0.01.

To summarize, the decision tree classifier was chosen as the top classifier for recognizing the wheelchair user's sitting posture in this project, followed by the random forest classifier with only 0.08% difference in terms of its accuracy. However, there is a significant difference in the accuracy value of the support vector machine classifier in comparison to the other two classifiers. Ma et al. [3] in their previous paper mentioned that the SVM is quite effective for binary classification, but it is considerably more difficult to configure its important parameters for multi classification. As a result, the accuracy of SVM classifiers is significantly lower than that of other classifiers. The summary of the classification report is tabulated in Table 4 below.

Table 4: Summary of the Classifier Performance

Classifiers	Accuracy	Scores		
		Precision	Recall	F1-Score
Support Vector Machine (SVM)	95.44%	0.9811	0.9798	0.9799
Random Forest	98.72%	0.9887	0.9884	0.9884
Decision Tree	98.80%	0.9898	0.9896	0.9896

3.3 Graphical User Interface (GUI)

A GUI mobile application was developed in this project as a complementary tool for detecting the sitting posture of the wheelchair user. The mobile application was developed using the open-source application inventor for android, namely MIT App Inventor. In this mobile application, Bluetooth was chosen as the mode of transmission between the Arduino

Microcontroller and user's smart device. Therefore, all the information was sent and received by the mobile application or vice versa via Bluetooth serial connection.

In this platform, the mobile application was built using a web browser where all the works were stored in the App Inventor server. The components that were used to build the mobile application were chosen based on their functionality in the mobile application. Firstly, a ListPicker button was used to display the list of available Bluetooth devices and handle the selection. Next, two buttons were chosen to instruct the Arduino to start and stop the data recording from the sensor. All the data were subsequently processed by the Arduino before the machine learning model, which has been deployed in the Arduino, used to classify the current sitting posture of the user. Figure 13 depicts the build workspace of the mobile application.

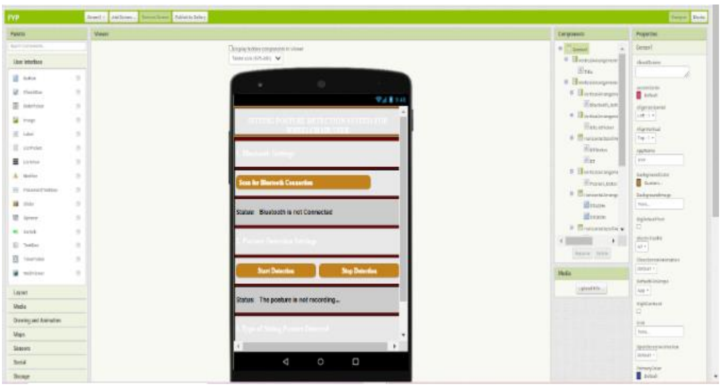
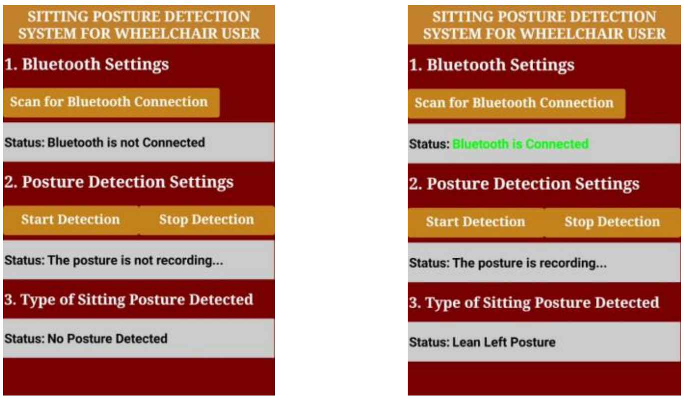


Fig. 13: MIT App Inventor workspace.

On the other hand, all the user interfaces were programmed and controlled using the blocks. The App Inventor technique assembled a sequence of blocks together and formed a group of blocks based on the logic that has been decided by the inventor. Then, all the group blocks were automatically generated into a Java programming code by the software. For instance, in this study, a letter 'n' was sent to the Arduino via Bluetooth serial connection which indicated start of the data recording. Prior to this, the Arduino code was also aligned in defining the receiving data from the mobile application for the start of the FSR sensor recording.



(a) (b)

Fig. 14: The Default view (a) and Running view (b) of mobile application.

3.4 Future Works

This work can still be enhanced by incorporating more predefined sitting postures based on the typical sitting posture possessed by the wheelchair user. The Rapid Upper Limb Assessment (RULA) method can also be used in order to calculate the risk of developing musculoskeletal disease while possessing the chosen predefined sitting posture [13]. Simultaneously, the number of subjects can be raised to collect a wider range of sensor data that could be used in this project and by recruiting real wheelchair users for better simulation of real-life settings. Finally, the GUI mobile application can also be improved with dedicated settings based on the wheelchair user's routine for better sitting posture monitoring.

4. CONCLUSION

All related aspects of the concepts, mechanisms and methodologies have been thoroughly discussed in this paper. In addition, a comprehensive literature review on the related topics that highlighted the sitting posture recognition system as well as the sitting posture classification has been done in order to kickstart the project work. Overall, this project managed to achieve all of its objectives. There were 5 sitting postures, including normal posture on the wheelchair that were analyzed. The improper sitting posture in a wheelchair was identified using pressure sensors and classified utilizing machine learning, whereby the decision tree was chosen as the top classifier with the accuracy of 98.8%. Finally, a sitting posture detection system in a wheelchair with DT classifier was developed, whereby the detected posture can be sent as a notification to a mobile phone via Bluetooth.

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