EMITTER International Journal of Engineering Technology
Vol. 13, No. 1, June 2025, pp. 156~172
DOI : 10.24003/emitter.v13i1.898

Sitting Posture Detection and Classification Using Machine Learning Algorithms on RapidMiner

Chawakorn Sri-ngernyuang[1], Prakrankiat Youngkong[2], Jinpitcha Mamom[3], Duangruedee Lasuka[4]

[1,2]Institute of Field Robotics, King Mongkut's University of Technology Thonburi, Bangkok, Thailand
[3]Faculty of Nursing, Thammasat University, Pathum Thani, Thailand
[4]Faculty of Nursing, Chiang Mai University, Chiang Mai, Thailand
Corresponding Author: chawakorn.srin@kmutt.ac.th

Received January 5, 2025; Revised March 1, 2025; Accepted May 15, 2025

Abstract

Integrating pressure sensors into cushion pads presents a viable posture monitoring and classification solution in innovative health care and ergonomic design. In this study, a cushion pad with a pressure sensor implanted that can recognize and classify different postures using machine learning techniques is developed and evaluated. The principal objective is to augment postural awareness and avoid disorders of the muscles. The cushion pad system was created and used by combining software algorithms with hardware sensors. Using a variety of machine learning approaches, RapidMiner, a data science platform, was used to analyze the pressure data to classify postures. The following algorithms are tested using cross-validation for a robust evaluation: Decision Tree, Naive Bayes, Neural Network, Random Forest, and K-Nearest Neighbors (K-NN). The outcomes showed that the various algorithms' levels of accuracy varied. The Naive Bayes algorithm demonstrated a lesser accuracy of 55.83% compared to the Decision Tree algorithm's 84.49% accuracy. The Random Forest algorithm surpassed the others with an accuracy of 85.98%, while the Neural Network approach produced an accuracy of 82.26%. The k-NN algorithm also yielded promising results, with an accuracy of 82.01%. According to these results, the Random Forest algorithm outperforms the Decision Tree algorithm for posture categorization in this specific example. A workable approach for enhancing ergonomic health and avoiding posture-related illnesses is to integrate such machine learning models into a cushion pad with pressure sensor integration that can significantly help proactive posture management.

Keywords: Cushion Sensors, Postures Classification, Arduino, Machine Learning

1. INTRODUCTION

Sedentary time means the hours spent at a desk, which can be a decisive factor in comfort and health problems known as office syndrome [1].

This condition includes symptoms associated with extended sitting at a desk and includes backache, tight neck, and shoulders [2]. These symptoms may be caused by poor posture and lack of standard arrangements in workplaces, which are common to most firms. Prolonged sitting can lead to disorders of the musculoskeletal system and, therefore, life-long, constant, painful feelings in the lower back, shoulders, and neck [3]. In addition, repetitive strain injuries such as carpal tunnel syndrome and tendonitis, Due to repeated usage or overwork of the the limbs, especially the hands and wrists [4]. Office syndrome, or sedentary disease, is not only a physical ailment but also entails visual strain from spending many hours in front of the computer screen, resulting in conditions like dry and tired-looking eyes, blurred vision, and headaches [5]. Such problems are not only largely attributable to unsuitable lighting conditions or ill-placed displays [6]. Moreover, prolonged sitting may result in inadequate blood circulation, leading to sensations of discomfort, pain, edema in the legs, and an elevated risk of deep vein thrombosis. Another thing that is unfavorable to mental health is the fact that work environments are passive in nature. In the same report, it was established that work environments are likely to cause high levels of stress, anxiety, and depression. To minimize these impacts, one needs to take a break, check the setting is correct, do some exercises, or consult doctors when the problems are prolonged [8]. For these difficulties, several possibilities of using technology exist, for instance, innovative smart cushions that help to define sitting posture and movements [9]. nevertheless, most devices now available are costly and involve extensive development processes that are challenging to implement and evaluate on a large scale. That is why this study will focus on designing a prototype of the seat cushion for office use, which is easy to manufacture, inexpensive, and will help a user avoid getting an office syndrome. Sitting postures will be assessed using pressure sensors and then analyzed via machine learning techniques. Most ergonomic interventions of the past have needed a lot of effort or specialized knowledge to implement, thus limiting their usability. In this work, simple sensor technology, along with the help of big data analysis and machine learning approaches, is used to address the gap between the functionality perspective and usability perspective, thereby improving the sitting behaviors and minimizing the adverse effects of sitting.

Adapting into real-life scenarios' The proposed system entails certain challenges that make the difference, and which must be confronted to ensure the best result and use of the platform. Among them, the pressure map acquisition from pressure sensors poses some difficulties due to fluctuations in the output of the sensors affecting the posture classification. This can be prevented by using high-quality sensors and performing periodic checks on their calibration to maintain accuracy over the long run [11]. Furthermore, adaptive machine learning methods may enhance system efficiency when differences in sensor data develop between users and the environment [11]. The other significant problem is a concern of comfort compared to functionality. The cushion must be created in a way that could provide comfort for a long time of usage without causing an incorrect identification of the user's posture. This can be made possible by incorporating good materials that do not cause discomfort to the user as well as proper arrangement of the sensors in a manner that will not discomfort the user. Also, producing feedback to the user in real time is something I discovered is very important in making the system function optimally. Accurate processing of data and proper algorithms will guarantee that users are informed on time about risks and using the app will make a right decision.

This research aims to provide several contributions essential for the development of effective posture monitoring systems. It begins with a solution that develops a low-cost prototype cushion with pressure sensors for detecting and categorizing sitting postures. Indeed, it is a functionality and cost-oriented construction aimed at users who are not large enterprises and can also be implemented individually or in small offices. The paper also focuses on enhancing information to incorporate machines to give feedback on sitting postures, hence improving the sitting habits and the overall health of an individual. This is made possible through the simplicity of the system and the flexibility of its integration that allows for its use across many areas without much demanding technical experience on assembly. In addition, the project result will be open-source, and it means that the design can be easily copied and modified by other researchers and developers to improve the system constantly.

2. RELATED WORKS

The development of cushions capable of detecting posture classification has made significant strides, leveraging sensor technology and machine learning advances. Various studies have demonstrated the effectiveness of integrating pressure sensor arrays and conductive fabrics into smart cushions [12],[13],[14] or a posture recognition system for wheelchair users using a cushion-based approach with pressure sensors [15], achieving high accuracy in posture detection using convolutional neural networks and other classification algorithms [16],[17]. These cushions, which are both cost-effective and flexible, have shown potential in real-time posture monitoring [18],[19] and feedback applications, particularly in settings that prioritize user comfort and health, such as nursing communities and office environments. The research highlights the importance of accurate posture recognition in preventing health issues [20]and enhancing productivity, suggesting a promising future for smart cushions in ergonomic and health monitoring interventions.

3. ORIGINALITY

This research includes a pressure sensor in the cushion connected to a microcontroller. The system will alarm you if you sit on the seat for more than 1 hour to remind you to adjust your sitting or standing position to prevent office syndrome. The data from sitting postures apply machine learning techniques from the Rapidminer platform to identify the sitting posture using sitting data. By categorizing sitting postures into four categories: upright, there are upright posture, leaning back posture, Right leg crossed over the left leg, and Left leg crossed over the right leg.

Several processes are employed to compare the work's outcomes based on the prediction of sitting posture: Decision Tree, Radom Forest, K-nearest neighbor, Neural Network, and Naïve Bayes approaches. Based on the findings, a fundamental examination of the analysis system's design will be conducted, and the user's seating position will be suitably modified going forward.

4. SYSTEM DESIGN

In designing the system, the design starts with installing the sensor on a thin, cloth-like cushion that can be conveniently installed on a chair. The cushion, the main leading equipment in the research, consists of force sensors that work with an Arduino microcontroller and store data in a computer. The working steps are shown in the picture.

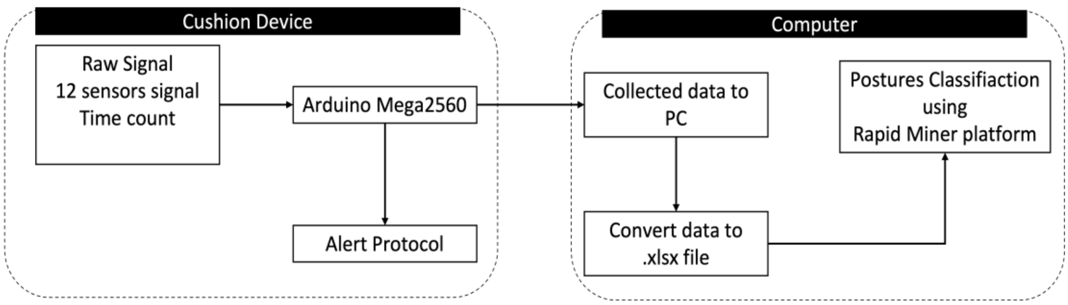
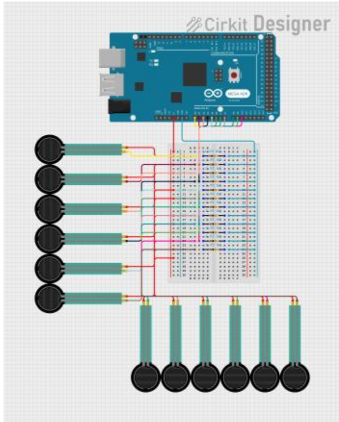


Figure 1. Diagram of research

The main system of this research included a cushion pad device which was intended to capture users sitting posture as shown in Figure 1. This cushion device consists of FSR sensors and an Arduino Mega2560 at its base parts of the cushion as shown in Figure 2.



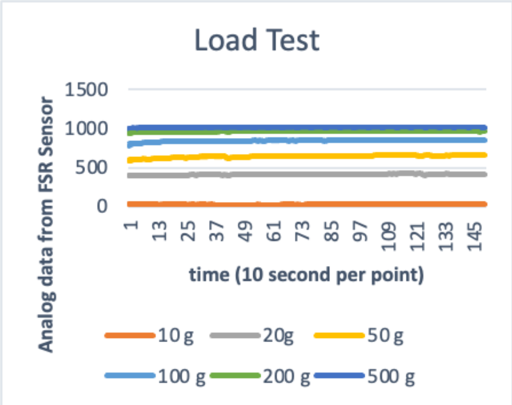
(a) (b)

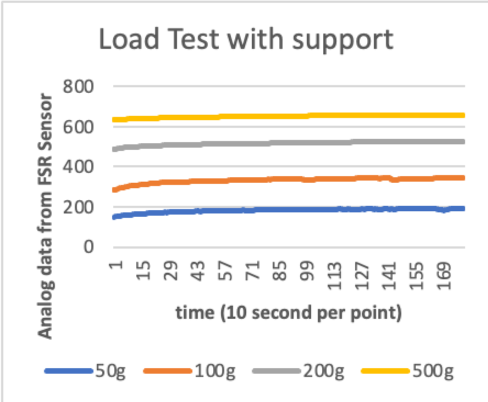
Figure 2. (a) Force-Sensitive Resistor (FSR), (b) Arduino Mega2560 board connected to sensors created by Cirkit Designer program [21]

FSRs function as resistors whose resistance (measured in ohms Ω) varies depending on the applied pressure. Although these sensors are economical and user-friendly, they lack precision and can vary by approximately 10% from one sensor to another. Consequently, when using FSRs, the outcome expects to receive only a range of responses. In the preliminary work test, the sensor measures the pressure that occurs. Due to the change in resistance to be used to display data on the pressure that arises appears on the cushion from equation (1) for validating and characterizing a Force-Sensitive Resistor (FSR) sensor [22],[23] installed on a cushion.

$$V_{meas} = \frac{R_0}{R_0+R_{FSR}} V_{cc} \tag{1}$$

where the variable resistance of the FSR is labeled as R_{FSR}, the known resistance value, R_0, is 1,000-ohm resistance, V_{cc} is the supply voltage (5V from Arduino Board), and V_{meas} the voltage measured by the Arduino's analog pin. This voltage divider methodology will allow for approximation of force incidents upon the FSR, which will be output as a voltage value. In the initial pressure reading test, a weight of 50 - 500 grams (Figure 3c) were used to test the reading of the sensor connected to a 1000-ohm resistance to test the response and readability of the sensor. The result of the sample test is shown in Figure 3a. Besides conducting voltage value testing by applying weighted pressure on the FSR sensor, pressure testing was also done on other soft and flexible articles using 4 mm thickness Natural Rubber sheet. The sheet can be elastically deformed to mimic some pressure values that are like weight distribution of a human. One of the pressure application examples of the system is shown in Figure 3d, and the results shown in Figure 3b can be seen that the weight test values of 10 grams and 20 grams were not displayed because the weight tested was equal to 0 or did not show a value in the test.





(a) (b)

(c) (d)

Figure 3. Show (a) Test FSR sensors from counterweight; (b) Test FSR sensors from counterweight on support; (c) counterweight 50-gram to 500-gram and (d) counterweight 50-gram to 500-gram on support

The Arduino Mega2560 control board is a microcontroller for receiving and sending sensor data to a computer and collecting files before using a machine-learning algorithm to classify postures. Arduino boards are widely used for creating convenient and inexpensive innovations, and they can be used in various ways [24],[25]. Arduino Mega2560 is used to connect force sensors. Each FSR sensor has an analog pin on the Arduino board as the Arduino board's analog pin, is connected to an analog pin on an Arduino board, as shown in Figure 4.

(a) (b)

Figure 4. Cushion circuit:
(a) cushion installed with FSR Sensors (b) cushion installed on the chair

5. EXPERIMENT AND ANALYSIS

Scenarios were studied in this research scenario. This research studied two experimental scenarios: an alert system that activates when a user sits on a cushion for more than an hour and the RapidMiner platform [26], which was used to classify four different postures. This experiment used neural network neighbors, decision trees, naive Bayes, a neural network, a random forest, and K-nearest neighbors (K-NN) as classification techniques.

5.1 Alert System

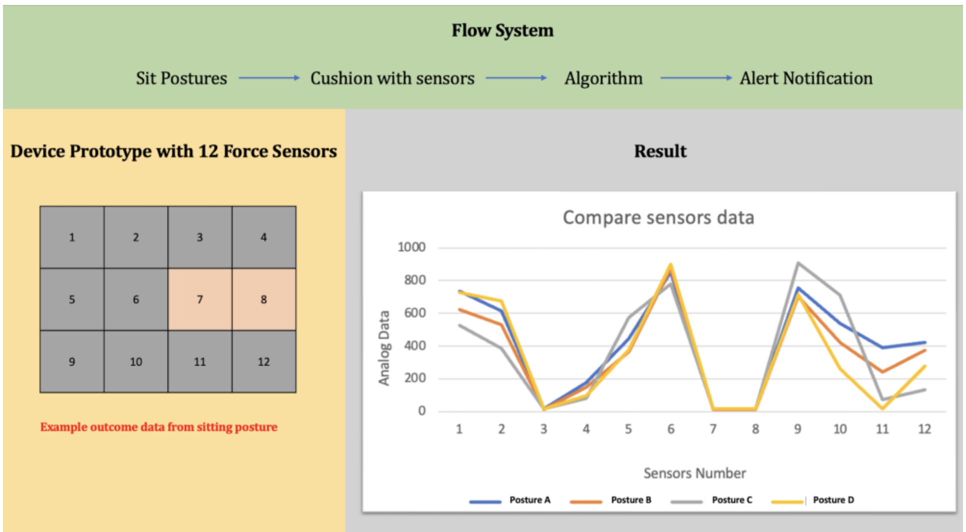


Figure 5. Alert system diagram

In this experiment, the system has been designed to alert when the user sits on a cushion installed on a chair for more than one hour. This system is an example of a protocol to prevent injuries from sitting for long time periods. In Figure 5, the picture shows the point of the sensors, which has figure 5 shows the point of the sensors, which have different colors, and the inside picture shows a graph that shows raw data from the sensor. In this system, the controller gets data for more than one hour, the force from the sensor receives data for more than one hour, and the force from the sensor is more than 100, as resulted in Figure 6. The system will alarm from a buzzer node connected to the Arduino Mega2560.

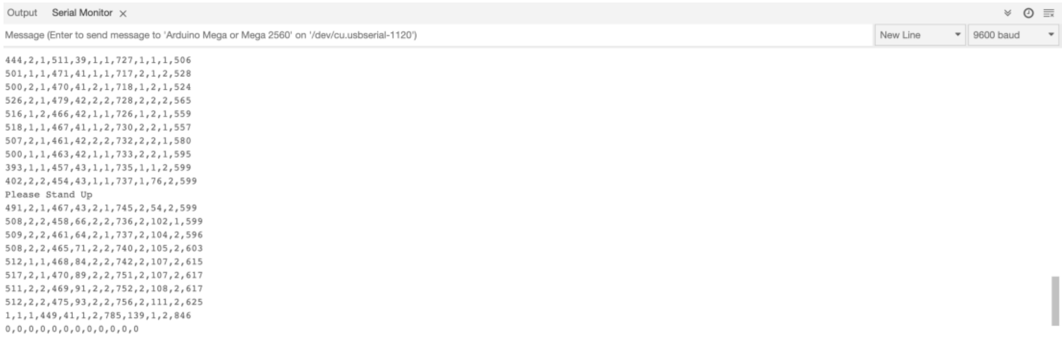


Figure 6. The result of the Arduino program

5.2 Postures Classification Method

Table 1. Example data from 12 sensors

Posture	Sample	Data from Sensors											
		1	2	3	4	5	6	7	8	9	10	11	12
A	1	0	509	597	203	467	701	85	0	419	426	374	306
	2	0	511	598	187	471	707	86	0	428	437	369	308
	3	0	510	603	222	470	713	86	0	410	425	311	301
	4	0	502	604	233	463	721	87	0	417	424	311	295
	5	0	507	603	234	469	725	89	0	426	423	328	306
B	6	770	641	695	496	746	893	522	0	419	457	687	485
	7	744	641	702	507	703	890	533	0	392	472	702	493
	8	744	643	713	507	702	891	545	0	405	474	709	497
	9	744	641	719	515	697	889	551	0	410	476	711	505
	10	752	641	723	443	711	885	570	0	424	503	735	520
C	11	8	8	254	68	701	8	16	8	715	478	733	8
	12	8	8	250	65	701	8	13	8	709	482	749	8
	13	8	8	247	66	696	8	16	8	710	482	758	8
	14	8	8	241	64	699	8	13	8	710	482	749	8
	15	8	8	243	62	697	8	11	8	713	480	748	8
D	16	0	497	769	259	449	785	333	264	171	338	697	581
	17	0	497	772	261	444	782	347	284	168	344	707	586
	18	0	501	776	270	445	785	350	301	169	350	705	589
	19	0	502	778	274	445	786	351	307	169	353	704	589
	20	0	503	780	272	441	786	353	312	169	354	703	590

*A = upright posture, B = leaning back posture, C = Right leg crossed over left leg, D = Left leg crossed over right leg

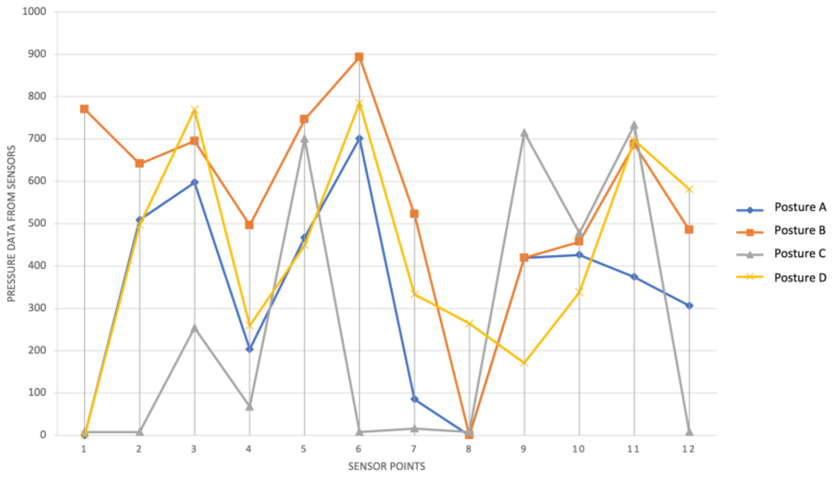


Figure 7. Graph from sensor data

Table 2. Performance Metrics of the Classifiers

Classification	Validation	Accuracy *(%)*	Precision *(%)*	Recall *(%)*	F1 SCORE *(%)*
Decision Tree	2-fold	84.49 +/- 0.53	85.02 +/- 0.35	84.50 +/- 0.53	84.41
	5-fold	85.24 +/- 1.03	86.03 +/- 0.90	85.23 +/- 1.07	85.14
	10-fold	86.36 +/- 3.43	87.29 +/- 3.15	86.36 +/- 3.42	86.65
Random Forest	2-fold	85.98 +/- 0.18	86.46 +/- 0.27%	85.98 +/- 0.17	86.22
	5-fold	86.97 +/- 3.49	87.78 +/- 3.18	86.99 +/- 3.47	87.27
	10-fold	87.10 +/- 5.33	88.20 +/- 4.72	87.08 +/- 5.33	87.43
Neural Network	2-fold	82.26 +/- 1.93	83.83 +/- 0.43	82.25 +/- 1.93	82.40
	5-fold	83.50 +/- 2.89	85.43 +/- 2.64	83.51 +/- 2.88	83.79
	10-fold	82.25 +/- 5.12	83.99 +/- 3.92	82.15 +/- 5.19	82.42
Naïve Bayes	2-fold	55.83 +/- 1.40	68.58 +/- 7.84	55.81 +/- 1.41	61.24
	5-fold	55.83 +/- 2.73	69.65 +/- 6.84	55.80 +/- 2.82	61.82
	10-fold	55.58 +/- 4.20	72.35 +/- 3.66	55.61 +/- 4.10	62.56
k-Nearest Neighbor	2-fold	82.01 +/- 1.58	85.40 +/- 0.03	82.05 +/- 1.57	83.63
	5-fold	81.15 +/- 2.46	85.24 +/- 2.89	81.17 +/- 2.45	83.07
	10-fold	81.89 +/- 2.50	86.13 +/- 2.69	81.90 +/- 2.44	83.83

The second experiment uses a posture classification method using a machine learning algorithm. Postures from a sitting position have four categories: upright posture, leaning back posture, Right leg crossed over left leg, and Left leg crossed over right leg. These are standard postures found in everyday life by a worker or student sitting on a chair. In the classification protocol, data was collected from 7 healthy participants with 800 data points for four postures.

Following the acquisition of information from the developed sensor cushion when sitting. The pressure measurement at each sensor point can be applied to obtain basic information. It is possible to identify sitting postures due to the sensor's ability to show significant pressure values for each position, as seen in Table 1 and Figure 7, an example of data from a total of 800 data points. Table 2 displays the findings of the classification of sitting positions about the study objectives.

To test the performance of the sitting postures classification model in the RapidMiner platform, the research set parameters in this detail for each model are:

• The Decision Tree model in RapidMiner has 10 as the maximum number of splits for the tree and the Gain Ratio that provide unbiased splits. Enforcement of pruning and pre-pruning is employed to minimize overfitting with a confidence level of 0.1 and minimal gain of 0.01 on split. The model also uses a minimum of two samples for splitting a node which guarantees that the minimum samples in the leaf node should be at least two.

• The Random Forest model set 100 trees with a maximum depth of 10 are to be created with Gain Ratio as the splitting factor. As with the Decision Tree, pruning and pre-pruning tests are used here at a confidence level of 0.1 and minimum gain 0.01. The model splits features with a guess subset ratio and applies a confidence vote technique to make the predictive model.

• The Neural Network model implemented is a feedforward one with 10 hidden layers with 32 neurons each. The model is trained for 200 cycles (epochs) where a learning rate of 0.01 is used to control the amount that weights were updated. To speed up learning and minimize fluctuations while training, it is proposed to set the momentum parameter to 0.9. The training of the model will only be stopped when the error value should fall below 1.0E-4 (0.0001).

• The k-Nearest Neighbor model will set k=5 in order make its predictions by getting the values of the 5 closer neighbors on the dataset. The majority of votes require that closer neighbors have a higher say in the prediction than those who are farther away. The model employed in the work utilizes the Mixed Euclidean Distance measure with an ability to measure distances on both numerical and categorical measures appropriately.

• The Naive Bayes model corrects them with smoothing alpha set to 1 while regarding the imbalanced classes in the dataset, it adopts automatic class prior probabilities. It can accommodate nominal and numeric attributes and for the numerical data it assumes Gaussian distribution and for the nominal data it has Kernal Density Estimation if it does not assume any distribution. It also provides strategies for dealing with missing values in that it gives an option of ignoring the values as they calculate probabilities.

Based on the experimental data, the Cross Validation Operator from the RapidMiner platform was used to estimate the statistical performance of a learning model, and K-fold cross-validation was used to improve the classifiers 'performance. The data is randomly split into training and testing data, and the Decision Tree, Naive Bayes, Neural Network, Random Forest, and K-Nearest Neighbors (K-NN) models are fitted to the training set and evaluated on the test set in the cross-validation process. Each iteration model chooses a different training and test data set from the program classification process. Table 2 shows that all the classification algorithms have more than 80% accuracy, but only the Naive Bayes algorithm has less than 60%. This outcome indicates that the relationships between features are non-linear or complex; models like neural networks and random forests can capture these relationships better than Naive Bayes. Generally, the data is not normally distributed because it comes from raw data from the FSR sensor. So, Naive Bayes might perform poorly, and other models like Random Forests or Neural Networks might handle these situations better due to their flexibility.

To measure the efficiency of the random forest model, further testing was done using the 70:30 division of the data set, divided between training and testing. The confusion matrix as shown in table 3 discussed in the following image shows the classification results of all four classes, namely A is upright posture, B is leaning back posture, C is Right leg crossed over left leg, and D is Left leg crossed over right leg, with an overall accuracy of 88.48% on the test dataset. As observed from the above results, the model has a high level of accuracy, both for precision and recall, in all classes, and this ranges from 76.81% to 94.44% for precision, as well as 83.61% to 98.36% for recall. We have seen that class D achieved the best group accuracy of 94.44%, which means the model is not reporting wrong results or false positives. Likewise, class C obtained the highest recall of 98.36; this indicates that nearly all the true instances of this class were correctly identified by the model. Of all the classes, class B achieved slightly lower precision at 76.81%, meaning that there is still some potential to differentiate it from other classes. In summary, based on the Random Forest model, the combined performance of all metrics used was fair with a slight enhancement compared with the previous study in the full dataset. Such a method of splitting up the database for the purpose of training the neural network and validating it by the independent test dataset lowers the chances of overfitting and increases the stability of the proposed model. The test set of 30% gives the evaluation of the model's generalization and minimizes the chances of overfitting and offers a better measure of the model when applied in real-world scenarios.

Table 3. The confusion matrix of Random Forest model

	True A	True B	True C	True D	Class Precision
Prediction A	51	4	0	0	92.73%
Prediction B	6	53	1	9	76.81%
Prediction C	1	3	60	1	92.31%
Prediction D	2	1	0	51	94.44%
Class Recall	85.00%	86.89%	98.36%	83.61%	

5.3 Comparison and Analysis

In this work, a random forest classifier has been developed, using 800 samples to train from 7 participants to classify four sitting postures with 85.98% accuracy. Comparing the performance of the proposed model to other studies shown in table 4, it is slightly lower, although considering the limited number of instances and simplified sensor setup, the results are encouraging. For example, Zemp et al. [27] obtained 90.8% accuracy employing 16 force sensors and a backrest angle on a sample dataset of 1,148 samples collected from 41 subjects and demonstrated that the robust classification accuracy may be obtained if larger datasets and additional features are incorporated. In the same manner, Ma et al. [15] constructed a smart cushion-based posture detection system with 12 pressure sensors installed on the seat and backrest and used the J48 Decision Tree algorithm to classify the five postures with an average accuracy of 99.48%. The disparity in the improvement between those two models compared to the random forest model is that the Ma et al. model performed better with the dataset of 36,000 posture recordings from 12 participants, as well as the seating system support sensors that are distributed over the seat and backrest, and therefore the model can identify more elaborate patterns. Further, Ma et al. employed a sensor backward selection method to minimize data redundancy and enhance the input of sensors, which would also help the authors achieve higher accuracy. Roh et al. [28] had earlier presented a low-cost load cell system for ERP to recognize six sitting postures, engaging the 9 participants with the maximum accuracy clocking 97.2% with the SVM classifier. This brings out the extent to which sensor positioning and selection of classification algorithms affect posture classification performance. Also, Kim et al. [29] implemented a system using an 8×8 pressure sensor matrix and used diverse deep learning approaches; the CNN has indicated an accuracy of 95.3%, where network classifiers become less efficient when handling richer data inputs. Ahmad et al. [30] and Luna-Perejón et al. [31] used decision trees and artificial neural networks to classify pressure sensors, respectively. Both methods showed lower efficacies, indicating that the type of sensors and algorithm integration significantly impact classification rate. In contrast, Najafi et al. [16] used anesthesia and set eight sensors on both the seat and backrest using an Echo Memory Network; the results were 91.68% accuracy on eight postures, which exemplifies the significance of sensor positioning in enhancing posture identification systems.

Finally, it can be stated that the position of sensors, the number of data points, and the type of the classifier are decisive for the accuracy of posture classification systems. Although there is certain inaccuracy in the proposed Random Forest model, this certainly indicates sound performance given that the database is small, and the sensors involved are basic. The improvement could be made in the future to augment the dataset information, adding the sensors at the seat and backrest; also implementing some other methods such as GBM and CNN for making more accurate and stable posture-detecting systems.

Table 4. Comparison and Analysis

Study	Participants	Samples	Sensors Used	Postures Classified	Algorithm	Accuracy (%)
[27] Zemp et al. (2016)	41	1,148	16 force sensors + backrest angle	7	Random Forest	90.8
[15] Ma et al. (2017)	12	36,000	12 pressure sensors	5	Decision Tree	99.48
[28] Roh et al. (2018)	9	720	4 load cells (seat cushion)	6	SVM	97.2
[29] Kim et al. (2018)	10	13,000	8x8 pressure sensor matrix	5	CNN	95.3
[30] Ahmad et al. (2018)	5	-	Screen-printed piezoresistive sensors	4	Decision Tree	80.0
[31] Luna-Perejón et al. (2021)	12	3,389	6 pressure sensors	7	ANN	81.0
[16] Najafi et al. (2022)	40	960 (dataset)	8 pressure sensors (seat and backrest)	8	Echo Memory Network	91.68
Proposed Model (2024)	7	800	12 pressure sensors (seat cushion)	4	Random Forest	85.98

6. CONCLUSION

The pressure cushion used in this study is based on a technique to prevent injuries caused by prolonged chair sitting. A warning against protracted sitting can be issued based on the test results of the operation. In addition, it warns against the need to adjust posture brought on by prolonged sitting. Data on the pressure experienced in each of the four sitting positions were also gathered for the study, including upright posture, leaning back posture, right leg crossed over left leg, and left leg crossed over right leg, to be used to test the classification of sitting postures from sensor data that received from the cushion. In classifying sitting postures, decision trees, naive bayes, neural networks, random forests, and K-nearest neighbors (K-NN) models were used from the Rapidminer platform. According to the Decision Tree algorithm, which displayed an accuracy of 84.49%, the Naive Bayes algorithm performed with a lower accuracy of 55.83%. With an accuracy of 85.98%, the Random Forest algorithm outperformed the others, while the Neural Network method had an accuracy of 82.26%. The K-NN algorithm performed well, with an accuracy of 82.01%. These results show that the Random Forest method performs better than the Decision Tree approach for posture categorization. As a result, the cushion pad can work as it is designed. Also, the classification results are in an acceptable direction. This cushion can be upgraded into an automatic device that can alert and recommend posture for users whose posture can prevent pain or injuries for long periods of sitting using sit data from the research database. Also, we can increase the accuracy of the classification model by keeping more data from sitting posture.

Further development related to the presented work can be designed and improved in the following aspects to boost the functionality of the posture detection system in future works. First, augmentation that involves collecting a larger dataset with more varied sitting postures, besides expanding the variability of the participating subjects, is expected to improve the classification model. Moreover, using the real-time posture monitoring application and incorporating the cushion device with various mobile applications could offer the users immediate feedback as well as recommendations on how to change the sitting position. Other future works can also consider extending the use of the classical machine learning algorithm into others like deep learning models to enhance the classification model performance. With wireless communication and IoT integration, a mobile and autonomic posture management system can be built. Furthermore, the cushion can be enhanced to incorporate the incorporation of extra sensors to get enhanced data of the position and pressure that the users place on the cushion. It will thus facilitate the development of a better structure responsible for identifying minor changes in posture and generating accurate advice on ways of avoiding potential permanent sitting harm.

Acknowledgments

The researcher gratefully acknowledges the support provided by "Petchra Pra Jom Klao Ph.D. Research Scholarship from the King Mongkut's University of Technology Thonburi" and thanks all the participants in this study.

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