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Design and development of an intelligent real-time pressure sensing system for sitting posture monitoring

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Abstract: Poor sitting posture is a common issue that can lead to musculoskeletal disorders and long-term health complications, especially with the rise in sedentary work. This study aims to design and develop an intelligent, real-time pressure sensing system to monitor and classify sitting posture accurately. The system uses Velostat-based pressure mats positioned on a seat and backrest, connected to an ESP32 microcontroller, to collect real-time data. A support vector machine (SVM) model processes this data to classify ten distinct postures. A Bluetooth interface transmits data to a graphical user interface (GUI), which offers real-time feedback and tracks the duration of poor posture. The SVM model achieved 100% classification accuracy on a dataset collected from 25 participants using a 90/10 train-test split. Cross-validation further confirmed the model's reliability, with an average accuracy of 99%. The system's precise classification and intuitive feedback make it a practical tool for posture correction in office and home settings. These results suggest significant potential for reducing posture-related health risks through early intervention and real-time monitoring.
Keywords: *Sitting Posture Monitoring, Support Vector Machine, Velostat Pressure Sensor.*

1. Introduction

In today's digital and technology-driven age, prolonged sitting has become an almost unavoidable aspect of modern life, deeply ingrained in our daily routines. This shift towards sedentary behaviour is evident across various domains, including work environments, education systems, and even leisure activities [1] as people spend long hours seated in front of computers, attending virtual meetings, working from home, or engaging in screen-based entertainment. According to study done by Saiful, et al. [2] the average daily sitting time of Malaysian office worker is 5.96 hours [3]. Besides, Bailey, et al. [4] reported that the average sitting time of American when they are not working is 8.07 hours per day [4]. As the average sitting time of people increases over the year, this widespread norm comes with significant consequences, as it causes a rise in posture-related health issues, raising concerns among health professionals and researchers [5]. One of the most prominent consequences of poor sitting posture is its association with musculoskeletal disorders (MSDs), which encompass a range of conditions affecting muscles, joints, and connective tissues. These disorders not only result in chronic back pain, discomfort, and reduced mobility but also contribute to decreased productivity and mental focus [6] thereby affecting both personal well-being and professional performance. Highlighting the severity of the issue, a study by Gill, et al. [7] revealed that MSDs rank as the second leading cause of non-fatal disability globally, impacting over a billion individuals and placing a substantial burden on healthcare systems and economies worldwide [7]. These findings show the importance of promoting correct sitting posture to mitigate the risk of developing such conditions. By adopting proper ergonomic practices and raising awareness about posture-related health risks, individuals can significantly reduce the likelihood of musculoskeletal problems, improve overall quality of life, and foster long-term physical

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and mental well-being [8]. Consequently, addressing this pressing issue is not merely a matter of individual health but a collective responsibility that demands attention from workplaces, educational institutions, and policymakers to create environments that support healthier sitting habits.

Traditional methods to address poor sitting posture, such as the use of ergonomic furniture and wearable posture-correcting devices are useful in encouraging proper posture alignment and reducing strain. These tools are designed to provide external support and reminders, making it easier for individuals to maintain a healthier sitting habit. According to research by Choobineh, et al. [9] ergonomic adjustments can alleviate pain and symptoms commonly associated with musculoskeletal disorders (MSDs) [9]. On the other hand, the widespread adoption of these solutions faces several critical barriers. High costs remain a significant deterrent, as many consumers are unwilling or unable to invest in these often-expensive products. Additionally, the intrusive nature of wearable devices can discourage consistent use, as they may feel uncomfortable or inconvenient for everyday activities. Accessibility also presents a challenge, as these products are not always readily available in all markets or regions, limiting their reach. Furthermore, many existing solutions lack the capability to deliver real-time corrective feedback—a feature that is crucial for enabling users to make immediate adjustments and develop long-term, sustainable improvements in their posture. This absence of dynamic feedback reduces their overall effectiveness and appeal. Consequently, most individuals are unlikely to seek out or invest in such products unless they have already been diagnosed with posture-related health issues or are experiencing significant discomfort. This reactive approach highlights a gap in preventative measures and underscores the need for innovative, accessible, and user-friendly solutions that address these limitations while encouraging proactive posture management.

Besides, camera-based systems for detecting poor sitting posture are increasingly popular due to advancements in computer vision and artificial intelligence [10]. These systems use cameras, sometimes combined with depth sensors, to monitor and analyse body positions, tracking key points like the spine, shoulders, and head. One of the application examples is Posture AI, which provides 360° posture monitoring and habit analysis. By recognizing deviations from optimal posture, camera-based solutions can offer real-time feedback, helping users to correct slouching or leaning. Despite their effectiveness, these systems come with significant drawbacks. Privacy is a major concern, as continuous monitoring can feel invasive, especially in shared or open spaces [11]. Additionally, their accuracy can be affected by environmental factors like lighting, background, and potential obstructions, which can interfere with posture tracking.

To solve the problem, this project proposes a low-cost, non-intrusive pressure mat system that leverages the unique properties of Velostat for detecting changes in pressure distribution associated with different sitting postures. Pressure mats provide a more discrete and private alternative. By placing a mat equipped with pressure sensors on the user's seat, the system can detect weight distribution and posture without visual monitoring. This approach not only preserves privacy but also works consistently regardless of environmental conditions, making it a practical solution for accurate and unobtrusive posture correction. By applying machine learning algorithms, the pressure mat will classify various sitting positions, allowing for real-time feedback and detailed posture analysis. This system aims to empower users to develop healthier sitting habits and reduce the physical risks associated with poor posture.

In addition to aiding individual users, this project has potential applications in offices, schools, and healthcare facilities, where it can contribute to preventive health strategies for employees and students alike. Through this approach, the study seeks to advance posture classification technology and create a practical tool for real-time posture correction.

2. Related Work

2.1. Sensors for Sitting Posture Monitoring

A pressure sensor is a device that measures the force or pressure applied to the surface. It typically converts this physical force into an electrical signal that can be read and processed by a system. Many pressures sensor-based methods have been proposed in recent years. The main idea is to install pressure sensors on the hip area and back area of a chair to capture signals of sitting postures. There are a few types of pressure sensors being adopted in the pressure mat for detecting the sitting posture.

Textile pressure sensors are innovative materials that integrate conductive fibres or threads into textiles to measure pressure or force [12]. The implementation of textile pressure sensor on the sitting posture classification were introduced by Meyer, et al. [13]. These sensors detect changes in electrical properties, such as resistance [14] piezoelectric voltages [15] or capacitance [13, 16, 17] to detect applied pressure. Typically, they are fabricated by embedding conductive materials (e.g., carbon-based fibres, metallic yarns, or conductive polymers) within the textile structure or coating textiles with conductive layers. When pressure is applied, the deformation of the textile alters its electrical properties, enabling the measurement of force distribution across a surface. Textile pressure sensors are lightweight, flexible, and conformable, making them ideal for wearable technology, healthcare monitoring, and ergonomic applications [18].

Force sensing resistors (FSRs) are a widely utilized type of sensor in pressure mats due to their simplicity and cost-effectiveness [19]. FSRs operate on the principle that their electrical resistance decreases as pressure increases [20]. This behaviour enables them to detect and measure force or pressure variations across a surface area. FSRs are typically composed of a thin polymer film embedded with conductive material [21] which makes them lightweight, flexible, and suitable for integration into pressure-sensitive applications such as mats and ergonomic devices.

Load cells are widely utilized sensors in pressure and weight measurement applications due to their high accuracy and reliability. Operating on the principle of strain gauge technology, load cells convert mechanical force into an electrical signal [22]. This signal is proportional to the applied load, allowing precise quantification of forces such as weight or pressure. Load cells are constructed using a rigid structure with strain gauges bonded to it, ensuring robustness and durability in various operational environments.

Hybrid sensors combine the functionalities of multiple sensing technologies to offer enhanced performance and versatility in pressure and weight measurement applications. By integrating the strengths of different sensor types, such as tilt sensor, distance sensor, load cell and FSR [23, 24] hybrid sensors provide improved sensitivity, accuracy, and adaptability to diverse operating conditions. These sensors are advantageous in applications requiring multi-modal data acquisition or operation under varying environmental conditions.

Velostat is a conductive piezoelectric polymer material that changes its electrical resistance when pressure is applied [25]. This property makes Velostat an ideal choice for constructing pressure-sensitive surfaces, while at the same time enabling the creation of large-area pressure sensor arrays capable of detecting and mapping pressure distribution across extensive surfaces.

2.2. Technologies for Sitting Posture Monitoring

Many pressures sensor-based systems have been introduced in recent years. The type of pressure sensors and techniques used by them were explained in the section above.

Xu, et al. [12] developed a system integrated with electronic textile (eTextile) pressure sensors as the sitting pressure mat and rule-based system to classify sitting postures. The eTextile was composed of fibers coated with a conductive polymer, while the conductive polymer was made of pressure and strain sensors. In overall, after the system collected the pressure data of the user sitting on the pressure mat, it will filter the background noise and use Dynamic Time Warping (DTW), a signal matching algorithm, to classify seven sitting postures. The system achieved an accuracy of only 85.9%. In another study, Kim, et al. [26] designed a washable textile pressure sensor and integrate it into their sitting posture monitoring system with a decision-tree algorithm. The system has high durability which can still function well after 1000 times of repetitive loading and unloading. However, the fabrication of the pressure mat was complicated, and the system could only detect seven sitting postures.

Wang, et al. [27] designed a pressure mat with 81 FSR sensors on the hip and 90 FSR sensors on the back. By using SNNs, the system can classify 15 sitting postures with an accuracy of only 88.52%. Besides, the implementation cost of the system was high as a total of 171 FSR sensors are needed. In 2023, Tsai, et al. [28] proposed a sitting posture recognition system called SPRS which integrated 13 FSR 406 sensor on the hip and SVM to classify 10 different sitting postures. The system can achieve an accuracy of 99.1%, but the system did not have pressure sensing on the back.

In 2018, Roh, et al. [29] designed a smart chair which consists of 4 load cell sensors on the hip. The smart chair was low cost and can have accuracy of up to 97.94% with SVM model being implemented. However, the system can only classify 6 sitting postures, and there was no pressure sensing on the back too.

In 2023, Tavares, et al. [30] developed a smart office chair which can detect the sitting posture, body temperature and respiratory frequency of the user. The chair consisted of 4 load cells, 4 FSR sensors, 1 body temperature sensor, 1 temperature and humidity sensor, 1 noise sensor, 1 light sensor, and 1 carbon dioxide (CO_2) sensor. The system can detect 6 different postures with 100% accuracy. Although the sensors implemented in the chair are low cost, the Raspberry PI used in the system significantly increased the overall cost. Jeong and Park [24] placed six pressure sensors on the hip and six Infrared Reflective Distance Sensors at the back in their smart chair system. The system can measure the spinal trunk angle, which is one of the main limitations seen with other smart chair systems. In summary, the proposed system can classify 11 sitting postures with an accuracy of 92% by implementing KNN.

In 2021, Anwary, et al. [25] designed a smart cover using Velostat for real time sitting behavior monitoring. The cover had a 5-layered architecture, 2 layers of conductor at the top and bottom, while 2 layers of Velostat and 1 layer of polyethylene foam sandwiched between the conductor layers. A rule-based system, named Fuzzy Logic System, was designed to analyze the sitting behavior of the users. One of the limitations of the system is that it only displayed the sitting behavior of the users, which is the sensor readings. It did not have a sitting posture classification function. In 2024, Cao, et al. [31] introduced Velostat-based pressure mat for sitting posture classification. The system has a high accuracy (99.14%), but it can only classify 5 sitting postures, and there is no real time monitoring function for the system.

3. Methodology

3.1. Hardware Design

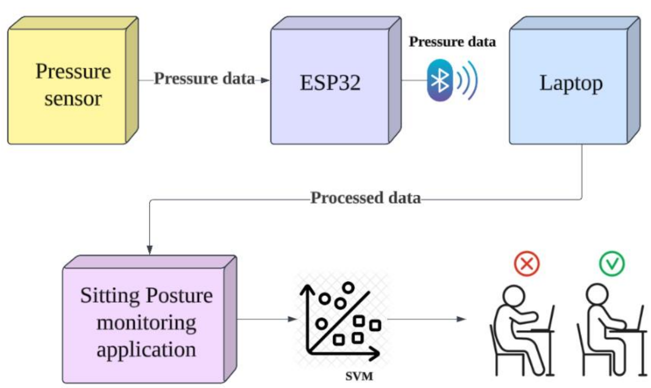

Figure 1.
Overall System Block Diagram.

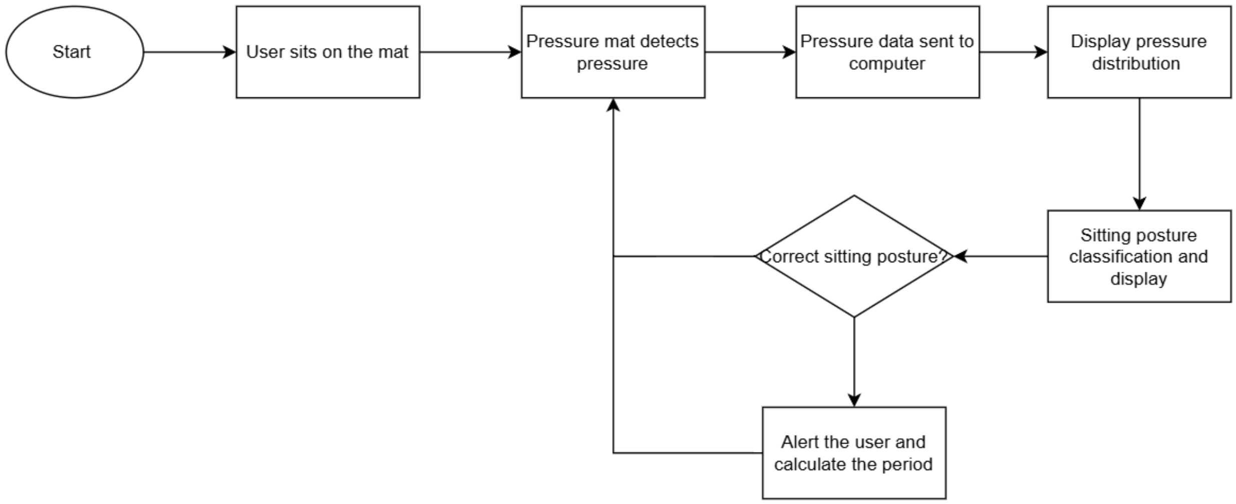

Figure 2.
Overall System Flowchart.

Figure 1 shows the overall system block diagram of the real-time pressure sensing system for sitting posture monitoring. The system consists of both hardware and software elements: pressure sensor, microcontroller (ESP32), laptop and sitting posture monitoring application, which consists of a trained Support Vector Machine (SVM) model. At the same time, Figure 2 shows the flowchart of the system. When the power of the pressure mat is on and a user sits on the mat, the pressure sensors will start to detect the pressure distribution of the user's sitting posture. The pressure value is sent to the ESP32 via the multiplexer, and the data is further sent to the laptop via Bluetooth connection. After the laptop receives the pressure data, it will start the pre-process the data before inputting the data into the trained model and display the pressure distribution on the screen. After that, sitting posture classification and display will be done on the software. If correct sitting posture is detected, the pressure mat will continue to detect the sitting posture. On the other hand, if wrong sitting posture is detected, the software will calculate the period of wrong sitting posture then display it out when the sitting posture is corrected.

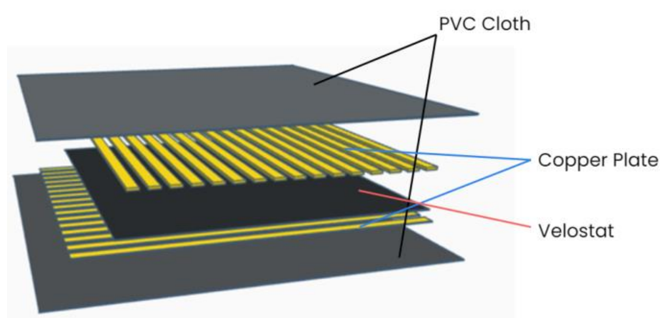

Figure 3.
Layers of pressure mat.

Figure 3 shows the layers of the Velostat-based pressure mat. The mat consists of 5 layers in total, 2 layers of PVC cloth, 2 layers of coper plate, and 1 layer of Velostat. The outermost layers are made of PVC cloth, which serves as a protective and durable covering, ensuring the structural integrity of the sensor while providing a comfortable surface for the user. Beneath these layers, two sets of copper plates

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act as electrodes, arranged in a grid-like pattern where one set is oriented horizontally and the other vertically, forming an X-Y sensor matrix. These copper electrodes are responsible for detecting pressure distribution when a user sits on the mat. Sandwiching between the copper electrodes is the Velostat, a conductive polymer material that exhibits changes in electrical resistance in response to applied pressure. When the user sits on the mat, the pressure exerted at different points causes Velostat's resistance to vary, allowing the system to capture detailed force distribution data. This data is then processed to generate a pressure map, which can be analyzed to classify the user's sitting posture. The combination of PVC cloth, copper plates, and Velostat enables the mat to function as a real-time sitting posture monitoring system, where variations in pressure distribution are translated into meaningful insights about the user's posture.

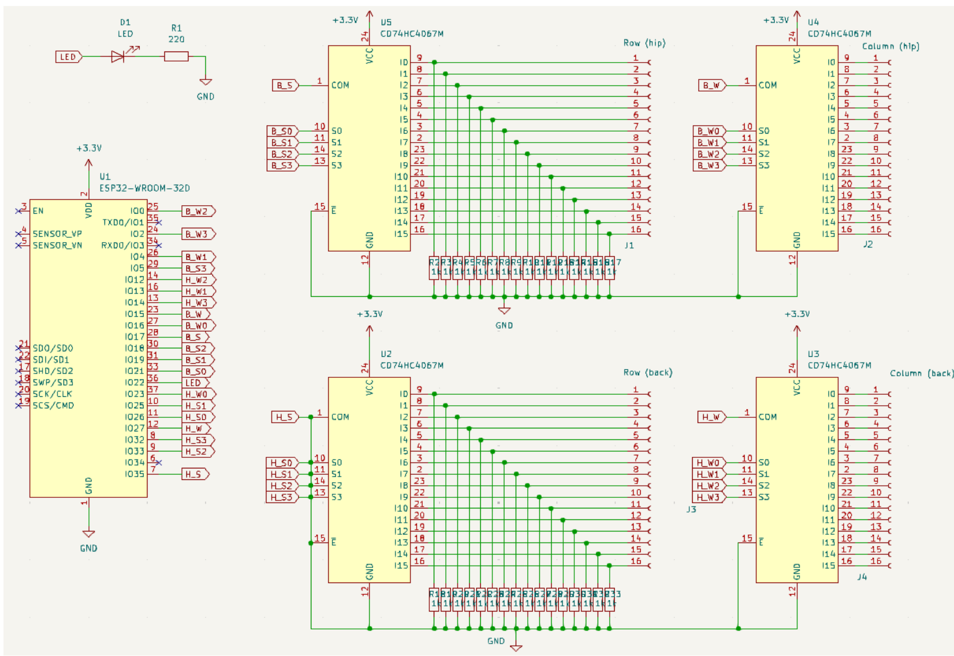

Figure 4.
Schematic circuit diagram of the system.

A schematic circuit diagram for the system as shown in Figure 4 has been designed. The circuit is consisting of 1 ESP32-wroom module with 38 pin, 4 CD47HC4067 16-channel multiplexer, 32 1kΩ resistors, 1 220Ω resistor, and 1 LED. Each pressure mat needs 2 multiplexers, one of which responsible for the pressure value on horizontal layer, while another responsible for the pressure value on vertical layer. The 1 kΩ resistors act as pull-down resistors. They are placed on the multiplexer for vertical layer. The COM port of horizontal multiplexer serves as voltage supply pin where 3.3V is supplied to this pin. On the other hand, the COM port of vertical multiplexer serves as input pin where the voltage value will be detected based on the selected port. For example, when S3 of vertical and horizontal multiplexer are set high, while others are set low, then the COM port of vertical multiplexer will store the voltage value of array channel. Hence, by alternating the S0, S1, S2 and S3 pin of the multiplexers, the voltage value of the corresponding channel can be obtained, and the pressure value of the channel can be obtained by converting the voltage value in 8-bit value (0-255).

Figure 5.
Sitting Pressure Mat.

The sitting pressure mat for sitting posture monitoring is as shown in Figure . The mat consists of two Velostat pressure mats to monitor and classify the user's sitting posture in real time. The system comprises a hip pressure mat placed on the seat and a back pressure mat attached to the backrest. These mats have array size of 16×16, allowing for high-resolution pressure distribution mapping.

The pressure mats are connected to a Printed Circuit Board (PCB) designed for the system, positioned on the right side of the chair for convenient access. The PCB integrates a microcontroller (ESP32-WROOM), multiplexers (CD74HC4067), and a power management system. The recorded pressure data is continuously transmitted to the posture classification algorithm, which processes the pressure distribution to determine whether the user is sitting correctly.

For power supply, a 12V rechargeable LiPo battery is used, ensuring portability and prolonged operation. The system also features a plug-and-play mechanism, allowing easy attachment and detachment of the pressure mats to accommodate different types of chairs.

3.2. Sitting Posture Monitoring with SVM

The core machine learning model used in this study is the Support Vector Machine (SVM), a supervised learning algorithm known for its effectiveness in classification tasks. SVM operates by finding an optimal hyperplane that best separates different classes—in this case, the ten sitting postures based on pressure distribution. Given the high dimensionality of the input data (pressure readings from 512 elements across the hip and back pressure mats), SVM is well-suited due to its ability to handle complex decision boundaries and high-dimensional feature spaces.

During the training phase, the SVM model is fitted using the 90% training data. The model learns to classify postures by mapping input features (pressure values) to predefined posture labels. The Radial Basis Function (RBF) kernel is used to enhance classification accuracy, as it effectively handles non-linear relationships between pressure distributions and posture categories. The training process involves optimizing the hyperparameters, such as the regularization parameter C and the kernel coefficient γ, to achieve the best balance between model complexity and generalization. Hyperparameter tuning is performed using techniques such as cross-validation, ensuring the model achieves high accuracy without overfitting.

3.3. Dataset Collection

To develop an accurate sitting posture classification system using Support Vector Machine (SVM), a dataset was collected from 25 volunteers within the age range of 20 to 50 years and weight range of 50 kg to 80 kg. These volunteers were selected to ensure diversity in body types and sitting behaviours, which would enhance the robustness of the trained model.

Each participant was instructed to sit on the pressure-sensing mat and perform 10 predefined sitting postures as shown in Figure (label 1-10): sitting upright (1), leaning left (2), leaning right (3), sitting at the front edge (4), upper body hunched (5), leaning forward (6), leaning backward (7), right leg crossed (8), left leg crossed (9), and crossed leg (10).

(a). Sitting Upright
(b). Leaning left
(c). Leaning right
(d). Sitting at the front edge
(e). Upper body hunched
(f). Leaning forward
(g). Leaning backward
(h). Right leg crossed
(i). Left leg crossed
(j). Cross-legged

Figure 6.
Types of sitting postures.

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The sitting upright posture as in Figure 6 (a) represents the ideal ergonomic position, where the user maintains a straight back, relaxed shoulders, and balanced weight distribution across both hips and the back. In the leaning left posture as in Figure (b), the user shifts their upper body toward the left side, resulting in increased pressure on the left half of the hip and back regions. Conversely, in the leaning right posture as in Figure (c), pressure is concentrated more on the right side as the user leans to the right. The sitting at the edge posture as in Figure (d) occurs when the user moves forward toward the edge of the seat, typically reducing contact with the backrest, leading to front-loaded hip pressure and minimal back pressure.

The upper body hunched posture as in Figure (e) involves a forward curvature of the upper spine while still maintaining some back support, often producing heightened pressure in the mid-back region. A more pronounced version of forward leaning is seen in the leaning forward posture as in Figure (f), where the user leans away from the backrest entirely, concentrating pressure at the front of the hips with little to no contact at the back. In the leaning backward posture as in Figure (g), the user reclines against the backrest, causing increased pressure on the upper and lower back areas, often with a backward shift in hip pressure.

Postures involving leg positions include the right leg crossed as in Figure (h), where the right leg is placed over the left, reducing pressure on the right side of the hip, and the left leg crossed as in Figure (i), where the left leg is placed over the right, reducing left hip pressure. Lastly, the crossed leg posture as in Figure (j) involves both legs being folded or crossed in a lotus-like manner, producing a central or uneven pressure distribution that differs distinctly from the other postures.

To capture sufficient variability in pressure distribution, 5 samples were collected for each sitting posture per individual, resulting in a total of 1250 data samples (25 participants × 10 postures × 5 samples per posture). Each sample consisted of pressure readings recorded from the 16×16 sensor array in both the hip and back regions.

The pressure data were recorded in real-time using a data acquisition system interfaced with the Velostat-based pressure mat. Each sample was saved as a 512-element vector for both the hip and back pressure mats, representing the distribution of pressure across the seating surface. These vectors were then labelled according to the sitting posture performed by the participant.

The dataset collection process was conducted in a controlled indoor environment, ensuring uniform seating conditions for all participants. Participants were asked to maintain each posture for a few seconds to allow stable pressure readings before moving to the next sample collection. The collected dataset was later pre-processed using min-max scaling before being split into 90% training and 10% testing sets for SVM model training and evaluation.

This dataset serves as the foundation for training the sitting posture classification model, enabling real-time posture monitoring and corrective feedback in the developed intelligent sitting posture system.

3.4. Software Design

A GUI was designed for displaying the user's pressure data in real time. In the GUI, by toggling the Bluetooth button, the user can connect to the ESP32 with the pressure sensor. After connection is established, the pressure data will be sent to the computer, and the sitting posture will be determined by the SVM model. The result will be displayed in the GUI. Besides sitting posture classification function, the GUI has features to track the correctness of the sitting posture and timer to calculate the total incorrect sitting posture duration.

4. Results and Discussion

4.1. Evaluation of Trained Model

The trained SVM model is evaluated by using the test data. The test data consists of 125 samples of different sitting posture data. The accuracy, precision, recall and F1 score of the SVM model are recorded in **Error! Reference source not found.**.

Table 1.
Evaluation matrix of trained SVM model.

Accuracy	1.00
Precision	1.00
Recall	1.00
F1 Score	1.00

The evaluation of the trained Support Vector Machine (SVM) model for sitting posture classification yielded an exceptional performance, achieving an accuracy of 100% (1.00) across all key evaluation metrics, including precision, recall, and F1-score. This result suggests that the model is capable of correctly identifying and classifying all tested sitting postures without any misclassification. The precision score of 1.00 indicates that whenever the model predicts a particular sitting posture, it is always correct, meaning that there are very little false positives in the classification results. Similarly, the recall score of 1.00 signifies that the model can correctly identify all instances of each sitting posture, without missing most of the true cases, ensuring that there are very little false negatives. The F1-score, which is a harmonic means of precision and recall, also being 1.00, further confirms the robustness and reliability of the trained SVM classifier.

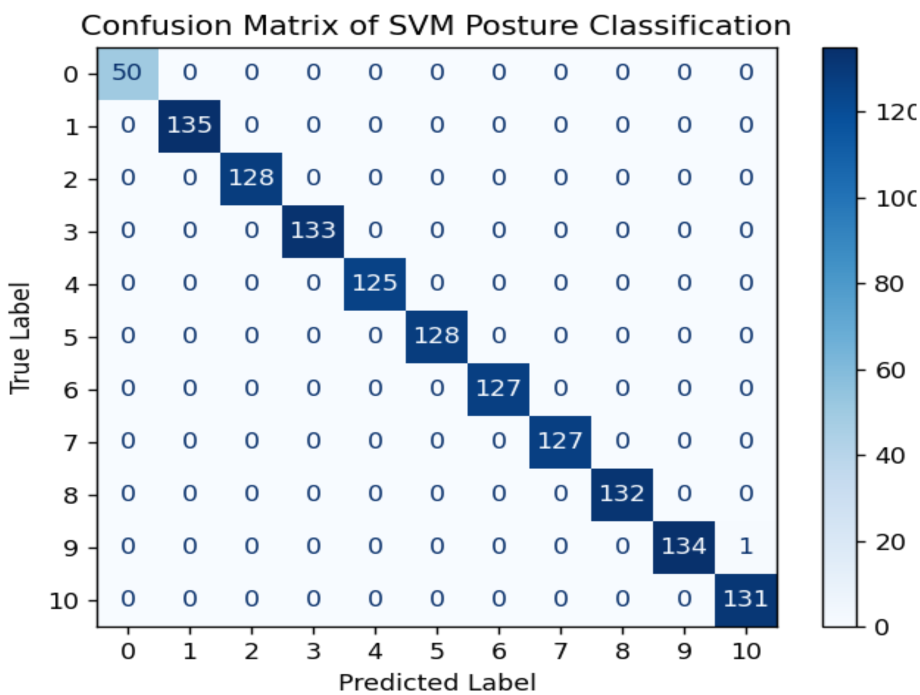

Figure 7.
Confusion matrix of trained SVM model.

Figure shows the confusion matrix for the SVM-based sitting posture classification model, which was trained using pressure data collected from velostat-based sensor mats. The system is capable of classifying 11 classes, including 10 different sitting postures and one "not sitting" condition (label 0). The diagonal elements of the matrix represent the number of correct predictions for each posture class, while the off-diagonal elements indicate misclassifications. The model demonstrates high classification accuracy across all postures, with most labels achieving over all correct predictions. Notably, the "Not sitting" class (label 0) had fewer samples (only 50), as the pressure data of not sitting is all zero all the time. Minimal confusion can be observed, with only a few instances of misclassification, such as 1 sample from "left leg crossed (label 9) being misclassified as "crossed leg" (label 10. These results indicate that

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the SVM model is highly effective in distinguishing between subtle variations in sitting postures, validating the capability of the proposed pressure sensing system for accurate posture monitoring.

4.2. Testing Under Different Train: Split Ratio

Table 2.
Evaluation of models under different train test split ratio.

Train: test split ratio	Accuracy	Precision	Recall	F1-score
90-10	1	1	1	1
80-20	0.99	0.99	0.99	0.99
70-30	0.99	0.99	0.99	0.98
60-40	0.99	0.99	0.99	0.99
50-50	0.99	0.99	0.99	0.99
40-60	0.98	0.98	0.98	0.98
30-70	0.95	0.95	0.95	0.95
20-80	0.93	0.94	0.93	0.93
10-90	0.84	0.85	0.84	0.84
5-95	0.73	0.78	0.73	0.69

To further investigate the performance and generalization ability of the SVM model under different data availability scenarios, a range of train-test split ratios were evaluated, from 90:10 down to 5:95. The evaluation metrics considered were accuracy, precision, recall, and F1-score, as shown in

. The results clearly illustrate the impact of training data size on the model's effectiveness.

When 90% of the dataset was used for training and 10% for testing, the model achieved perfect scores across all evaluation metrics, with an accuracy, precision, recall, and F1-score of 1.00. This indicates that the model had sufficient data to learn the patterns associated with each sitting posture and could generalize well to unseen test data. Similarly, the 80:20 split also yielded excellent performance, maintaining high scores of 0.99 in all four metrics, showing that even with a slightly reduced training set, the model retained robust classification capabilities.

As the proportion of training data continued to decrease, a gradual decline in performance was observed. This trend became more significant in the lower split ratios. For instance, with only 10% of data used for training and 90% for testing, the model's accuracy dropped to 0.84, with corresponding decreases in precision, recall, and F1-score. The decline became even more pronounced in the 5:95 split, where accuracy fell to 0.73, and F1-score dropped to 0.69. These results reflect the model's limited ability to learn effective decision boundaries with insufficient training data, particularly given the complexity of distinguishing between 10 subtle sitting postures.

Overall, the results emphasize the importance of having a sufficiently large and diverse training dataset for accurate posture classification. While the model performs exceptionally well with 80–90% of the data allocated for training, its predictive power diminishes significantly with very small training sets, highlighting a trade-off between training data size and model generalization.

4.3. Cross-Validation

Table 3.
5-fold cross validation results.

K-fold	Accuracy	Precision	Recall	F1 Score
Fold 1	0.9885	0.9888	0.9885	0.9885
Fold 2	0.9923	0.9929	0.9923	0.9923
Fold 3	0.9923	0.9925	0.9923	0.9923
Fold 4	0.9923	0.9925	0.9923	0.9923
Fold 5	0.9962	0.9963	0.9962	0.9962

Average	0.9923	0.9926	0.9923	0.9923

To evaluate the robustness and generalization performance of the SVM classification model, 5-fold cross-validation was performed using the complete dataset. The samples from dataset were randomly divided into five equal subsets (folds), ensuring that each fold maintained a balanced representation of all posture classes. In each iteration of the cross-validation, four folds were used for training while the remaining fold was used for testing, with this process repeated five times to ensure that each subset served as the testing set once. The results, summarized in Table , show consistently high performance across all folds, with an average accuracy of 99.23%, precision of 99.26%, recall of 99.23%, and F1-score of 99.23%. The slight variation observed in Fold 1 can be attributed to the random split of data and potentially higher intra-subject or inter-posture variability in that subset. Overall, the high and stable metrics across all folds confirm the model's effectiveness in accurately classifying various sitting postures using pressure data from the Velostat-based sensing system.

4.4. Overall System Performance

The trained Support Vector Machine (SVM) model achieved a high classification accuracy of 100%, as validated through testing with 1 additional volunteer who was not part of the training dataset. This result demonstrates the model's effectiveness in recognizing different sitting postures based on the pressure distribution obtained from the Velostat-based pressure mat. The high accuracy indicates that the system can reliably distinguish between correct and incorrect sitting postures, which is essential for real-time posture monitoring and feedback.

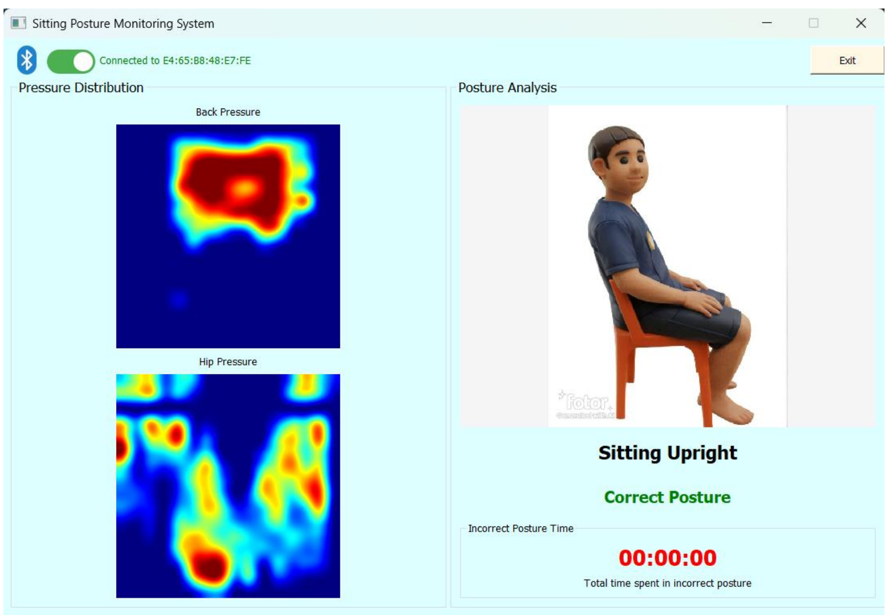

Figure 8.
Testing of system on correct posture.

Figure 8 shows the performance of the system when the user performs correct sitting posture: sitting upright. As shown in the figure, the pressure data are displayed on the left side of the GUI, back pressure data followed by hip pressure data. On the right side, the predicted sitting posture by the trained SVM model is displayed, along with the icon indicating the respective posture. The correctness of the user's sitting posture is displayed below the predicted posture. Then, the timer at the bottom right of the GUI indicated the total wrong sitting posture duration by the user. As shown in Figure ,

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the system can detect "sitting upright" accurately and classify it as correct sitting posture. From the pressure heatmap, it has a symmetrical pressure distribution on hip because this posture ensures an even weight distribution across the buttocks. Since the user is performing correct sitting posture, the timer is not started, hence it remains at 0.

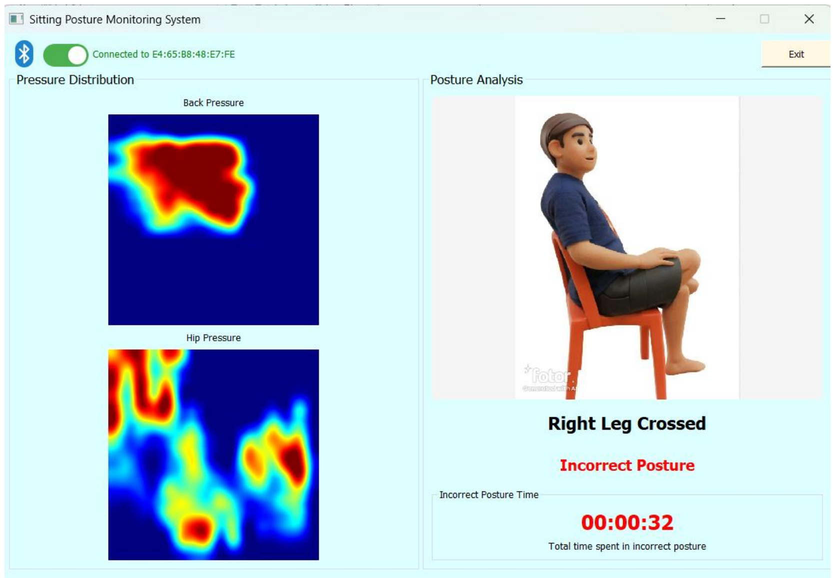

Figure 9.
Testing of system on wrong posture (right leg crossed).

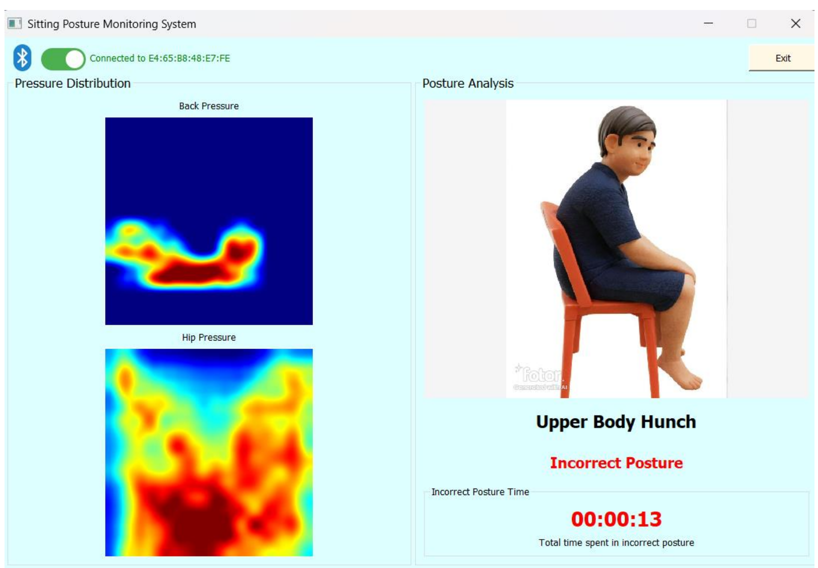

Figure 10.
Testing of system on wrong posture (upper body hunched).

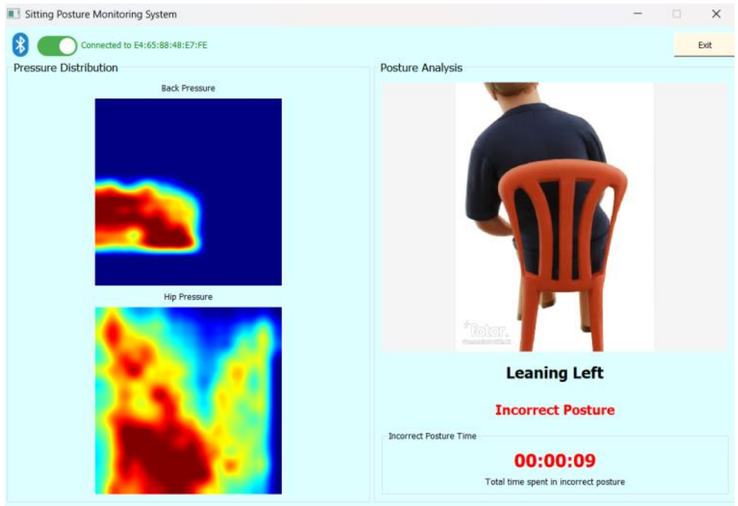

Figure 11.
Testing of system on wrong posture (Leaning left).

Figure shows the performance of the system when the user is performing a wrong sitting posture: right leg crossed. In the heatmap, there is higher pressure on the left buttock and a leftward shift in back pressure. On the right side, the SVM model can detect and classify the posture correctly and label it as "Incorrect Posture". Right after that, the timer is started as wrong sitting posture is detected. The figure shows the timer value as 00:00:32, which means the user has maintained the wrong sitting posture for 32 seconds. Then, Figure and Figure shows the system performance when the user is sitting with upper body hunched and leaning left on real time. The SVM model can predict the output of the pressure data immediately when the user changes their sitting posture accurately. As in the heatmap in Figure , the pressure distribution of the back is on the mid back region, while the hip data is similar to sitting upright posture. As in Figure , when the user is leaning left, there is increased pressure on the left half of the hip and back regions.

5. Conclusion

This study displayed an intelligent real-time pressure sensing system for sitting posture monitoring, integrating velostat-based pressure mats with SVM model for posture classification. The system achieved 100% accuracy using an SVM classifier, demonstrating its ability to reliably detect 10 different sitting postures. A graphical user interface (GUI) was implemented to provide real-time feedback, track incorrect posture duration, and help users improve their sitting habits. The successful integration of sensor hardware, machine learning, and a user-friendly interface highlights the system's effectiveness in posture monitoring applications.

The project has strong potential for applications in ergonomics, workplace health monitoring, and rehabilitation. By providing real-time feedback on sitting posture, the system can help notifying the user to maintain a good posture habit. Future improvements could include deep learning models for enhanced classification, mobile app integration for accessibility, and power-efficient hardware for portability. With further refinement, this system could become a valuable tool for promoting better posture habits and reducing posture-related health issues in daily life.

6. Limitations

Despite the high accuracy achieved by the system, certain limitations exist when applied to real-world scenarios. One notable limitation is that the model was primarily trained on data collected from individuals weighing between 50 to 80 kg. As a result, the system's performance may be affected when used by individuals outside this weight range, as pressure distributions could differ significantly. This could impact on the accuracy of posture classification, requiring additional calibration or retraining with a more diverse range of users.

Furthermore, external factors such as chair type, cushion thickness, and surface material could influence pressure readings, potentially requiring additional tuning to maintain accuracy across different seating conditions.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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