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Embedded System

Sitting Pressure Distribution Monitoring System Using K-Nearest Neighbor and Rule-Based Logic

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A B S T R A C T

An embedded sitting-pressure monitoring system is developed to identify asymmetric pressure distribution and detect prolonged static sitting. Four FSR402 sensors connected to a 12-bit ADC on an ESP32 measure seat pressure, using Left_percent, Right_percent, and P_ratio as classification features. A K-Nearest Neighbor (KNN) classifier (K = 5) is implemented directly on the ESP32 to classify Balanced, Lean Left, and Lean Right postures. Classification results are combined with duration-based rules to determine NORMAL, WARNING, and HIGH RISK conditions, supported by vibration feedback, Firebase Realtime Database, and a Flutter application. The results show an average relative pressure measurement error of 1.05% (98.95% accuracy), with pressure shifts of 17.32–18.29%. KNN achieves 98.89% mean cross-validation accuracy and 97.78% test accuracy, with a macro F1-score of 0.9776, while end-to-end posture detection achieves 90% accuracy. Haptic feedback delays range from 0.784 to 1.127 seconds. These findings demonstrate the feasibility of implementing KNN-based posture classification directly on an ESP32 and integrating it with duration-based rules for real-time monitoring of asymmetric and prolonged static sitting.

INTRODUCTION

Prolonged sitting has become common among university students and office workers who perform computer-based activities for extended periods. During sitting, body weight is transmitted through the pelvis and gluteal region to the seat surface. The resulting interface pressure is not distributed uniformly and may change according to body posture, movement, and sitting duration. Akkarakittichoke and Janwantanakul showed that seat-pressure distribution changes during prolonged sitting, indicating that pressure characteristics can reflect postural behavior over time [1]. Kamegaya also reported that different sitting postures affect gluteal pressure distribution [2].

Changes in sitting posture, particularly leaning to one side, cause the center of body load to shift and alter the pressure received by the left and right sides of the sitting surface. Lee et al. demonstrated that sitting-pressure measurements can identify body imbalance under different sitting conditions [3]. Pressure sensing therefore provides an objective alternative for monitoring sitting behavior without requiring continuous camera observation or wearable orientation sensors.

Pressure-based posture recognition has also been investigated using classification methods. Tsai et al. developed an automated sitting-posture recognition system based on pressure sensors [4]. More recent embedded posture-monitoring studies have also

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combined sensing systems with automated classification and warning mechanisms [5], [6]. These studies demonstrate the feasibility of using sensor-based approaches to detect sitting behavior and provide feedback.

However, the computational method used in an embedded monitoring system must remain suitable for limited hardware resources. A rule-based method has low computational complexity but depends on fixed thresholds, making it sensitive to variations in individual body characteristics and sitting behavior. Support Vector Machine can provide good classification capability but requires higher computational complexity. In comparison, K-Nearest Neighbor provides a pattern-based approach using similarity between sensor data and stored reference samples, while maintaining relatively simple computation for embedded implementation. The final system therefore uses KNN to classify sitting-pressure patterns and rule-based logic only to evaluate the duration of the detected condition.

This study proposes a sitting-pressure monitoring system using four FSR402 sensors and an ESP32 microcontroller. The sensor readings are converted into relative left-right pressure features and classified into Balanced, Lean Left, and Lean Right conditions using KNN executed directly on the ESP32. Duration-based rules are then applied to identify sustained asymmetric posture and prolonged static sitting. The main contributions of this work are the implementation of KNN inference directly on the ESP32 using stored training samples, the combination of KNN classification and temporal rule-based logic, and system validation through controlled measurements, posture classification tests, haptic-response testing, and natural-use evaluation.

METHOD

A. Proposed Solution

The proposed system combines pressure-based posture classification with duration-based risk detection. Four FSR402 sensors are used to obtain relative pressure information from the left and right sides of a sitting cushion.

The pressure pattern is classified using KNN rather than relying only on a fixed pressure threshold. After a posture class is obtained, a rule-based mechanism evaluates how long the detected condition persists. This approach separates posture-pattern recognition from duration-based warning logic.

The complete system consists of the FSR402 sensors, an ESP32, a vibration motor, Firebase Realtime Database, and a Flutter mobile application.

B. System Architecture

The overall processing flow of the system is shown in Figure 1. The user sits on a sensor-equipped cushion containing four FSR402 sensors. The sensors capture changes in the pressure-related response generated by the sitting load and transmit the readings to the ESP32.

The ESP32 performs sensor acquisition, preprocessing, feature extraction, and KNN-based posture classification. The resulting condition is categorized as Balanced, Lean Left, or Lean Right. A rule-based duration mechanism then evaluates whether an asymmetric or static condition has persisted long enough to trigger a warning.

When a HIGH RISK condition is reached, the system activates the vibration motor and updates the notification status. Monitoring data are transmitted to Firebase Realtime Database and displayed through the Flutter mobile application.

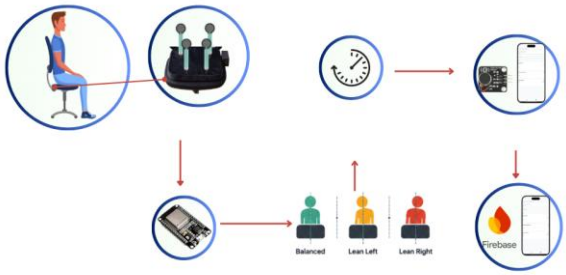

Figure 1. System Architecture and Processing Flow of the Sitting Pressure Monitoring System

C. Hardware Implementation

The four FSR402 sensors [7] are connected to GPIO 32, GPIO 34, GPIO 35, and GPIO 33 of the ESP32. The ADC is configured at 12-bit resolution, producing digital values from 0 to 4095. Each sensor is sampled ten times per measurement cycle and averaged to reduce short-term fluctuations. A threshold value of 350 is applied so that very low readings do not affect further processing. The readings from S1 and S2 are combined to represent the left-side load, while S3 and S4 represent the right-side load. These values are normalized against the total response of all four sensors to obtain *Left_percent* and *Right_percent*. The absolute difference between the two values is represented as *P_ratio* [8]. These three features are used as the input to the KNN classifier



Figure 2. Hardware Implementation of the Sitting Pressure Monitoring System

D Dataset and KNN Classification

The primary dataset was collected from three subjects. Each subject performed three sitting conditions: Balanced, Lean Left, and Lean Right. Fifty samples were collected for each condition, resulting in 450 samples in total.

A sensor threshold of 350 is applied to remove low-level readings before feature calculation. Sensor values below the threshold are set to zero.

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Table 1. Dataset Composition

Class	Samples
Balanced	150
Lean Left	150
Lean Right	150
Total	**450**

The dataset was divided using an 80:20 stratified train-test split, resulting in 360 training samples and 90 held-out test samples. Several values of K (1, 3, 5, 7, 9, 11, and 15) were evaluated using Stratified 5-Fold Cross-Validation. K = 3 through K = 15 produced the same mean validation accuracy of 98.89%, while K = 1 achieved 97.78%. K = 5 was retained as the implementation configuration, as it fell within the group of K values with the highest validation accuracy.

The training data were converted into a C++ header file named ModelKNN.h and stored directly on the ESP32. During operation, the ESP32 compares the current feature vector with the stored training samples using Euclidean Distance, selects the five nearest samples, and determines the class using majority voting. The five most recent predictions are also used to stabilize the final output.

E. Rule-Based Warning and Monitoring

The KNN output consists of Balanced, Lean Left, or Lean Right. A duration-based rule is then applied to determine the user status.

Table 2. Rule-Based Status Determination

Condition	Duration	Status
Balanced	normal variation	NORMAL
Lean Left / Lean Right	< 5 min	WARNING
Lean Left / Lean Right	≥ 5 min	HIGH RISK
Static Balanced	≥ 30 min	HIGH RISK

When Lean Left or Lean Right persists for at least five minutes, the status changes to HIGH RISK. Static sitting is considered HIGH RISK when the pressure distribution remains nearly unchanged for at least 30 minutes.

When HIGH RISK is reached, the vibration motor is activated and the warning status is transmitted to Firebase. The Flutter application displays the left-right distribution, posture condition, risk status, sitting duration, warning notification, and historical monitoring data.

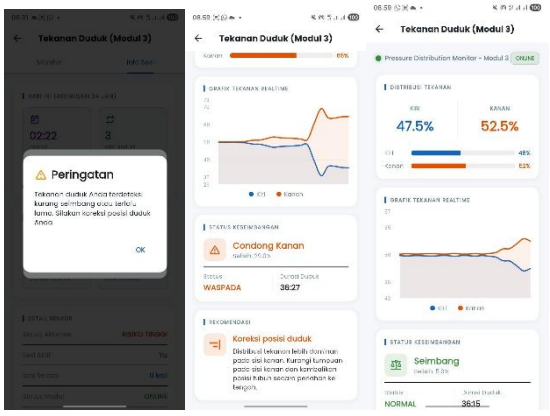

Figure 3. Mobile Monitoring and Warning Interface

RESULTS AND DISCUSSION

A. Relative Pressure Measurement

Relative pressure measurement was evaluated using Balanced, Right-Dominant, and Left-Dominant load conditions. Each condition was repeated five times.

The mean error was 1.06% on the left side and 1.03% on the right side, resulting in an overall mean error of 1.05%. The corresponding estimated relative-distribution accuracy was 98.95%.

Table 3. Relative Pressure Measurement Results

Parameter	Result
Mean Error	1.05%
Estimated Accuracy	98.95%
Detected Pressure Shift	17.32–18.29%

The system also detected pressure-distribution changes between 17.32% and 18.29% when the dominant load was shifted from one side to the other.

The reported accuracy represents agreement of relative left-right load distribution and should not be interpreted as absolute pressure accuracy in Pa or kPa.

B. KNN Model Evaluation

The classifier achieved a mean cross-validation accuracy of 98.89%. The final model was then evaluated using 90 held-out test samples. From 30 Balanced samples, 28 were correctly classified, while all 30 Lean Left and all 30 Lean Right samples were correctly identified. The two misclassified Balanced samples were most likely located near the decision boundary with the adjacent Lean classes, where the left-right pressure difference approached the point at which the system begins to register a lean condition; the Lean Left and Lean Right classes, in contrast, occupy pressure-distribution regions that are spatially well separated from Balanced, which is consistent with their perfect recall.

The overall test accuracy was 97.78%, with a macro F1-score of 0.9776.

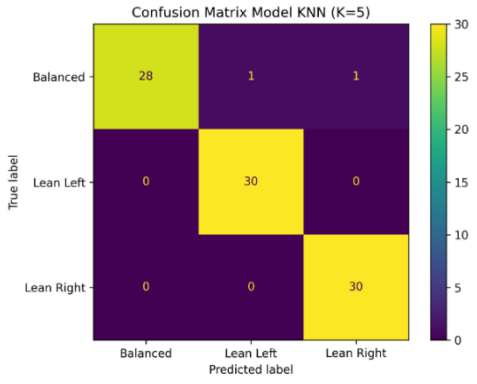

Figure 4. Confusion Matrix of the KNN Model Evaluation

Table 4. KNN Model Evaluation Metrics

Metric	Result
Mean CV Accuracy	98.89%
Test Accuracy	97.78%
Macro F1-Score	0.9776

C. End-to-End Classification

The complete system was tested using 30 physical posture trials verified using an inclinometer. Ten trials were performed for each posture condition.

Table 5. End-to-End Classification Results

Condition	Correct	Accuracy
Balanced	10/10	100%
Lean Left	8/10	80%
Lean Right	9/10	90%
Overall	**27/30**	**90%**

The total end-to-end classification accuracy was 90%, exceeding the minimum target of 80%.

The lower result compared with the 97.78% offline model accuracy is reasonable because physical testing introduces additional variations from sensor contact, body movement, and posture reproduction

D. Haptic Feedback

The warning mechanism was tested for Lean Left, Lean Right, and prolonged static sitting.

Table 6. Haptic Feedback Response Delay

Condition	Delay
Lean Left	0.784 s
Lean Right	0.936 s
Static Sitting	1.127 s

All haptic delays remained below the 3-s response requirement, and Firebase warning transmission was successful for all tested conditions.

E. Natural-Use Testing

Natural-use testing was conducted with one university student and one office worker during normal computer-based activities.

For the university student, 96 valid data entries were analyzed after removing transition-related anomalies. Lean Left was the dominant condition, representing 58.3% of the valid data.

For the office worker, 193 valid entries were analyzed, with Balanced representing 98.96% of the recorded conditions.

Table 7. Summary of Natural-Use Testing

Subject	Valid Data	Dominant Condition	Percentage
University Student	96	Lean Left	58.3%
Office Worker	193	Balanced	98.96%

These results indicate that the system can capture different sitting patterns during natural computer use. However, the natural-use evaluation involved only two subjects and should therefore be considered a functional demonstration rather than a population-level ergonomic assessment.

CONCLUSION

This study developed an embedded sitting-pressure monitoring system using four FSR402 sensors, an ESP32, KNN classification, and duration-based rules. The system achieved an estimated relative pressure measurement accuracy of 98.95% and detected pressure-distribution shifts ranging from 17.32% to 18.29%.

The KNN classifier achieved 97.78% accuracy on held-out test data and a macro F1-score of 0.9776, while the complete physical system achieved 90% end-to-end classification accuracy. Haptic feedback was generated with response delays between 0.784 and 1.127 s.

The results demonstrate that on-device KNN classification combined with duration-based rules can be applied for real-time sitting-pressure monitoring. Future work should involve a larger participant population, additional posture classes, improved sensor calibration, and higher-resolution pressure sensing.

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