

Development of a Smart Chair for Real-Time Posture Detection to Promote Ergonomic Habits in Sedentary Workspaces

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ABSTRACT

Prolonged sitting in academic and office settings is strongly linked to occupational musculoskeletal disorders, including lower back pain, neck tension, shoulder stiffness, and spinal strain. Traditional ergonomic interventions often fail because they rely on user self-regulation, which diminishes during periods of high cognitive load or fatigue. This study presents the design, empirical evaluation, and socio-technical assessment of a smart chair with sitting posture detection. The system combines six force sensitive resistor (FSR402) sensors mounted on a seat cushion, an ESP32 microcontroller, a 128x64 OLED display, and an active piezo buzzer for real-time edge computing and immediate corrective feedback. The system classifies six distinct sitting postures: slouching, forward leaning, side leaning right, side leaning left, sliding forward, and crossed legs. Using a K-Nearest Neighbors algorithm trained on 660 observations across 11 participants, the offline validation accuracy reached 93.8% with an average Receiver Operating Characteristic Area Under the Curve of 0.9627. Real-time testing on 5 unseen participants achieved a classification accuracy of 67.58% post-feature engineering. By integrating real-time sensory feedback into daily seating, this low-cost innovation advances United Nations Sustainable Development Goal 3 (Good Health and Well-Being) and provides an accessible framework for workplace and educational health management.

Keywords— Smart Seating, Posture Detection, Machine Learning, K-Nearest Neighbors, Workplace Ergonomics

INTRODUCTION

In the modern digital era, the amount of time individuals spends sitting for occupational, academic, or leisure activities has increased significantly. Office workers, students, and computer operators routinely maintain seated positions for long hours, often without continuous awareness of their posture. This prolonged sitting behavior, particularly when combined with incorrect posture, is strongly associated with musculoskeletal disorders (MSDs) including lower back pain, neck tension, shoulder stiffness, and spinal strain. Incorrect posture exerts uneven pressure on the lumbar spine and surrounding muscular structures, elevating the risk of long-term musculoskeletal complications [1].

Traditional ergonomic interventions, such as static posture guidelines and adjustable chairs, rely heavily on individual awareness and voluntary behavioral self-regulation [2]. However, users commonly revert to poor sitting habits such as leaning forward, slouching, or sitting asymmetrically when fatigued or deeply focused on tasks [3]. Over time, these uncorrected habits result in muscular imbalances, physical discomfort, and reduced productivity [4]. Recent developments in smart seating technology highlight the potential of pressure sensors, load cells, and capacitive textiles for real-time posture detection. Smart seating systems utilizing multi-sensor arrays have achieved classification accuracies above 90% across multiple sitting positions using machine learning algorithms [5].

Furthermore, despite technological advancements, existing smart chair solutions present key practical gaps: many depend on large, complex sensor arrays or specialized pressure mats that are prohibitively expensive and impractical for everyday use [6], while others rely solely on periodic alerts that fail to capture subtle postural shifts [7], [8]. Consequently, a clear research gap exists for an affordable, non-invasive smart chair that combines point-source pressure sensing with real-time edge processing to detect poor sitting posture and prompt voluntary self-correction without disrupting primary workflows.

To bridge this gap, this project develops an automated smart chair that uses embedded pressure sensors and edge machine learning to monitor sitting posture in real time. The system provides immediate acoustic and visual feedback to encourage self-correction, thereby mitigating long-term musculoskeletal risks. The primary objectives of this study are:

- (i) To develop a posture detection system utilizing an FSR402 sensor circuit and ESP32 microcontroller.
- (ii) To build a sitting posture classification algorithm using a machine learning approach.
- (iii) To test and analyze the performance of the developed posture detection system.

LITERATURE REVIEW

This section reviews current literature on postural ergonomics, pressure-sensing technologies, microcontroller platforms, and classification algorithms to establish the empirical foundation for the proposed smart chair framework.

Postural Deviations and Health Implications

Prolonged static sitting in corporate and educational settings is a primary contributor to occupational MSDs, spinal disc compression, chronic back pain, and shoulder tension. When individuals become engrossed in cognitive tasks or experience fatigue, they involuntarily adopt improper postures without continuous awareness. Passive interventions such as static ergonomic chairs or timer-based breaks fail to foster sustained behavioral compliance, as users consistently revert to biomechanically detrimental positions. Biomechanical research demonstrates that improper posture distribution alters the load-bearing dynamics of the pelvic girdle and vertebral column.

Ergonomic research emphasizes six primary postural deviations that disrupt pelvic loading and spinal alignment [5], [6]. The six most common postural deviations observed in sedentary environments carry specific long-term health risks, including slouching, forward leaning, side leaning (left/right), sliding forward, and crossed legs, as detailed in Table I.

TABLE I COMMON SITTING POSTURAL DEVIATIONS

Posture Pattern	Description	Long Term Effect
Slouching	Spine curves into a C-shape	Lumbar disc compression, lower back pain
Forward Leaning	Head shifts forward, shoulders hunched	Neck tension, shoulder fatigue
Side Leaning to right and left	More weight on one hip	Spinal asymmetry, hip imbalance
Sliding Forward	Pelvis rotates backward	Reduced spinal stability
Crossed Legs	Uneven pelvic load	Hip rotation, circulation issues

Sensing Modalities and Controller Platforms

Various sensor modalities have been explored for smart seating applications, including load cells [1], [6], capacitive textile fabrics [3], ultrasonic sensors [12], and resistive pressure arrays [4], [5]. Advanced iontronic pressure sensors achieve high sensitivity over broad linear ranges [11], but their fabrication cost remains restrictive for widespread consumer adoption. Load cells deliver linear force outputs and high force stability, but add structural bulk and mechanical complexity to chair fabrication [6]. Force Sensitive Resistors (FSRs) are widely utilized due to their thin physical profile, low cost, and ease of non-intrusive integration into standard seat cushions, despite non-linear resistance characteristics that require calibration [4], [13].

Alternatively, wearable Inertial Measurement Units (IMUs) which track body orientation using accelerometers and gyroscopes achieve exceptional posture classification accuracy [14]; however, they suffer from low long-term user compliance because individuals frequently forget or dislike wearing physical hardware throughout the day. Embedded pressure-sensing chairs effectively resolve these compliance barriers by enabling unobtrusive, continuous posture tracking directly within the user's primary seating environment [13].

TABLE II COMPARISON OF MICROCONTROLLER PLATFORMS FOR EDGE-BASED SMART CHAIR POSTURE DETECTION SYSTEMS

Controller	Clock Speed	ADC Channels	Wireless Connectivity	Suitability
Arduino UNO	16 MHz	6	External Module Required	Limited
ESP8266	80 MHz	1	Built-in Wi-Fi	Moderate
Raspberry Pi 3	1.2 GHz	0 (External required)	Built-in Wi-Fi/Bluetooth	High Cost
ESP32	Up to 240 MHz	18	Built-in Wi-Fi & Bluetooth	High Performance

As detailed in Table II, the ESP32 microcontroller provides the optimal balance of clock speed (240 MHz), onboard ADC channels (18 channels), low power consumption, and built-in Wi-Fi/Bluetooth networking required for real-time edge processing and potential Internet of Things (IoT) cloud integration [15].

Machine Learning Algorithms in Posture Recognition

For processing at the edge, lightweight classifiers are necessary to run on low-power microcontrollers without external cloud dependencies [13]. Algorithms such as Support Vector Machines (SVM) [1], [3], [6], [14], Random Forests (RF) [5], [9], Artificial Neural Networks (ANN) [2], [11], and K-Nearest Neighbors (KNN) [1] have shown high accuracy on low-dimensional pressure datasets. KNN is particularly well-suited for embedded deployments due to its non-parametric nature, low computational overhead for inference, and high effectiveness on structured spatial feature maps. While Deep Learning models such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), achieve strong pattern recognition on complex spatial-temporal data [2], [7], [10], their memory footprint and training time render them impractical for real-time inference directly on microcontrollers.

Lightweight classifiers like KNN, SVM, and RF offer low computational complexity, fast inference times, and small compiled model sizes, making them superior for embedded smart chair applications.

Related Works

A comparative review of state-of-the-art posture detection systems highlights key strengths and operational

limitations in existing literature, as summarized in Table III. Existing research demonstrates strong offline classification accuracy, but many systems suffer from high hardware costs, complex sensor arrays, or a lack of real-time feedback. To bridge this gap, the proposed framework integrates a strategic 6-point FSR402 array with an ESP32 microcontroller and a KNN machine learning classifier, delivering real-time visual and acoustic feedback to actively encourage postural self-correction.

Table III : Comparative Summary of Smart Seating and Posture Detection Literature

Reference	Sensing Technology	Machine Learning	Accuracy	Limitations
Pereira & Silva (2023) [1]	Load Cells & ECG	KNN / SVM	87.5%	Lacks real-time adaptive feedback
Nadeem et al. (2024) [2]	Seat & Backrest Pressure	CNN / ANN	92.3%	Lacks context-aware real-time correction
Martínez-Estrada et al. (2023) [3]	Capacitive Textiles	SVM	91.8%	High fabrication cost; no instant feedback
Odesola et al. (2024) [5]	FSR & IMU Array	RF / ANN	93.7%	High complexity; depends on dual placement
Tavares et al. (2023) [6]	Load Cells & FSR	SVM	97.2%	Static sensor system without personalized feedback
Najafi et al. (2022) [7]	FSR & Infrared Array	CNN / LSTM	91.7%	High computational load; no dynamic user prompts
Proposed System	FSR402 Array + ESP32	Embedded KNN	93.8%	Low-cost, non-invasive, with OLED + Buzzer alert

METHODOLOGY

The methodology integrates hardware development, machine learning software design, and empirical evaluation to establish a real-time posture monitoring system. The development was executed across three interconnected phases: physical prototype fabrication (embedding force-sensing resistors, microprocessing units, power regulation circuits, and feedback modules), software integration (sensor data acquisition, dataset curation across participant trials, and KNN model training), and system validation (evaluating classification accuracy, feedback responsiveness, and posture correction in controlled environments). This system design directly supports United Nations Sustainable Development Goal 3 (Good Health and Well-Being) by addressing occupational MSDs). By providing continuous posture sensing and immediate corrective feedback, the smart chair acts as an automated preventive health tool that reduces spinal strain and promotes long-term ergonomic posture habits.

System Architecture and Operational Workflow

The smart chair architecture consists of four interconnected functional layers: sensing, processing, classifying, and feedback. The system block diagram outlining these functional layers is shown in Fig. 1.



Fig. 1 System block diagram of the smart chair posture detection.

The operational workflow follows a continuous sense-and-react control loop, as illustrated in the flowchart in Fig. 2.

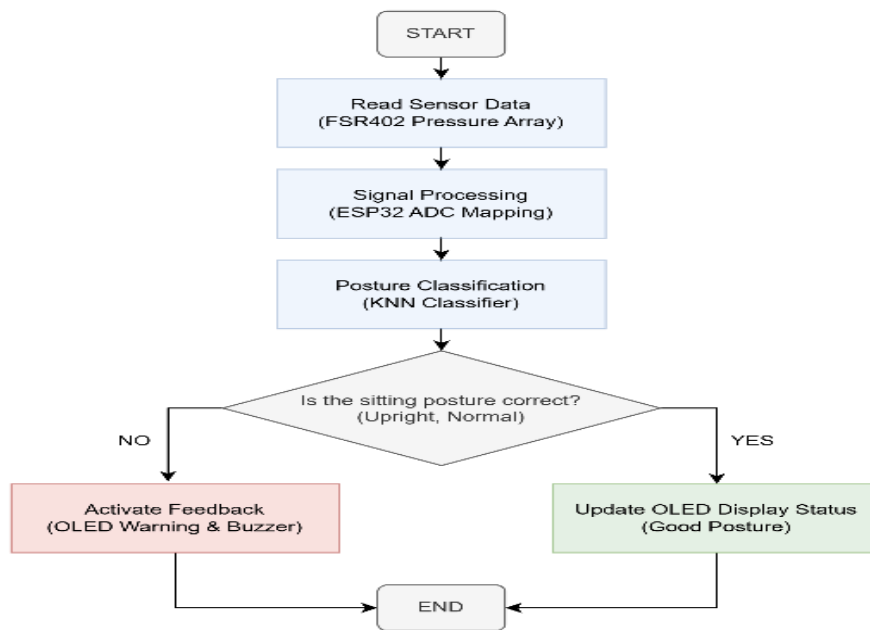


Fig. 2 Operational flowchart for posture detection and alert execution.

When a user sits on the chair, six FSR402 sensors capture weight distribution shifts across the seating surface. The raw analog voltage signals are sampled by the ESP32 microcontroller, digitized, and evaluated against the trained posture classifier. If proper posture is maintained, the OLED display confirms normal alignment. If a bad posture (such as slouching, forward leaning, side leaning (left/right), sliding forward, or crossed legs) persists, the system activates a buzzer warning alongside visual status alerts on the OLED screen to prompt user self-correction.

System Integration

The physical prototype incorporates selected low-power electronic components to ensure real-time responsiveness and non-intrusive seat cushion integration. Main components are described as follows:

- (i) **Force Sensing Resistors (FSR402):** Passive polymer-film sensors whose electrical resistance decreases predictably as applied mechanical force increases. Six sensors are positioned across the seat surface to measure localized pressure distribution.
- (ii) **ESP32 Microcontroller:** Serving as the central processing unit, the ESP32 features a dual-core 32-bit Xtensa LX6 processor operating at up to 240 MHz, integrated Wi-Fi/Bluetooth networking, and multi-channel 12-bit Analog-to-Digital Converters (ADCs).
- (iii) **MP1584 DC-DC Buck Regulator:** Steps down variable input battery voltage (4.5V–28V) to a stable regulated DC output, operating at up to 92% efficiency with thermal shutdown and overcurrent protection.
- (iv) **Visual & Acoustic Feedback Output:** A 0.96-inch monochrome 128x64 OLED screen (I2C interface) renders real-time textual and status graphics. An active piezo buzzer (>85 dB output at 10 cm, 2.3 kHz resonant frequency) produces distinct warnings when improper sitting postures are sustained.

Machine Learning Classification

System firmware was developed within the Arduino IDE using C/C++. Sensor sampling is set to 12-bit ADC resolution (0 to 4095 digital range). To prevent signal noise, a lower-bound threshold filter discards micro-

fluctuations resulting from minor movement artifacts. Training process shows that KNN is suitable because it is simple to implement, effective for small datasets, and does not require complex model training.

The posture data collected from the FSR sensors can be classified by measuring the similarity between pressure patterns. By selecting an appropriate value of K, the system can accurately classify different sitting postures based on sensor input. KNN is a supervised machine learning algorithm that is commonly used for classification tasks. It works by comparing a new data sample with existing labelled data based on a distance measurement, such as Euclidean distance as described by Equation (1).

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1)$$

The algorithm identifies the K closest data points (neighbours) and assigns the class that appears most frequently among them. KNN was selected due to its straightforward implementation on embedded edge microcontrollers, rapid inference speed, and high classification accuracy on spatial pressure distributions without requiring computationally intensive neural network architectures.

Model evaluation was conducted quantitatively using standard classification metrics, including Precision, Recall, F1-Score, Validation Accuracy, and Receiver Operating Characteristic Area Under the Curve (ROC-AUC).

RESULT AND DISCUSSION

Hardware Integration and Prototype Validation

The physical prototype of the smart chair with sitting posture detection was constructed by integrating the FSR402 pressure sensor array, ESP32 microcontroller, MP1584 DC-DC buck regulator, 128x64 I2C OLED display, and active piezo buzzer onto a standard office chair frame as shown in Fig. 3. Hardware functional testing confirmed that all six FSR402 sensors reliably detected pressure distribution shifts across the seat surface. Unloaded seating states produced baseline ADC values near zero, whereas seated users generated distinct force profiles corresponding to specific posture classes. The ESP32 microcontroller successfully acquired sensor inputs via its 12-bit ADC channels and executed signal filtering without thermal degradation or processing delays. The visual display and acoustic feedback components operated as designed: the OLED display rendered the classified posture name and bad-posture timer in real time, while the piezo buzzer sounded an alert whenever improper sitting postures persisted beyond the set threshold.

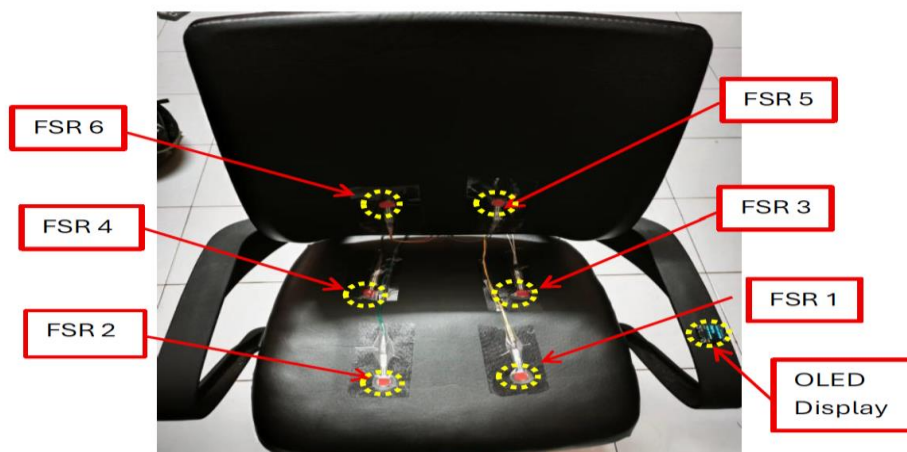


Fig. 3 Physical prototype of the developed smart chair showing FSR402 sensor layout (FSR 1 to FSR 6) and OLED display mounting.

Machine Learning Model Validation (Offline)

The KNN classification algorithm was trained and evaluated using the Data Fsr dataset, which contains 660 observations collected from 11 participants across six posture classes (110 samples per class). In offline 10-fold cross-validation, the KNN model achieved an overall validation accuracy of 93.8% with a validation error rate of 6.2% and a total validation cost of 41. The KNN model demonstrated computational efficiency suitable for edge deployment on low-power microcontrollers. Local inference was executed directly on the ESP32 without relying on external cloud servers, achieving real-time, sub-second posture classification and prompt feedback execution. The normalized validation confusion matrix in Fig. 4 details the exact classification hits and off-diagonal misclassification rates across all six sitting posture classes. Class a achieved the highest True Positive Rate (TPR) at 96.4% with a low False Negative Rate (FNR) of 3.6%, misclassifying only 2.7% into Class d and 0.9% into Class e. Class c recorded a 95.5% TPR (4.5% FNR), with minor misclassification occurring into Class b at 3.6%. Class f achieved a 94.5% TPR (5.5% FNR), while Class d reached 93.6% TPR (6.4% FNR) and Class b achieved 92.7% TPR (7.3% FNR). The lowest TPR was recorded by Class e at 90.0% (10.0% FNR), where 4.5% of samples crossed into Class d and 2.7% into Class b due to similar anterior-posterior ischial pressure distribution shifts.

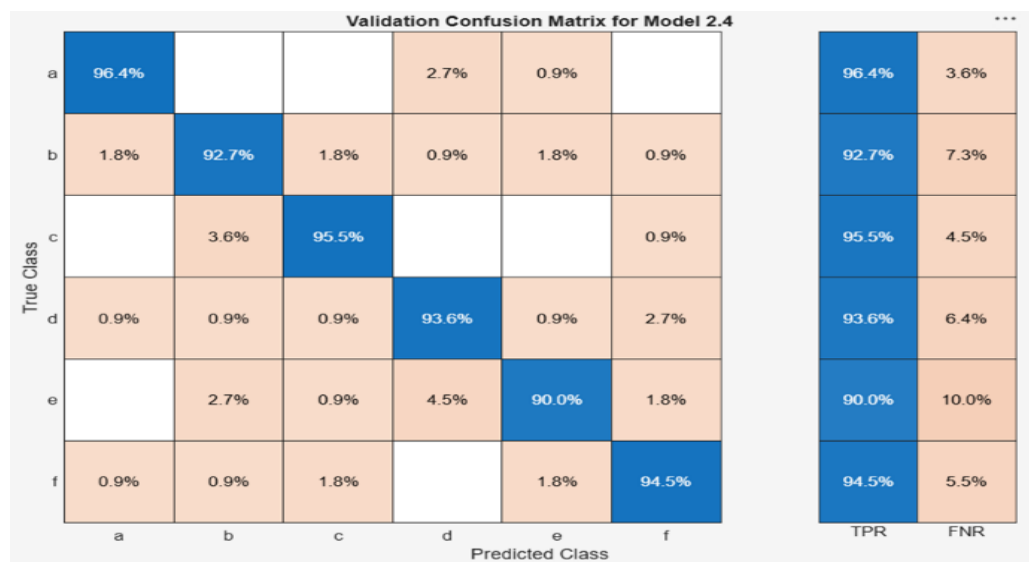


Fig. 4 Validation confusion matrix for the KNN classification model showing per-class percentage distribution, TPR, and FNR.

As shown in Table IV, evaluation metrics across all six posture classes demonstrated consistently strong performance. Individual F1-scores ranged from 92.1% (Sliding Forward) to 96.4% (Slouching), with recall reaching up to 96.4%. Across all evaluated metrics and categories, performance averaged 93.8%, confirming a well-balanced classification capability without significant bias toward any specific posture class.

TABLE IV PER-CLASS VALIDATION PERFORMANCE METRICS FOR THE KNN MODEL

Posture Class	Precision	Recall	F1-Score	ROC-AUC Score
Class a: Slouching	96.4%	96.4%	96.4%	0.9782
Class b: Forward Leaning	91.9%	92.7%	92.3%	0.9555
Class c: Side Leaning Right	94.6%	95.5%	95.0%	0.9718
Class d: Side Leaning Left	92.0%	93.6%	92.8%	0.9600
Class e: Sliding Forward	94.3%	90.0%	92.1%	0.9446
Class f: Crossed Legs	93.7%	94.5%	94.1%	0.9664

Class discrimination capability was further evaluated using ROC curve analysis. As illustrated in Fig. 5, the

ROC curves for all six posture classes exhibit a sharp vertical rise along the y-axis (True Positive Rate) near zero FPR, aligning closely with the top-left corner of the coordinate space. The model achieved an average macro ROC-AUC score of 0.9627. Class a attained the highest AUC of 0.97818, followed closely by Class c with the AUC of 0.97182 and Class f with AUC of 0.96636. Even the lowest performing class (Class e, AUC = 0.94455) maintained an AUC well above 0.94, confirming high sensitivity and specificity across the 6-point FSR array.

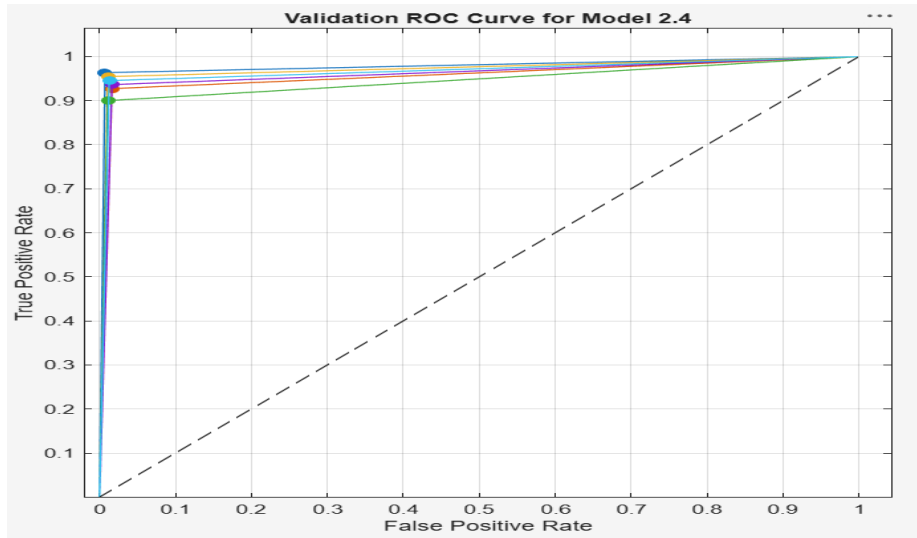


Fig. 5 ROC curves for KNN model (Model 2.4) across all six sitting posture classes.

Real-Time Prediction and Validation

To evaluate system generalization on new users, empirical testing was conducted with 5 unseen participants using the KNN model. Three aggregate features were extracted from the sensor array: Total Pressure (P_{total}), Left-to-Right Pressure Ratio (R_{LR}), and Front-to-Back Pressure Ratio (R_{FB}). Under real-time testing conditions on unseen subjects, the system achieved an overall testing accuracy of 67.58%. The testing confusion matrix in Fig. 6 deconstructs the operational performance and misclassification boundaries when the system encounters new physical body builds. Class c (Side Leaning Right) demonstrated the highest resilience to user variance, maintaining an 81.8% real-time accuracy with minor misclassifications split between Class a and Class f (9.1% each). Class a (Slouching) achieved 72.7% accuracy, but exhibited minor dispersion into Class d (10.0%), Class f (9.1%), and Class c (8.2%). Both Class e (Sliding Forward) and Class f (Crossed Legs) maintained reliable detection rates of 71.8%

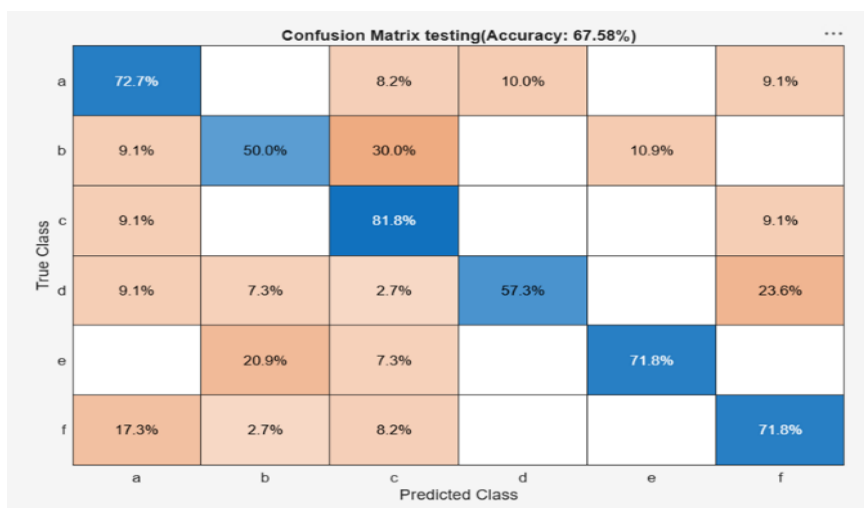


Fig. 6 Testing confusion matrix depicting real-time accuracy (67.58%) and cross-class misclassification patterns across 5 unseen participants.

In contrast, Class d (Side Leaning Left) dropped to 57.3% accuracy, experiencing significant misclassification into Class f (Crossed Legs, 23.6%) due to overlapping unilateral pelvic tilt vectors. The lowest performance occurred in Class b (Forward Leaning) at 50.0% accuracy, where 30.0% of instances were misclassified as Class c (Side Leaning Right) and 10.9% as Class e (Sliding Forward). This confusion stems from users resting an arm or elbow on desks while leaning forward during typing tasks, converting symmetric forward trunk flexion into asymmetric lateral force profiles.

Table V summarizes these real-time accuracy figures alongside their dominant misclassification drivers. As detailed in Table V, Side Leaning Right achieved the highest real-time accuracy (81.8%), followed by Slouching (72.7%), Sliding Forward (71.8%), and Crossed Legs (71.8%). Conversely, Forward Leaning recorded lower recognition accuracy (50.0%) and was frequently misclassified as Side Leaning Right (30.0%). Similarly, Side Leaning Left (57.3%) exhibited misclassification overlap with Crossed Legs (23.6%).

TABLE V ACCURACY TESTING ACROSS 5 UNKNOWN PARTICIPANTS

Posture Class	Real-Time Correct Accuracy	Misclassification
Side Leaning Right (Class c)	81.8%	Slouching / Crossed Legs (9.1%)
Slouching (Class a)	72.7%	Forward Leaning (10.0%)
Sliding Forward (Class e)	71.8%	Forward Leaning (20.9%)
Crossed Legs (Class f)	71.8%	Slouching (17.3%)
Side Leaning Left (Class d)	57.3%	Crossed Legs (23.6%)
Forward Leaning (Class b)	50.0%	Side Leaning Right (30.0%)

The end-to-end operational execution of the prototype is demonstrated in Fig. 7, illustrating the real-time feedback displayed on the 128x64 OLED screen during participant trials. Fig. 7(a) shows the system output during proper upright seating, displaying "Normal" with a "Status: GOOD" confirmation. When a user transitions into an improper posture, such as slouching (Fig. 7(b)) or side leaning left (Fig. 7(c)), the OLED screen immediately displays the classified posture title alongside a live active bad-posture timer. If the bad posture persists past the programmed time threshold, the ESP32 triggers the active piezo buzzer to deliver an acoustic correction prompt.

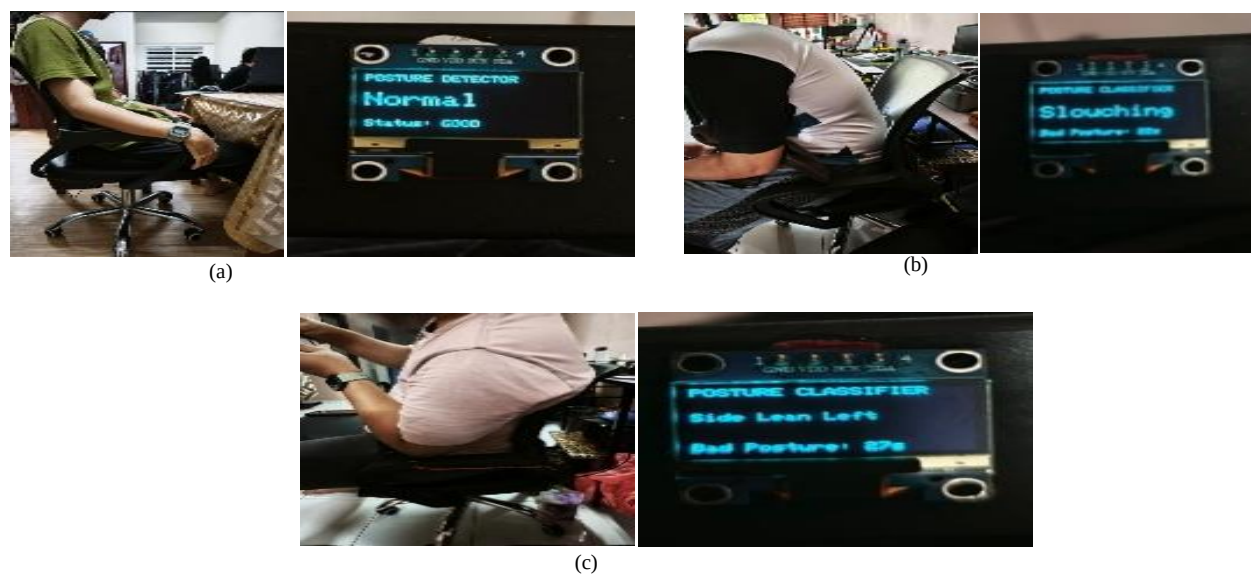


Fig. 7 Real-time posture classification snapshots with live OLED visual feedback: (a) Normal posture status display, (b) Slouching posture warning alert with bad posture timer, and (c) Side leaning left posture alert.

Performance Discussion and Socio-Technical Impact

Comparing the offline validation accuracy (93.8%) with real-time testing accuracy on unseen users (67.58%) reveals key biomechanical and technical insights. First, differences in participant body weight, pelvic width, and thigh dimensions shift absolute pressure values on the fixed FSR array. Unseen users with different physical builds generate pressure magnitudes that deviate slightly from the initial training baseline. Second, postures such as Forward Leaning often involve subtle asymmetric arm resting or desk leaning, producing pressure maps that closely resemble lateral leaning or slouching. Finally, despite testing variations, the embedded system delivered sub-second classification throughput, enabling immediate visual (OLED) and acoustic (buzzer) prompts upon bad posture detection.

From a socio-technical perspective, deploying non-invasive posture monitoring directly into office and classroom environments addresses workplace health sustainability. By automating posture awareness, the smart chair mitigates physical strain, reduces absenteeism associated with musculoskeletal disorders, and supports long-term occupant well-being.

CONCLUSION

This study successfully designed, implemented, and empirically evaluated a smart chair with sitting posture detection to address the growing prevalence of occupational MSDs in sedentary office and academic environments. By integrating a six-point Force Sensitive Resistor (FSR402) pressure sensor array, an ESP32 microcontroller, and an embedded KNN machine learning classifier, all three project objectives were achieved. The system provides a non-invasive, low-cost posture monitoring solution capable of real-time classification and feedback via a 128x64 OLED display and an active piezo buzzer.

Empirical evaluation demonstrated strong operational capabilities across offline validation and live testing phases, beginning with the KNN classifier achieving a 93.8% validation accuracy across 660 observations from 11 participants, a 6.2% validation error rate, and an average ROC-AUC score of 0.9627. Furthermore, real-time live generalization across five unseen participants post-feature engineering achieved an overall accuracy of 67.58%, highlighting robust detection capabilities for asymmetric postures such as Side Leaning Right at 81.8% while identifying distinct misclassification boundaries in more subtle positions like Forward Leaning at 50.0%.

To address current system limitations and prepare the technology for institutional commercialization, future work will focus on five key directions:

1. Expanding data collection beyond the initial participant cohort to capture a broader diversity of body weights, heights, and natural physical movement patterns.
2. Implementing a self-calibrating weight-normalization algorithm upon initial seating to mitigate inter-user anthropometric variations.
3. Positioning strategic sensing points on the seat backrest to disambiguate complex postural combinations, such as forward trunk flexion coupled with desk arm-resting.
4. Comparing embedded KNN against RF, SVM, and lightweight ANN to improve generalization on unseen subjects.
5. Leveraging the built-in Wi-Fi of the ESP32 to log longitudinal posture data to cloud platforms for extended ergonomic risk analytics.

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