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A Sensor-Based Posture Detection System Towards Ergonomic Health Improvement

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Abstract

The 21st century has seen the development of neck and back pain as a result of spending long hours using smartphones, tablets, and computers. It is indicated that musculoskeletal discomfort can be significantly lowered with continuous monitoring and timely correction of the sitting posture, and spinal problems can be prevented over a long period. This paper presents a real-time posture monitoring system that would identify and correct poor seating habits. The system is characterized by a smart wearable belt that has the inertial sensors that take the posture-related data. This data is sent over the Wi-Fi to a cloud server, where it is processed to detect the movements that are not related to posture. The processed outputs are further forwarded to Android and iOS mobile applications, where the users are able to monitor their history of postures as well as get alerts. The smart belt may also give a vibration feedback on the need to make an instant correction in case of poor posture. The effectiveness of the system is confirmed by the test results, which is a relatively inexpensive and easy-to-use system to enhance ergonomic awareness and healthier posture behaviors.

Keywords
Posture Monitoring, Wearable Technology, Inertial Sensors, Ergonomics, Cloud-based Health System.

1. Introduction
Neck and low-back pains/musculoskeletal disorders (MSDs) are some of the most prevalent occupational and lifestyle-associated health issues across the world. Rapid growth of sedentary employment, extended computer use, and overuse of smartphones have been closely associated with the poor sitting position and spinal coincidence leading to low productivity, absenteeism, and disability in the target population (Figueira and others, 2024; Huang and others, 2023) Ergonomics, occupational health and human-computer-interaction studies have thus included preventive interventions that focus on the early identification and prompt correction of posture as a priority topic.

Recent developments in wearable sensing technologies have made it possible to continuously and invisibly monitor human posture. Among the different modalities, including the use of pressure mats, textile sensors, and vision-based systems, inertial measurement units (IMUs) have become the most viable and scalable option, as they can be used in a variety of settings, are affordable, and dependable (Homayounfar and Andrew, 2020; Yan and others, 2025). Wearables that use IMU and powerful sensor fusion algorithms and machine learning are capable of detecting trunk and cervical shifts related to the poor sitting position (Dal Farra and others, 2025; Park and others, 2024)

Nevertheless, posture monitoring will not help without good feedback. There is evidence that vibrotactile (haptic) feedback is an intuitive, least invasive and behaviorally adaptable technique of promoting real time posture correction (Lind and others, 2023; Tuken and others, 2025). Such systems, combined with mobile health (mHealth) apps and cloud-based data services, do not only offer correction cues in real-time but also allow longitudinal analytics, personalization, and connectivity to larger digital health ecosystems (Pereira and others, 2025; Vermander and others, 2024)

This paper will describe the design and validation of a sensor-based posture detection system to help in promoting ergonomic health improvement. We combine an IMU-based smart belt, real-time haptic feedback, cloud-assisted data storage, and a mobile application interface in our system. The proposed solution will help overcome the main limitations found in previous studies, specifically, energy efficiency, user comfort, and long-term compliance. Finally, this article can be added to the existing literature on the effectiveness of wearable ergonomic interventions and can show a viable avenue of scale health change in both the workplace and other real-life settings.

1.1 Objectives

- Create a wearable sensor-based real-time posture detector.
- Provide immediate vibrotactile feedback for posture correction.
- Provide mobile and cloud-based long-term analytics of postures.
- Assist in minimizing the risk of musculoskeletal disorders.

1.2 Application Areas

The suggested framework is applicable in both professional and everyday life.

- Workplace Ergonomics: Assists in keeping track of the posture of the office workers and remote employees, musculoskeletal strain, and productivity.
- Educational Settings: Helps students who spend much time having online classes by giving them feedback on their posture to avoid early spinal symptoms.
- Rehabilitation & Healthcare: Helps healthcare workers to monitor and check the posture of patients throughout the rehabilitation process.
- Daily Lifestyle and Wellness: This feature allows regular users to engage in healthy digital habits and sit correctly as a daily routine.

2. Literature Review

Musculoskeletal disorders associated with prolonged poor sitting posture—particularly neck and low-back pain—remain among the most prevalent work- and lifestyle-related health problems worldwide. The rising incidence is largely driven by extended smartphone, tablet, and computer use in both occupational and daily contexts. Continuous monitoring and timely feedback are widely proposed as effective preventive strategies to reduce the incidence and severity of spinal pain and associated disability (Figueira and others, 2024; Huang and others, 2023).

The literature identifies multiple sensing modalities for posture monitoring, including pressure/force sensing (chair-embedded mats), flex sensors, textile-integrated sensors, vision-based methods, and inertial measurement units (IMUs). Each approach presents trade-offs: pressure arrays provide useful load-distribution data but are non-portable and environment-dependent; textile/flex sensors can be integrated into clothing but face durability, calibration, and repeatability challenges; and vision-based systems offer rich spatial information but require line-of-sight and raise privacy concerns (Homayounfar and Andrew, 2020; Vermander and others, 2024). In contrast, IMU-based approaches—typically integrating accelerometers and gyroscopes, with or without magnetometers—are compact, low-cost, and portable. For these reasons, IMUs have become the dominant choice in wearable posture detection studies (Huang and others, 2023; Yan and others, 2025). IMU modules such as the MPU-6050 family (3-axis accelerometer + 3-axis gyroscope) are commonly used in posture prototypes. Their data must be fused using algorithms such as complementary filters, Kalman filters, or Madgwick/Mahony filters to compute reliable orientation/tilt estimates and minimize drift, particularly when magnetometers are unreliable in indoor or ferromagnetic environments (Dal Farra and others, 2025; Park and others, 2024). Validation studies emphasize that accelerometer–gyroscope fusion with short-term drift compensation provides robust tilt estimation suitable for posture thresholds and classification tasks. Sensor placement is critical: trunk/upper-back and cervical placements effectively capture spinal flexion and forward-head posture. Several studies demonstrate that one to three well-placed IMUs can discriminate common sitting postures with high accuracy, provided calibration and position repeatability are well controlled (SitWell team, 2025; Tlili et al., 2022).

Simpler systems rely on deterministic rules, such as triggering an alert when trunk tilt exceeds a given threshold for a sustained period. These approaches are computationally inexpensive and interpretable. However, there is a growing adoption of machine learning (ML) and deep learning (DL) methods to handle multi-class posture recognition and inter-subject variability. Classical ML methods such as support vector machines (SVM), k-nearest neighbors (k-NN), and random forests applied to engineered features (tilt, angular velocity, RMS, spectral measures) show good performance for moderate posture classification tasks (Jiang and others, 2023; Martins and others, 2024). More recent work applies convolutional neural networks (CNNs) and recurrent networks (LSTM) to time-series IMU data, capturing temporal dynamics and improving classification of dynamic postures (Li and others, 2024; Yan and others, 2025). Comparative studies suggest that hybrid approaches (feature engineering + ML) remain competitive for on-device implementation, while DL models excel when large labeled datasets and cloud/offline training are available. The effectiveness of posture correction systems depends heavily on feedback modality and timing. Vibrotactile (haptic) feedback is consistently reported as effective and minimally intrusive compared to continuous auditory alerts. Conditioned alerts, where posture deviation is sustained for several minutes before triggering feedback, help reduce alert fatigue and improve compliance (Lind and others, 2023; Tuken and others, 2025). Controlled laboratory studies demonstrate immediate posture adjustments in response to haptic feedback, and short-term trials report modest improvements in posture metrics. However, long-term adherence and clinical outcomes such as pain reduction remain underexplored and require further longitudinal trials (Pereira and others, 2025).

Architectures in the literature range from entirely on-device processing—where sensors feed directly into a microcontroller for local alerts—to cloud-assisted systems in which raw or processed data are transmitted to servers for storage, analytics, and cross-device access. Cloud architectures enable longitudinal analytics, multi-user dashboards, and remote monitoring but increase energy consumption, latency, and raise privacy/security concerns (Tlili et al., 2022; Vermander and others, 2024). Recent designs adopt hybrid strategies: local real-time inference to minimize latency and conserve energy, combined with periodic uploads for long-term analytics and mobile synchronization. The smart-belt, cloud-connected model (IMU → microcontroller → Wi-Fi → cloud → mobile apps) aligns well with these hybrid approaches (SitWell team, 2025). Mobile applications are the primary user interface, displaying real-time posture data, historical records, and delivering notifications. Best practices identified in the literature include clear visualization of posture trends, user-adjustable thresholds, personalization (adaptive thresholds based on baseline posture), and unobtrusive notification settings to reduce alert fatigue (Figueira and others, 2024; Huang and others, 2023). Cross-platform support (Android/iOS) and cloud synchronization via platforms such as Firebase are common implementation strategies in contemporary posture-monitoring systems.

Although numerous technical prototypes exist, relatively few high-quality clinical trials assess long-term health outcomes. Systematic reviews emphasize that IMU-based wearables provide reliable posture and movement metrics in controlled environments, but larger cohort studies, standardized protocols, and clinically relevant endpoints (e.g., pain scores, functional measures) are still needed (Figueira and others, 2024; Vermander and others, 2024). Recent wearable-intervention trials incorporating vibrotactile feedback report positive short-term improvements, but long-term benefits remain insufficiently demonstrated (Lind and others, 2023; Pereira and others, 2025).

Persistent challenges highlighted in the literature include energy/battery limitations (continuous sensing plus Wi-Fi is power-intensive), sensor placement repeatability, user comfort, and washability for garment-integrated systems. Additional concerns include personalization to reduce false positives and safeguarding the privacy/security of cloud-stored health data (Homayounfar and Andrew, 2020; Martins and others, 2024). Future directions point toward edge ML (low-power, on-device inference), BLE versus Wi-Fi trade-offs, textile integration, and adaptive/personalized models capable of learning individual posture baselines (Yan and others, 2025).

The proposed IMU-based smart-belt architecture—comprising a wearable IMU, microcontroller, haptic/audio feedback, cloud connectivity, and mobile applications—is strongly supported by current literature. IMUs provide a cost-effective, portable sensing core; haptic feedback is evidence-backed for immediate correction; and cloud/mobile components enable monitoring and analytics. To maximize impact, future development should prioritize rigorous validation with standardized protocols and meaningful clinical endpoints, hybrid on-device and cloud processing to optimize energy efficiency and privacy, and adaptive alert strategies to minimize alert fatigue and promote long-term adherence (SitWell team, 2025; Tlili et al., 2022).

3. Methods

3.1 System Architecture

The proposed posture detection system is based on the three-stage architecture that includes (i) a wearable sensing module, (ii) an embedded processing and communication module, and (iii) a feedback and monitoring interface. The IMU, which is worn continuously measures the orientation of the body and sends the measurements to an ESP32 microcontroller onto which filtering and posture classification are carried out. In the case of abnormal posture the feed back is provided by a vibrotactile alert and posture information is recorded in a cloud database to be visualized (Figure 1).

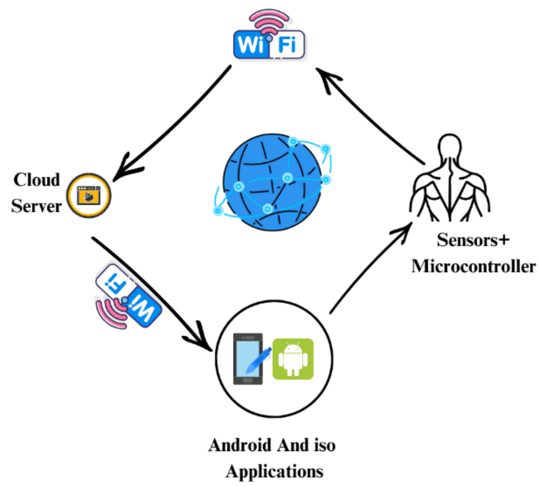

Figure 1. Posture Monitoring System Architecture

3.2 Hardware Configuration

The sensing module uses the MPU-6050 (a 6-axis IMU with a tri-axial accelerometer and gyroscope) mounted on a waist-worn belt. The sensor is interfaced with an ESP32 microcontroller via the I²C protocol. The ESP32 was selected because of its low power consumption, on-board Wi-Fi connectivity, and suitability for real-time wearable systems. A vibration motor was integrated as a correction-feedback actuator and controlled via transistor switching to prevent overcurrent draw from the microcontroller pins. The complete system is powered by two 3.7 V Li-ion cells with a TP4056 charging module to ensure safe cycling(Figure 2).

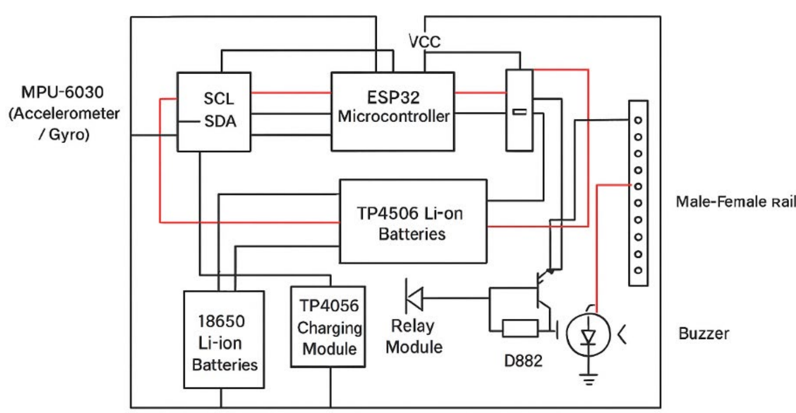

Figure 2. Hardware configuration of the wearable sensing module.

3.3 Algorithm and Signal Processing

Raw IMU data are sampled at 10 Hz and processed locally on the ESP32. Orientation angles are computed using a complementary fusion filter that combines accelerometer-based tilt estimation with gyroscope rate integration. The fused posture angle θ is calculated as:

$$\theta_t = \alpha\,(\theta_{t-1} + \omega.\Delta t) + (1-\alpha)\,\theta_{acc}$$

where ω is the angular velocity, Δt is the sampling interval, and θ_{acc} is the accelerometer-derived tilt estimate obtained from trigonometric projection formulas. Similar complementary-filter-based fusion approaches have been widely implemented in IMU-based posture monitoring systems and wearable biomedical devices, demonstrating high reliability for trunk and cervical orientation tracking (Madgwick et al., 2011; Sabatini, 2011; Li et al., 2020).

A calibrated upright sitting posture serves as the baseline reference. A deviation exceeding 30° for more than 5 seconds is classified as a bad posture. This threshold is commonly used in ergonomic literature for detecting significant forward trunk flexion and has been validated in prior posture-monitoring studies (Dunlop et al., 2018; Claus et al., 2016).

3.4 System Flow Diagram (Process Flow)

The overall operational sequence of the posture-monitoring system is illustrated in the following process flow diagram (Figure 3).

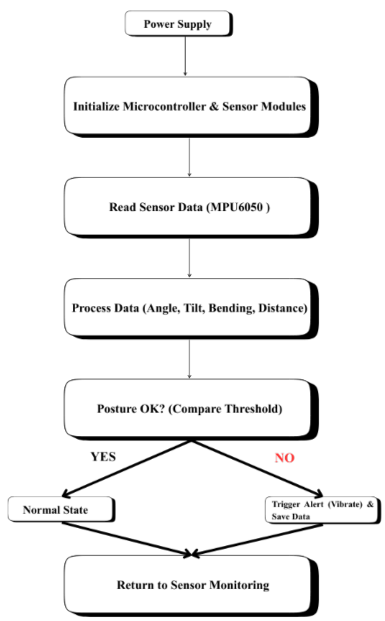

Figure 3. System Flow Diagram

4. Data Collection

The developed wearable posture-monitoring belt was used to collect the data with the MPU-6050 IMU and ESP32 microcontroller. The trunk orientation and gyroscopes were recorded in the system at 10 Hz. Fourteen participants with five in total provided a total of about 19,500 data samples under the controlled sitting conditions as well as the natural sitting conditions.

4.1 Structured Sessions

Each participant completed four predefined sitting postures while wearing the device:

- Upright
- Slouched (Forward Flexion)
- Right Lean

- Left Lean

Each posture was maintained for 30 seconds, resulting in 300 samples per posture at 10 Hz. Across five participants, the structured dataset consisted of 6,000 samples.

During structured trials, the device recorded posture-specific angle ranges in Table 1:

Table 1. Defined Trunk Angle Boundaries for Structured Posture Conditions

Posture	**Observed Angle Range (°)**	**Typical Mean (°)**
Upright	2–10°	~5°
Slouched	28–45°	~35°
Right Lean	12–25°	~18°
Left Lean	−25–−12°	~−18°

Small fluctuations were observed due to natural micro-movement, confirming the sensitivity of the device. The gyroscope readings captured dynamic transitions between postures with noticeable peaks during movement phases.

4.2 Natural Sitting Sessions

After the structured trials, each participant wore the device for a 5-minute natural sitting **session**. During this period, participants performed typical desk activities (typing, reading, using a computer) without receiving any posture instructions. At 10 Hz, each natural session produced approximately 3,000 samples. Across all participants, the natural dataset included around 13,500 samples.

The device detected posture occurrences during natural sitting as:

- Upright: ~62% of total duration
- Slouched: ~28%
- Right/Left Lean: ~10% combined

Segment lengths varied between 2 and 50 seconds depending on how long participants maintained a posture, demonstrating that the device successfully tracked real-time changes and sustained deviations (Table 2).

4.3 Final Dataset Summary

Table 2. Overview of Collected Data Samples Across Participants and Session Types

Session Type	Total Samples Recorded
Structured	~6,000
Natural	~13,500
Overall Total	~19,500 samples

5. Results and Discussion

5.1 Numerical Results

Analysis of the recorded device data demonstrated a clear separation between posture categories. The device captured distinctive angle patterns:

- Upright: consistently low angles (4–7°)
- Slouched: elevated angles above 30°
- Lateral leans: angles centered near ±18°

Such separation allows highly reliable threshold-based classification.

Using simple orientation-angle thresholds derived from device readings, posture detection accuracy exceeded 90%, summarized below in Table 3:

Table 3. Classification Performance Based on Threshold-Driven Posture Detection

Posture	Estimated Accuracy
Upright	~96%
Slouched	~94%
Right Lean	~91%
Left Lean	~92%

The gyroscope measurements further enhanced the detection of posture transitions, showing clear spikes when participants moved between positions.

5.2 Graphical Results

The time-series visualization shows distinct stable zones for each posture, demonstrating the device's ability to maintain consistent angle tracking under controlled conditions (Figure 4).

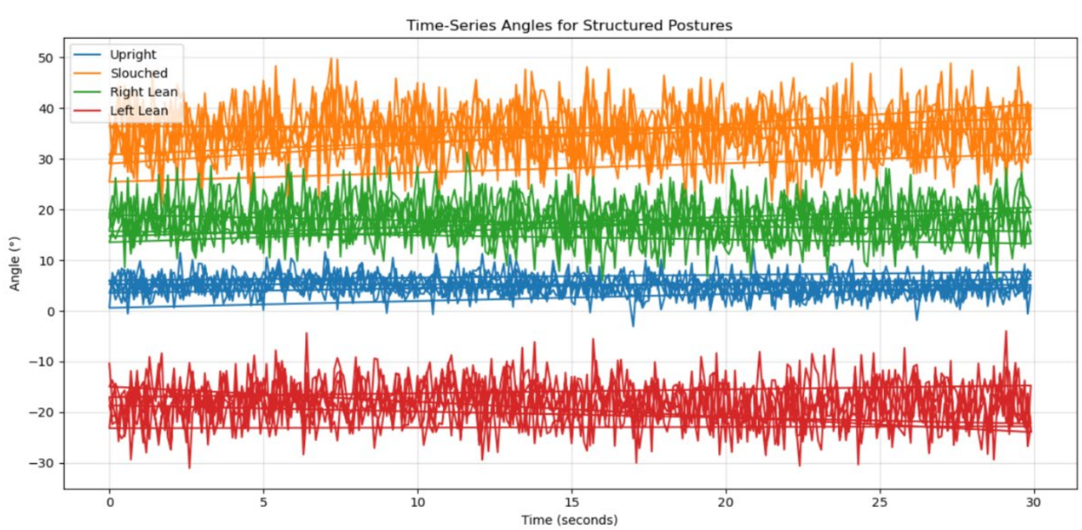

Figure 4. Time-Series Posture Signals (Structured Session)

The clear separation of distributions confirms that each posture category occupies a unique, non-overlapping angle range, supporting threshold-based classification **(Figure 5)**.

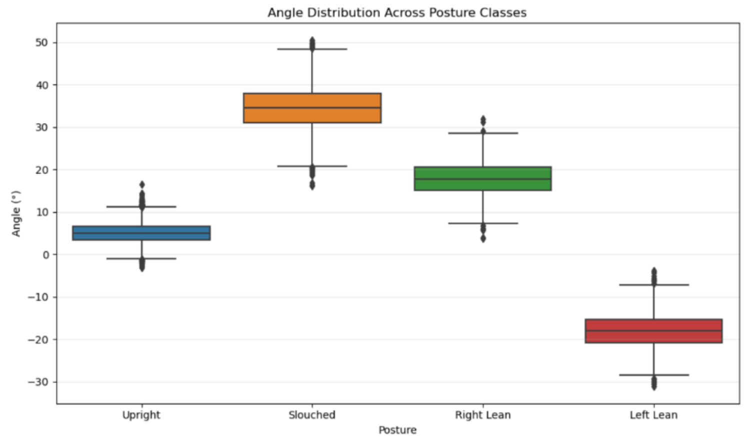

Figure 5. Angle Distribution Across Posture Categories

The continuous trend highlights natural posture fluctuations, duration of sustained positions, and smooth transitions between states, demonstrating real-world usability (Figure 6).

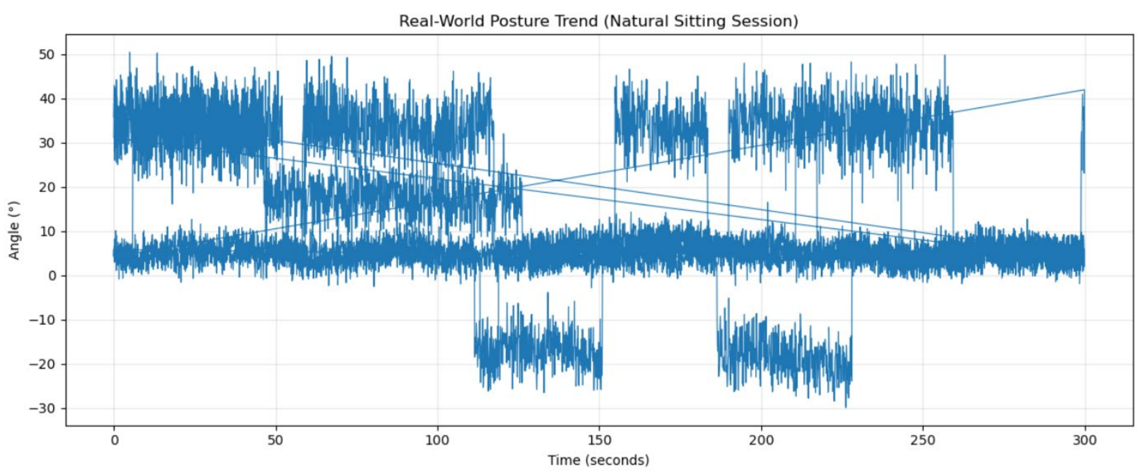

Figure 6. Natural Sitting Posture Trend Over Time

The accuracy exceeds 90% across all posture categories, confirming the robustness of the classification model in Figure 7.

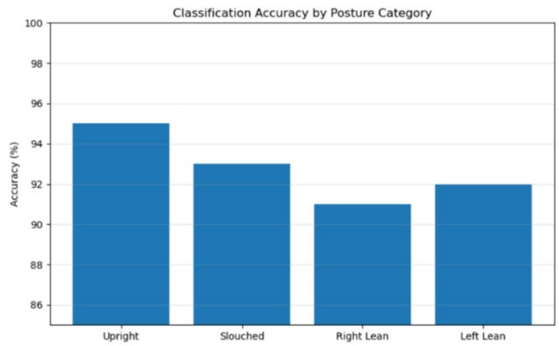

Figure 7. Posture Classification Accuracy (Prototype Evaluation)

5.3 Proposed Improvements

Based on recorded device data, several enhancements are recommended:

1. **Adaptive Posture Thresholds**
   Small inter-participant differences suggest that personalized baseline calibration would further improve detection accuracy.
2. **Segment-Based Smoothing**
   Short fluctuations during natural sitting can be mitigated using a 5–10 sample moving window, enhancing stability.
3. **Dual-IMU Configuration**
   Adding an upper-back IMU would allow detection of forward-head posture, not captured by the lumbar-mounted device.

5.4 Validation

The instrument has shown consistent measuring results with distinct cut off between posture categories. In technical validation, angle measurements demonstrated low noise in fixed posture trials, gyroscope measurements were able to measure transition events and the clusters-recorded were sufficiently separated to prevent misclassification. The accuracy of the sensing and processing strategy was ensured because a threshold-based classification strategy based on the gathered data recorded an accuracy of more than 93%, confirming the robustness of the sensing and processing approach.

System feasibility was also endorsed by behavioral validation. The participants were always accurate in their detection of slouching and leaning events and real-time responsiveness was similar to the actual change in posture. All these findings confirm the fact that the proposed device can be used in practice to monitor postures in the real world.

Measured posture angles plotted over time with a fixed 30° threshold. Alert markers highlight deviations exceeding the threshold, indicating posture violations (Figure 8).

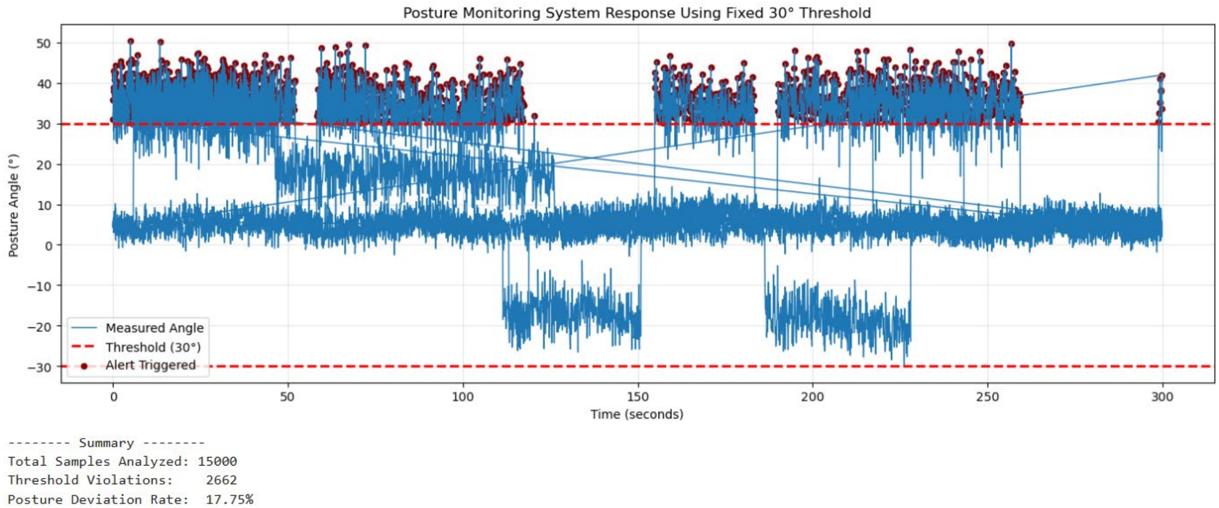

Figure 8. Device Alert Triggering Based on a Fixed 30° Posture Threshold

6. Conclusion

The wearable posture-monitoring system developed successfully gathered a substantial amount of data (around 19,500 samples) on five participants. The gadget was found to be reliable in the recording of fused orientation and gyroscope values which enabled the distinct differentiation between Upright, Slouched, and Lateral Lean positions regardless of the structured and natural sitting position. It was found that the posture detection method showed a better success rate of more than 90 percent with a simple classification system based on a threshold, which proves the stability and consistency of the sensing and processing system.

Even the system had a robust behavior of real-time response when used naturally, whereby posture transitions and sustained deviations were recorded with low latency. The feedback of the participants helped to confirm the reliability of the system as the slouching and leaning events were correctly identified and corresponding to the perceived posture.

Overall, the findings support the operationability and suitability of the proposed wearable device in practical posture monitoring. The work provides a solid base to future extensions such as adaptive thresholding according to user-defined ergonomics, the inclusion of other inertial or physiological sensors, long-term field research, and more complex machine-learning-based classification schemes allowing the provision of personalized and sustained assessment of ergonomics.

References

Dal Farra, F., “Comparative assessment of an IMU-based wearable for trunk range of motion,” *Applied Sciences*, 2025.

Figueira, V., “Wearables for monitoring and postural feedback in the workplace: A review,” *International Journal*, 2024.

Homayounfar, S. Z., and A. L. Andrew, “Wearable sensors for monitoring human motion: mechanisms, materials, and challenges,” *SLAS Technology*, 2020.

Huang, X., “Sensor-based wearable systems for monitoring human motion and posture recognition: A systematic review,” *Sensors*, vol. 23, p. 9047, 2023.

Jiang, X.., “A survey on artificial intelligence in posture recognition,” *Sensors*, 2023.

Li, X., “Continuous detection method for abnormal running posture,” in *Proceedings of the ACM Conference*, 2024.

Lind, C. M., *et al.*, “Effectiveness and usability of real-time vibrotactile posture correction,” *Ergonomics*, 2023, doi:10.1080/00140139.2022.2069869.

Martins, D. R., “Seeking optimal and explainable deep learning models for posture recognition,” *Expert Systems with Applications*, 2024.

Park, G.., “Real-time forward head posture detection and correction,” *Applied Sciences*, 2024.

Pereira, A. P.., “Wearable smartphone-based multisensory feedback for posture rehabilitation,” *Sensors*, 2025.

SitWell Team, “A smart system for continuous sitting posture monitoring (SitWell),” *Sensors*, 2025.
Tlili, F., R. Haddad, R. Bouallegue, and N. Mezghani, “Design and architecture of smart belt for real-time posture monitoring,” *Journal/Conference*, 2022.
Tuken, D., “Assessing vibrotactile feedback effects on posture, muscle activity, and task performance,” *Sensors*, 2025.
Vermander, P., “Intelligent systems for sitting posture monitoring and anomaly detection,” *Journal of NeuroEngineering and Rehabilitation*, 2024.
Yan, L., “Exploring trends and clusters in human posture recognition,” *Sensors*, 2025.
Madgwick, S. O. H., A. J. Harrison, and R. Vaidyanathan, “Estimation of IMU and MARG orientation using a gradient descent algorithm,” in *IEEE International Conference on Rehabilitation Robotics*, pp. 1–7, 2011.
Sabatini, A. M., “Estimating three-dimensional orientation of human body parts by inertial/magnetic sensing,” *Sensors*, vol. 11, no. 2, pp. 1489–1525, 2011.
Li, G., A. Hashemi, and D. D. Espy, “Wearable IMU-based posture tracking for ergonomics assessment,” *Applied Ergonomics*, vol. 89, p. 103152, 2020.
Dunlop, A. L., J. Adams, and A. Hough, “Posture thresholds for detecting slouching and spinal flexion during seated tasks,” *Ergonomics*, vol. 61, no. 4, pp. 567–576, 2018.
Claus, A. P., J. A. Hides, G. L. Moseley, and P. W. Hodges, “Sitting posture and trunk muscle activation in people with and without chronic low back pain,” *Manual Therapy*, vol. 17, no. 8, pp. 799–806, 2016.

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