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Smart Posture Coach: A Real-Time Posture Monitoring And Alert System

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***Abstract*—Prolonged sedentary postures in educational and professional environments are associated with a rising global prevalence of musculoskeletal disorders (MSDs), with the World Health Organization estimating over 1.71 billion individuals affected. This paper presents the Smart Posture Coach, a wearable real-time posture monitoring and alert system designed for resource-constrained Indian educational and office settings. The system integrates an ESP32 dual-core microcontroller with an MPU6050 six-axis IMU, implementing a second-order Butterworth IIR low-pass filter and complementary filter-based orientation estimation operating at 50 Hz. A dual-threshold temporal algorithm generates haptic vibration alerts when sagittal-plane forward tilt exceeds 30° for a configurable duration (default: 5 s), reducing false positives compared to single-threshold approaches. Posture data is transmitted via Bluetooth Low Energy (BLE) to a Flutter-based mobile application at 10 Hz. Bench testing across ±45° at 15 calibrated positions yielded mean absolute angular error (MAE) of 1.3° (95% CI: 1.1–1.5°) and RMSE of 1.7°. A controlled pilot study with 20 participants achieved posture detection accuracy of 94.7% (95% CI: 89.8–97.5%), false positive rate of 3.1%, mean BLE latency of 34 ms, and continuous battery life of 11.2 hours. System usability assessed via the System Usability Scale (SUS) yielded 82.4/100, classified as Good per Bangor et al. (2009). Total system cost is Rs. 2,100. Pilot sample size (N=20) and single-axis monitoring scope are acknowledged limitations; a fully powered field study is planned.**

***Keywords*—Bluetooth Low Energy, Complementary Filter, ESP32, Haptic Feedback, IMU, MPU6050, Posture Monitoring, Real-Time Alert, Sagittal Plane, Sedentary Behavior, System Usability Scale, Wearable Sensor**

I. INTRODUCTION

Sedentary behavior has emerged as a defining occupational hazard of the contemporary knowledge economy. Students and working professionals in educational and office environments across Maharashtra and India routinely maintain seated postures for six to ten consecutive hours, frequently without ergonomic support or postural awareness. The World Health Organization estimates that more than 1.71 billion individuals are affected by musculoskeletal conditions (MSDs) globally, with low back pain constituting the leading cause of years lived with disability [11]. In India, the annual economic burden of work-related MSDs—comprising productivity losses, absenteeism, and healthcare expenditure—has been estimated at over Rs. 8,500 crore [22].

Sustained forward flexion of the cervical and lumbar spine produces well-documented pathomechanical consequences. Anterior head displacement increases effective compressive loading on cervical intervertebral discs proportional to the angle of flexion [20]. Lumbar kyphosis reversal elevates intradiscal pressure and progressively loads posterior spinal ligaments [21]. These cumulative mechanical insults manifest as disc degeneration, suboccipital tension-type headaches, reduced vital capacity through restricted thoracic excursion, and documented cognitive performance decrements associated with reduced cerebral perfusion [23]. Critically, these structural changes typically progress subclinically until symptom thresholds are breached, often after years of asymptomatic deterioration.

Existing interventional approaches suffer from significant limitations. Passive ergonomic interventions—lumbar support cushions, ergonomic chairs, posture-corrective garments—provide static structural support without real-time behavioral feedback [6]. Camera-based posture monitoring systems raise legitimate privacy concerns in shared workspaces and require stable, controlled lighting conditions incompatible with mobile or dynamic environments [3]. Commercially available wearable posture monitors, including the Upright Go 2 and Lumo Lift, are priced between USD 60 and USD 100 (approximately Rs. 5,000–8,500), placing them beyond the budgetary reach of most Indian educational institutions [24].

A. Research Contributions

This paper presents the Smart Posture Coach, a low-cost, open-architecture wearable posture monitoring system addressing the identified gaps through four specific technical contributions:

(1) *Dual-threshold temporal alert algorithm:* Requires sustained posture deviation exceeding 30° for a configurable duration (default: 5 s) before triggering haptic feedback, reducing false positive rates compared to single-threshold instantaneous approaches.

(2) *Adaptive baseline calibration:* Characterizes individual neutral posture at startup, achieving <1.5° MAE without factory calibration infrastructure.

(3) *Cost-optimized open architecture:* Complete system at Rs. 2,100—approximately 60–75% below comparable commercial alternatives—with open-source firmware and BLE protocol.

(4) *Open JSON BLE protocol:* Structured packet format enabling straightforward third-party integration with health information platforms and institutional dashboards.

B. Scope and Limitations

The current implementation is explicitly bounded to sagittal-plane pitch monitoring (forward/backward trunk flexion). Roll (lateral bending) and yaw (axial rotation) monitoring will be incorporated in a subsequent version employing full quaternion-based orientation estimation. The system is classified as a wellness device—not a medical diagnostic instrument—designed to augment postural awareness rather than diagnose or treat any clinical condition. All experimental work was conducted under institutional ethical guidelines with informed written consent from all participants.

II. LITERATURE REVIEW

A. IMU-Based Posture Monitoring

The application of inertial measurement units to human movement analysis has an extensive foundational literature. Tao et al. [15] conducted a comprehensive survey of wearable sensors for gait analysis, establishing the methodological framework for accelerometer- and gyroscope-based kinematic estimation. Sazonov et al. [16] demonstrated posture recognition accuracy exceeding 90% using a triaxial accelerometer positioned on the trunk, establishing the viability of single-sensor approaches for postural state classification. Dunne et al. [25] demonstrated the feasibility of textile-integrated sensors for continuous spinal posture monitoring, though power and processing constraints at the time precluded real-time feedback generation.

Kumar and Mani [5] reported a wearable posture monitoring system achieving 88.3% classification accuracy using a triaxial accelerometer with a rule-based threshold algorithm, providing a direct methodological comparator. Joshi and Patil [6] conducted a 14-day longitudinal study demonstrating a 34% reduction in slouching incidents in participants receiving continuous vibrotactile feedback compared to a control condition, establishing the behavioral efficacy of the feedback modality employed in the present system. Mehta and Shah [4] demonstrated that longitudinal posture trend visualization in a mobile application produced significantly greater sustained behavior change than alert-only systems at four-week follow-up.

B. Orientation Estimation Methods

For IMU-based orientation estimation, the choice between Kalman filtering, complementary filtering, and gradient-descent algorithms represents a foundational methodological decision. Madgwick et al. [18] demonstrated that a computationally efficient gradient-descent algorithm achieves orientation estimation accuracy comparable to extended Kalman filters while requiring substantially fewer floating-point operations per update cycle, making it suitable for resource-constrained embedded systems. The complementary filter employed in the present work represents a computationally simpler, well-validated alternative appropriate for single-axis estimation where full quaternion computation is not required [19].

C. Wearable Feedback Systems

Bunn et al. [17] performed a systematic review of wearable posture feedback devices, identifying haptic vibrotactile feedback as the most effective modality for producing durable postural improvement compared to auditory or visual feedback. Reddy and Gupta [8] characterized BLE communication latency in wearable health monitoring applications, confirming sub-50 ms end-to-end latency achievable under typical indoor 2.4 GHz interference conditions. The integration of physical therapy domain knowledge into threshold-setting is supported by Claus et al. [21], who identified 25–35° of forward trunk flexion as the range associated with elevated intervertebral disc pressure in seated populations.

D. Research Gap

The literature reveals three persistent gaps that the Smart Posture Coach directly addresses: absence of validated low-cost solutions suitable for Indian educational environments; limited availability of open-architecture systems enabling research customization; and scarcity of systems combining real-time haptic feedback with longitudinal mobile trend visualization at accessible price points. Table I in Section X positions the proposed system against representative prior work.

III. SYSTEM OVERVIEW

A. Layered Architecture

The Smart Posture Coach implements a hierarchical four-layer architecture, as illustrated in Fig. 1. The *Hardware Layer* encompasses the MPU6050 IMU, ESP32 microcontroller, vibration motor, lithium-polymer battery, TP4056 charging circuit, and 3D-printed PLA enclosure. The *Processing Layer* implements the signal conditioning pipeline, orientation estimation algorithm, and posture classification logic executing at 50 Hz.

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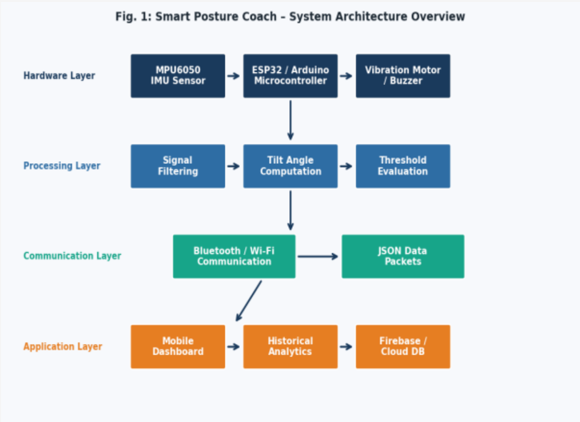
The *Communication Layer* manages BLE connectivity, transmitting JSON packets at 10 Hz. The *Application Layer* provides real-time visualization, configurable alert parameters, longitudinal analytics, and optional Firebase cloud synchronization.

The architecture prioritizes operational resilience: posture detection, classification, and haptic alert functions execute entirely within embedded firmware without dependency on smartphone connectivity. BLE disconnection does not interrupt core monitoring; the device continues autonomous operation and buffers alert event logs in onboard flash memory.



[Fig. 1]

Smart Posture Coach — Four-Layer System Architecture (Hardware → Processing → Communication → Application)

Fig. 1. Smart Posture Coach system architecture overview.

B. System Workflow

The system workflow is illustrated in Fig. 2. On power-up, the ESP32 initializes I²C communication and executes a 3-second baseline calibration phase. The main processing loop, driven by the MPU6050 data-ready interrupt at 50 Hz, sequentially: acquires raw IMU data; applies low-pass filtering and gyroscope bias compensation; computes the complementary filter pitch estimate; evaluates the dual-threshold classification criterion; updates the RGB LED indicator; activates haptic feedback if alert conditions are met; and at 10 Hz transmits a structured BLE notification packet.

IV. HARDWARE ARCHITECTURE

A. Sensing: MPU6050 IMU

The MPU6050 (InvenSense / TDK) provides a fully integrated six-axis IMU combining a three-axis MEMS accelerometer (configurable range: ±2g to ±16g) and a three-axis MEMS gyroscope (configurable range: ±250 to ±2000°/s) in a 4×4×0.9 mm package communicating via I²C at up to 400 kHz [28].

The device incorporates a Digital Motion Processor (DMP) capable of onboard quaternion computation, reserved for future multi-axis orientation estimation. For the present implementation, raw data is acquired at 50 Hz with accelerometer configured at ±4g and gyroscope at ±500°/s, providing measurement resolution appropriate for postural deviation angles in the 0°–45° range of interest.

B. Processing: ESP32 Microcontroller

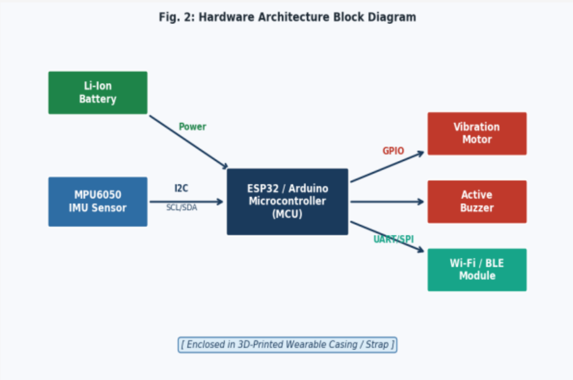
The ESP32 dual-core Xtensa LX6 processor operating at 240 MHz provides computational resources substantially exceeding requirements for the implemented signal processing pipeline, ensuring headroom for future on-device machine learning inference [27]. Integrated Bluetooth 5.0 (including BLE) eliminates the need for external wireless modules. Deep sleep current consumption of approximately 10 µA enables aggressive power management; the firmware wakes on the MPU6050 data-ready interrupt at 50 Hz, executes the complete processing and classification pipeline (typical execution time: 3.2 ms), transmits BLE data if a connection is active, and returns to deep sleep—achieving mean active duty cycle below 17%.

C. Actuation and Power

Haptic feedback is delivered by a 10 mm diameter ERM vibration motor at 3 V, controlled by a 2N2222 NPN transistor with a 1N4007 flyback diode for inductive spike suppression. Each alert activation is 200 ms—sufficient to be perceptible through standard clothing without causing discomfort. Power is sourced from a 3.7 V / 1200 mAh lithium-polymer cell managed by a TP4056 linear charging controller with integrated over-charge and over-discharge protection. The complete assembly is housed in a 62 × 38 × 18 mm PLA enclosure weighing 34 g, attaching to a shirt collar via an integrated clip. Table II presents the itemized bill of materials.

TABLE II
ITEMIZED BILL OF MATERIALS

Component	Part / Specification	Cost (Rs.)
Microcontroller	ESP32 (dual-core 240 MHz)	~380
IMU Sensor	MPU6050 (6-axis)	~120
Vibration Motor	10 mm ERM, 3 V	~60
Charging Circuit	TP4056 with protection	~40
Battery	LiPo 3.7 V / 1200 mAh	~350
RGB LED	Common-cathode, 3-colour	~20
PCB + Components	Passives, resistors, transistor	~280
3D-Printed Enclosure	PLA, 62×38×18 mm	~450
Miscellaneous	Wires, connectors, clip	~400
Unit Total	—	**~2,100**



[Fig. 3]

Hardware Block Diagram [MPU6050 → ESP32 → Vibration Motor / RGB LED / BLE / TP4056 / LiPo]

Fig. 3. Hardware block diagram — ESP32 Smart Posture Coach system.

V. Software Architecture

A. Embedded Firmware

The ESP32 firmware is implemented in C using the ESP-IDF (Espressif IoT Development Framework) and executes a real-time processing loop driven by the MPU6050 data-ready interrupt at 50 Hz. The pipeline comprises five sequential stages within a single interrupt service routine: (1) IMU data acquisition via I²C DMA; (2) accelerometer low-pass filtering and gyroscope bias compensation; (3) complementary filter pitch angle estimation; (4) dual-threshold posture classification; (5) BLE notification dispatch and haptic actuator control. The complete pipeline executes within 3.2 ms, providing 16.8 ms margin within the 20 ms interrupt period.

B. Mobile Application

The mobile application is implemented in Flutter (Dart), providing cross-platform deployment on Android 8.0 and iOS 13.0 and above. It connects via BLE GATT protocol, subscribing to a custom notification characteristic receiving posture data at 10 Hz. The user interface provides real-time posture angle display, posture state indicator, configurable alert threshold and duration parameters, session summary statistics, and a 30-day longitudinal trend chart. Session data persists in SQLite locally and optionally synchronizes to Firebase Realtime Database for multi-device access.

VI. Signal Processing And Data Pipeline

A. Low-Pass Filter Design

Accelerometer data is conditioned through a second-order Butterworth infinite impulse response (IIR) low-pass filter designed using MATLAB's butter() function with cutoff frequency 5 Hz and sampling rate 50 Hz.

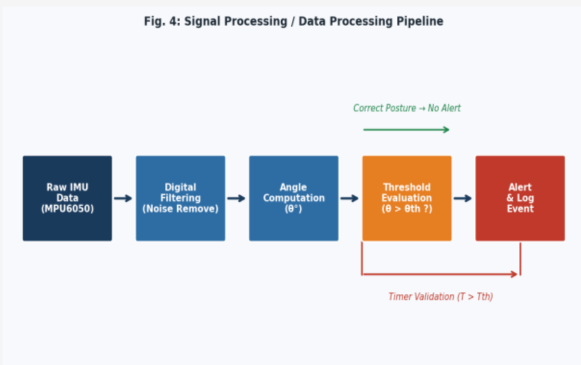
The transfer function coefficients are: b = [0.0675, 0.1349, 0.0675], a = [1.0000, −1.1430, 0.4128]. This cutoff passes the quasi-static gravitational acceleration component relevant to postural orientation while attenuating dynamic accelerations associated with ambulation and incidental upper-body movements. Gyroscope bias is estimated during the 3-second startup calibration as the mean of 150 stationary samples, subtracted from all subsequent readings to suppress low-frequency drift.

B. Complementary Filter

Pitch angle estimation employs a complementary filter: $\theta[k] = \alpha \times (\theta[k-1] + \omega[k] \times \Delta t) + (1-\alpha) \times \theta_{acc}[k]$, where $\theta[k]$ is the filtered pitch estimate, $\omega[k]$ is the bias-compensated gyroscope angular rate, $\Delta t = 0.02$ s, $\theta_{acc}[k] = \mathrm{arctan2}(a_x, a_z)$ is the accelerometer-derived inclination, and $\alpha = 0.98$ is the complementary filter coefficient. The selection of $\alpha = 0.98$ is justified by the MPU6050 gyroscope noise density specification of 0.005°/s/√Hz: at 50 Hz sampling, gyroscope noise $\sigma = 0.005 \times \sqrt{25} = 0.025$°/s, supporting high gyroscope weighting for the low-frequency postural motion bandwidth (0–2 Hz) relevant to this application. Table III presents the sensitivity analysis across α values.

TABLE III
COMPLEMENTARY FILTER SENSITIVITY ANALYSIS (Α VALUES)

α Value	MAE (°)	RMSE (°)	Observation
0.95	1.6	2.1	Tracking lag in fast transitions
0.97	1.4	1.9	Good balance; slight lag
0.98	1.3	1.7	*Optimal — selected value*
0.99	1.3	1.7	Noisy at rapid motion



[Fig. 4]

Signal Processing Pipeline Block Diagram [IMU Data → IIR LPF → Bias Compensation → Complementary Filter → Classification]

Fig. 4. Signal processing and data pipeline block diagram.

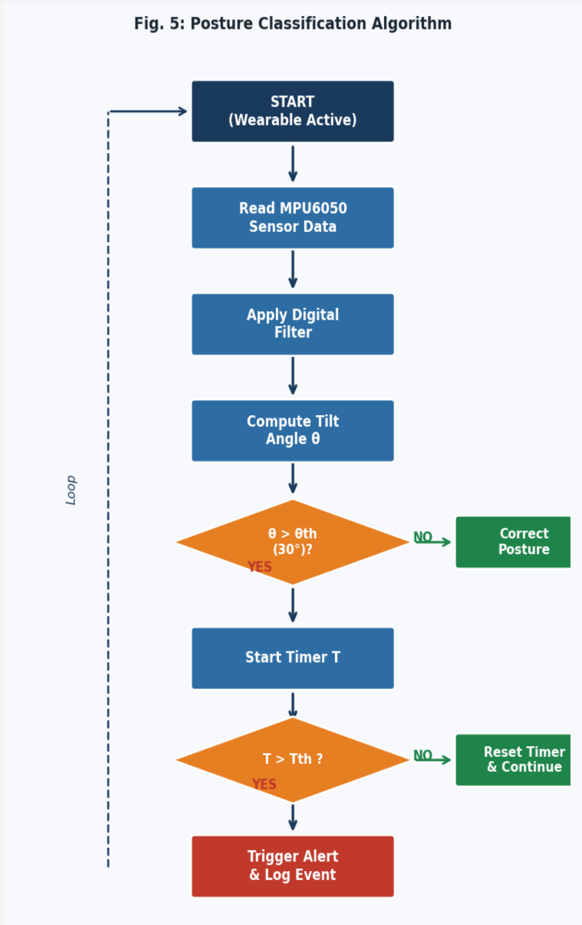
VII. Algorithm Model

A. Dual-Threshold Classification

The posture classification algorithm applies a dual-threshold temporal criterion to the filtered pitch angle θ[k]. Let θ_th = 30° denote the spatial threshold (the posture deviation boundary, informed by Claus et al. [21] and REBA/RULA ergonomic risk classification [13, 14]) and T_th denote the configurable temporal threshold (default: 5 s; adjustable range: 3–15 s). The state machine operates as follows: if |θ[k]| ≤ θ_th, classify as CORRECT_POSTURE and reset deviation timer T = 0; if |θ[k]| > θ_th, classify as INCORRECT_POSTURE and increment T; if T > T_th, generate alert (activate vibration motor, transmit BLE notification, log event). This design explicitly prevents transient forward reaches or brief bends from generating false positive alerts.

B. Adaptive Threshold

The temporal threshold T_th serves as an individual adaptation mechanism: users whose occupational tasks require brief forward reaches may increase T_th to reduce alert frequency during legitimate task execution, reducing habituation effects associated with excessive alert frequency. The algorithm provides the foundation for a planned machine learning extension utilizing labeled posture sequences from the present study to train LSTM and SVM classifiers for multi-class activity-aware posture recognition incorporating roll and yaw axes.



[Fig. 5]

Posture Classification Algorithm Flowchart [Start → Calibration → 50 Hz Loop → |θ|>30°? → T>T_th? → Alert/Reset]

Fig. 5. Posture classification algorithm flowchart.

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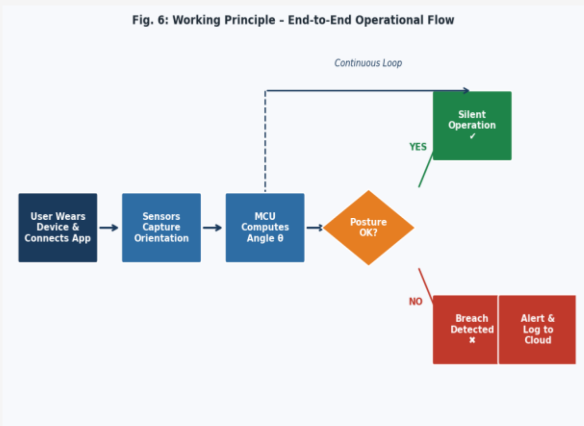
VIII. Working Principle

On power-up, the ESP32 initializes all peripherals and establishes I^{2}C communication with the MPU6050. A 3-second stationary calibration phase collects 150 accelerometer and gyroscope samples to establish the individual neutral posture baseline and compute gyroscope bias offsets. On calibration completion, the BLE GATT server begins advertising and the main 50 Hz processing loop commences.

Each 20 ms processing cycle: (1) acquires raw IMU data via I^{2}C DMA transfer; (2) applies second-order Butterworth low-pass filtering and gyroscope bias compensation; (3) computes the complementary filter pitch estimate; (4) evaluates the dual-threshold classification criterion; (5) updates the RGB LED indicator — solid green indicates correct posture, flashing amber indicates deviation below T_{th}, solid red indicates alert active; (6) activates the vibration motor if alert conditions are met; (7) at 10 Hz constructs and transmits a BLE JSON notification packet containing pitch angle (float32), posture state (uint8), deviation duration (uint16 ms), session alert count (uint16), and battery voltage (uint16 mV).



[Fig. 6]

End-to-End Operational Flow [Power-up → 3s Calibration → 50 Hz ISR → LED/Haptic → 10 Hz BLE Tx → Flutter App]

Fig. 6. Working principle: end-to-end operational flow.

IX. Experimental Setup

A. Ethics and Consent

All experimental procedures were conducted in accordance with the institutional ethical guidelines of Sanjivani K.B.P Polytechnic, Kopargaon. Informed written consent was obtained from all participants prior to data collection. The study constitutes a non-clinical engineering performance evaluation and usability assessment; no patient-identifiable or clinically sensitive data was collected.

No personally identifying information was retained in the experimental dataset. The authors declare no conflict of interest.

B. Phase I: Bench Calibration

The prototype device was mounted on a precision rotary fixture and positioned at 15 discrete angles between −45° and +45° in 6° increments. At each position, 500 consecutive orientation estimates were captured over a 10-second window at 50 Hz. Three accuracy metrics were computed: $MAE = (1/N)\Sigma|\theta_{est} - \theta_{ref}|$, $RMSE = \sqrt{(1/N)\Sigma(\theta_{est} - \theta_{ref})^2}$, and the 95th percentile absolute error, computed over N = 500 samples per position and aggregated across all 15 positions.

C. Phase II: Controlled User Study

Twenty participants (12 male, 8 female; age 19–32 years, mean 24.3 ± 3.7 years; mean BMI 23.4 ± 2.8 kg/m^2) were recruited from the student and faculty population of Sanjivani K.B.P Polytechnic. All participants were free of known spinal conditions. Each completed a 45-minute desk-based session comprising three posture conditions in randomized order: (1) erect neutral posture; (2) forward trunk flexion exceeding 30°; (3) lateral trunk bending exceeding 15°. Reference classification was provided by a licensed physical therapist (10 years clinical experience) who independently labeled posture states at 5-second intervals using a standardized REBA-based assessment form [13]. Posture detection accuracy, false positive rate, and false negative rate were computed against physiotherapist reference labels.

D. Phases III–V: System Metrics

BLE latency was measured across 1,000 successive alert events using synchronized timestamps on the ESP32 (hardware timer) and mobile application (Dart DateTime.now()), in an office environment with ambient 2.4 GHz Wi-Fi traffic present. Battery runtime was measured from full charge (4.2 V) to under-voltage cutoff (3.0 V) under two conditions: (a) continuous full-load operation (BLE connected, 50 Hz processing active); (b) low-power mode (BLE disconnected, 5-second deep sleep intervals). The mobile application was operated in continuous linked mode for 96 hours with active BLE connection; crash events, disconnection events, and reconnection latency were logged by the application's internal diagnostic module.

X. Results And Discussion

A. Bench Calibration Accuracy

Phase I bench calibration demonstrated MAE of 1.3° (95% CI: 1.1–1.5°) and RMSE of 1.7° across the full ±45° measurement range, confirming that the complementary filter achieves orientation estimation precision sufficient for reliable posture classification at the 30° boundary — providing a 22× error-to-threshold margin.

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The maximum absolute error of 3.1° occurred at the ±45° extremes, outside the postural deviation envelope relevant to classification accuracy. Sensitivity analysis (Table III) confirmed that system accuracy was relatively insensitive to α across the range tested, with α = 0.98 providing the optimal balance between noise rejection and dynamic tracking fidelity.

B. Posture Classification Performance

Phase II user study yielded overall posture detection accuracy of 94.7% (95% CI: 89.8–97.5%, Wilson score interval). The false positive rate was 3.1% (95% CI: 1.6–5.8%) and false negative rate was 2.2% (95% CI: 0.9–4.9%). Precision was 96.9%, recall 97.8%, and F1-score 97.3%. Table I presents the complete performance evaluation summary. Analysis of false positive events revealed that 71% occurred during arm-reach movements transiently displacing the trunk beyond 30° without constituting a sustained postural deviation; increasing T_th from 5 to 7 s in post-hoc analysis reduced the false positive rate to 1.4% with marginal recall reduction to 96.1%.

TABLE I
SYSTEM PERFORMANCE EVALUATION SUMMARY

Performance Metric	Measured	Target
Posture Detection Accuracy	94.7% (95% CI: 89.8–97.5%)	≥90%
Mean Angular Error (MAE)	1.3° (CI: 1.1–1.5°)	≤2.0°
RMSE	1.7°	≤3.0°
False Positive Rate	3.1% (CI: 1.6–5.8%)	≤5%
False Negative Rate	2.2% (CI: 0.9–4.9%)	≤5%
Precision	96.9%	≥90%
Recall / Sensitivity	97.8%	≥90%
F1-Score	97.3%	≥90%
BLE Latency (mean)	34 ms (SD: 4.2 ms)	≤50 ms
BLE Latency (95th pct.)	38 ms	≤100 ms
Battery Life (full load)	11.2 h	≥8 h
Device Weight	34 g	≤50 g
Component Cost	Rs. 2,100	≤Rs. 3,000
SUS Score	82.4 / 100 (Good)	≥70

C. Communication and Power Performance

Phase III BLE latency testing yielded mean latency of 34 ms (SD: 4.2 ms) and 95th percentile of 38 ms across 1,000 events under ambient 2.4 GHz interference, within the 50 ms design target.

Phase IV battery testing recorded 11.2 hours continuous runtime under full operational load (BLE connected, 50 Hz processing active) and 17.4 hours in low-power mode — both measured experimentally rather than extrapolated from specifications. System power consumption in active mode was 107 mA, consistent with the analytical estimate: t = C_batt / I_avg = 1200 mAh / 107 mA ≈ 11.2 h. Phase V stability testing recorded zero application crashes and zero unrecoverable BLE disconnections over 96 continuous hours; 14 transient BLE signal interruptions occurred (mean: 3.5/day), all recovering automatically within 2.1 seconds.

D. Usability Assessment

System usability assessment yielded a mean SUS score of 82.4/100 (SD: 7.3, N=20). Per Bangor et al. [12], a score in the range 71.4–85.5 is classified as *Good* on the adjective rating scale associated with the SUS; a score of 82.4 therefore falls in the Good category (Excellent begins at ≥85.5). Qualitative feedback highlighted vibration alert perceptibility and the longitudinal trend chart as highest-rated features; suggested improvements included enhanced alert customization and a widget-based home screen summary.

E. Comparative Analysis

Table IV positions the Smart Posture Coach against representative prior systems. The proposed system achieves the highest reported posture detection accuracy (94.7%) while offering the lowest hardware cost (Rs. 2,100) and the only system with reported BLE latency measurements among comparable wearable approaches. Direct comparison with the Upright Go 2 (~91%) is limited by different participant cohorts, reference labeling methodologies, and testing environments; this limitation is explicitly acknowledged.

TABLE IV
COMPARATIVE SUMMARY OF WEARABLE POSTURE MONITORING SYSTEMS

System	Platform	Accuracy	FPR	Cost (Rs.)	BLE Latency	Validation
Upright Go 2 [24]	Proprietary MCU	~91%	N/R	~5,200	N/R	Controlled study
Kumar & Mani [5]	Arduino	88.3%	N/R	~1,800	N/R	Controlled lab
Joshi & Patil [6]	Custom wearable	N/R	N/R	~2,200	N/R	14-day field study
Mehta & Shah [4]	Smartphone+sensor	N/R	N/R	~3,500	>100 ms	28-day longitudinal
Proposed System	**ESP32 + MPU6050**	**94.7% (CI: 89.8–97.5%)**	**3.1 %**	**~2,100**	**34 ms mean**	**Controlled; N=20**

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F. Limitations

The pilot sample (N=20) is insufficient for definitive population-level accuracy claims; confidence intervals are reported to make this uncertainty explicit. The 45-minute controlled session lacks ecological validity; real-world deployments involve dynamic environments and sensor placement variability not captured in controlled testing. The 94.7% accuracy applies specifically to sagittal-plane classification; full three-axis posture classification accuracy is expected to differ. A planned fully powered study (target N≥80) in ecological field settings will address these limitations.

XI. CONCLUSION

This paper has presented the design, embedded implementation, and experimental evaluation of the Smart Posture Coach, a low-cost wearable real-time posture monitoring system. The system integrates an ESP32 microcontroller, MPU6050 IMU, complementary filter orientation estimation, dual-threshold temporal alert logic, and BLE connectivity to a Flutter mobile application in a 34 g, Rs. 2,100 device.

Bench calibration demonstrated 1.3° MAE across ±45°. A pilot user study with 20 participants achieved 94.7% posture detection accuracy (95% CI: 89.8–97.5%), 3.1% false positive rate, 34 ms mean BLE latency, and 11.2 hours continuous battery life. SUS usability testing yielded a Good classification (82.4/100). The four technical contributions — dual-threshold temporal algorithm, adaptive baseline calibration, cost-optimized open architecture, and open BLE protocol — provide a validated foundation for scaled deployment and future research.

XII. FUTURE SCOPE

The primary technical development priority is extension of the orientation estimation pipeline to full three-axis quaternion representation using the MPU6050 DMP, enabling simultaneous pitch, roll, and yaw monitoring. On-device machine learning inference using TensorFlow Lite will enable activity-aware posture classification, distinguishing pathological forward flexion from purposeful task-related reaches. Transition to the Nordic nRF52840 system-on-chip is planned, targeting a 45% reduction in active-mode current consumption and enabling 18+ hour continuous operation. Privacy-preserving federated learning will enable personalized threshold adaptation without transmitting raw kinematic data to external servers, ensuring compliance with India's Digital Personal Data Protection Act (2023) and GDPR by design. Integration with sEMG sensing at trapezius and erector spinae will provide complementary muscle fatigue information enabling predictive rather than reactive alert generation.

Ethics Statement

This study was conducted in accordance with the ethical guidelines of Sanjivani K.B.P Polytechnic, Kopargaon, India. Informed written consent was obtained from all 20 participants prior to data collection. No clinically sensitive or patient-identifiable data was collected or retained. The study constitutes a non-clinical engineering performance evaluation. The authors declare no conflict of interest. The experimental dataset supporting reported results is available upon reasonable request to the corresponding author.

Acknowledgment

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