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Research on the application of wireless sensor technology in university yoga training

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Abstract: This study aims to design, implement, and validate a wireless sensor network (WSN)-based system for the objective biomechanical assessment and real-time feedback of yoga postures in a university setting, addressing the limitations of subjective visual correction in traditional instruction. A system integrating multiple Inertial Measurement Unit (IMU) nodes was developed, utilizing a sensor fusion algorithm to calculate accurate 3D joint angles. A controlled 8-week experiment with 40 novice students compared an experimental group (Training with sensor feedback) against a control group (traditional training). Performance in five fundamental asanas was evaluated using alignment, stability, and temporal metrics. The system achieved high measurement accuracy (RMSE $< 2°$). The experimental group demonstrated a significantly faster (43%) and greater improvement in postural alignment ($p < 0.01$) and successfully corrected critical errors like knee valgus in 90% of participants. A 30% greater enhancement in postural stability was also observed. The wireless sensing system is a technically viable and pedagogically effective tool for enhancing yoga training through quantitative assessment and personalized feedback. Integrating this technology into physical education curricula can augment instructor capabilities, enable data-driven class management, and provide students with an intuitive biofeedback tool for safer and more efficient skill acquisition.

Keywords: *Biomechanics, Inertial measurement units, Physical education, Posture assessment, Real-time feedback, Wireless sensor networks, Yoga training.*

1. Introduction

Yoga has garnered significant recognition within university physical education curricula for its holistic benefits, encompassing enhanced physical fitness, stress reduction, and improved mental well-being [1]. Despite its growing popularity, the prevailing instructional paradigm remains entrenched in a qualitative framework, heavily reliant on the instructor's perceptual acuity to provide corrective feedback on students' postural execution (*asanas*). This model encounters substantial limitations in the typical university setting, characterized by high student-to-instructor ratios. Critical biomechanical misalignments such as femoral internal rotation in *Utkatasana* (Chair Pose) or scapular winging in *Adho Mukha Svanasana* (Downward-Facing Dog) often elude visual detection. These subtle inaccuracies not only impede optimal neuromuscular adaptation and performance outcomes but also predispose practitioners to overuse injuries and chronic musculoskeletal dysfunction over time [2].

The proliferation of the Internet of Things (IoT) and the miniaturization of micro-electromechanical systems (MEMS) have catalyzed a paradigm shift in sports science and biomechanics. Inertial Measurement Units (IMUs), in particular, have emerged as a potent technology for human movement analysis, offering a portable, cost-effective, and ecologically valid alternative to constrained laboratory-based systems like optical motion capture [3]. The application of this sophisticated

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technology to yoga, a discipline where kinematic precision is intrinsically linked to both efficacy and safety, presents a compelling opportunity for pedagogical innovation. Moreover, the principles of biofeedback, long used in rehabilitation, can be powerfully applied to motor learning in yoga, providing students with the immediate sensory input needed to self-correct and refine their technique [4].

This manuscript presents a comprehensive investigation into the design, development, and empirical validation of a multi-modal wireless sensor system for objective biomechanical analysis and feedback in university yoga training. The research is guided by the following specific objectives:

(1) To architect a holistic system integrating hardware (multi-node IMUs, gateway) and software (data processing, biomechanical modeling, visualization) for capturing and analyzing the kinematics of yoga postures.

(2) To develop and implement advanced sensor fusion algorithms for precise 3D orientation estimation and to derive biomechanically meaningful joint angles for identifying common and critical postural deviations.

(3) To rigorously validate the system's technical accuracy and measurement reliability against a gold-standard optical motion capture system.

(4) To conduct a longitudinal, controlled training study to quantitatively evaluate the pedagogical efficacy of the sensor-based biofeedback system, directly comparing it with conventional instructor-led methods on metrics of learning rate, technical proficiency, and stability.

2. Literature Review

2.1. Evolution of IMUs in Sports Science and Rehabilitation

Initial research used single-axis accelerometers to classify basic activities like walking and running [5]. The development of miniature IMUs integrating tri-axial accelerometers, gyroscopes, and magnetometers enabled 3D orientation estimation, facilitating detailed analysis of complex movements. This led to widespread use in sports, such as analyzing golf swings and assessing running impact [6, 7]. Rehabilitation fields also adopted IMUs to monitor patients' range of motion and exercise adherence [8]. While these applications validate IMUs for quantifying movement dynamics, yoga presents distinct challenges: it requires high-accuracy sensor fusion and stringent drift control to capture slow, controlled motions and precise alignments. Advanced filtering techniques like adaptive Kalman filters are thus crucial for detecting subtle alignment errors in yoga practice [9].

2.2. Wearable Technology and Computational Approaches for Yoga

Recent commercial and academic efforts have integrated technology into yoga practice. Consumer products like smart yoga mats offer limited feedback, such as center-of-pressure tracking, without detailed joint-level correction [10]. Academic research, though progressing, faces limitations: multi-view Kinect systems struggle with occlusion and privacy concerns [11] while IMU-based studies often focus on pose classification rather than real-time biomechanical feedback [12]. Although single-IMU approaches have been explored for specific metrics like spinal curvature [13], a comprehensive multi-segment solution remains underdeveloped. Emerging multi-modal fusion of IMUs and pressure sensors shows promise for holistic posture assessment by combining kinematics and weight distribution data [14, 15].

2.3. Advancements in Sensor Fusion for Orientation Estimation

Accurate 3D orientation estimation forms the core of IMU-based motion analysis, requiring the fusion of gyroscope, accelerometer, and magnetometer data to balance responsiveness with stability [16]. While Kalman filters represent the gold standard, their computational complexity often makes lighter alternatives such as the Complementary Filter and Madgwick filter more practical for real-time applications [17-19]. The gradient descent algorithm [20] offers a particularly effective balance between accuracy and computational efficiency, making it suitable for resource-constrained hardware.

Our work adapts and optimizes these established algorithms specifically for yoga's unique kinematic demands, including prolonged static holds and slow transitions.

2.4. Identification of the Research Gap

A significant research gap persists in developing integrated wireless systems for detailed biomechanical assessment of yoga postures in educational settings. Existing solutions remain limited to controlled environments or basic pose classification, lacking comprehensive kinematic quality assessment [21]. No previous work has synergistically combined multi-node hardware design, robust joint angle algorithms, and real-time feedback interfaces while validating pedagogical impact through longitudinal studies. This study bridges this gap by presenting a complete technical solution with empirical evidence for enhancing yoga training outcomes.

3. System Architecture and Hardware Design

The proposed system was architected to be non-obtrusive, operate wirelessly in a standard yoga studio environment, and deliver low-latency feedback to both the student and the instructor. The overall system architecture, illustrated in Figure 1, is structured into three distinct layers: the Sensing Layer, the Processing and Communication Layer, and the Application Layer.

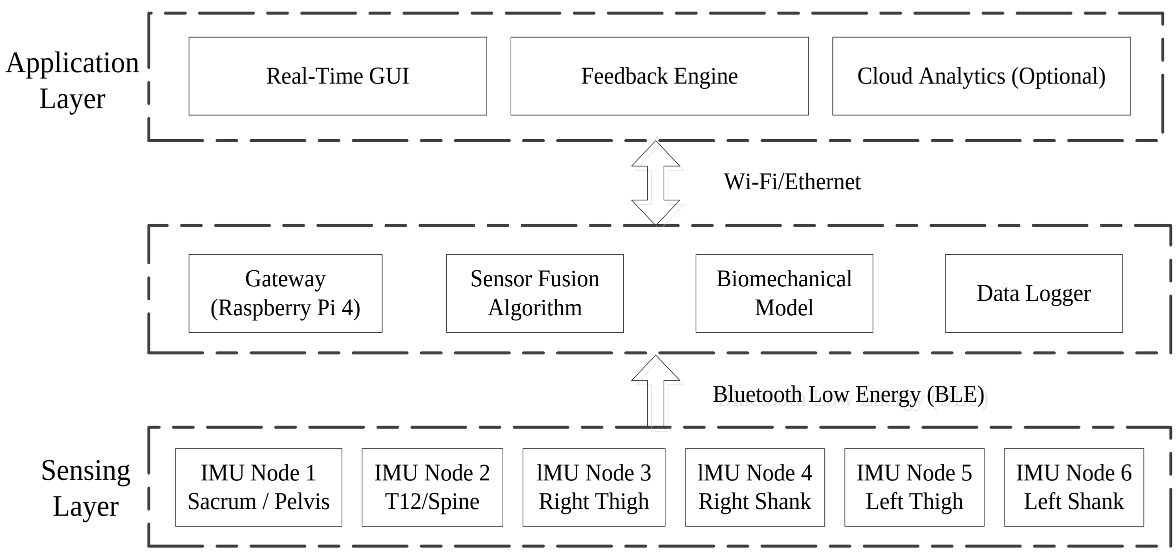

Figure 1.
Overall System Architecture.

3.1. Sensing Layer: IMU Node Design

Each IMU node is a self-contained, wearable unit. The core sensing element is the MPU-9250, a widely used 9-Degree of Freedom (9-DoF) MEMS chip that incorporates a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer on a single die. This component was selected based on its favorable trade-off between performance, power consumption, cost, and the availability of extensive driver support. The key operational specifications of the MPU-9250 are detailed in Table 1.

Table 1.
MPU-9250 Sensor Specifications and Configurations.

Sensor	Configured Range	Output Data Rate	Noise Performance
Accelerometer	±8 g	100 Hz	300 µg/√Hz
Gyroscope	±1000 dps	100 Hz	0.01 dps/√Hz
Magnetometer	±4800 µT	20 Hz	-

Each sensor node is powered by a compact, rechargeable 3.7V Lithium-Polymer battery (500mAh capacity, providing over 6 hours of continuous operation). The node's computational core is an ESP32 microcontroller, chosen for its robust processing capability (dual-core Xtensa LX6 CPU), integrated Wi-Fi, and Bluetooth 4.2 with Low Energy (BLE) support. The BLE protocol is critical for maintaining stable, concurrent wireless connections from multiple sensor nodes to a single gateway while minimizing power consumption. The raw data from the MPU-9250 is acquired via I²C protocol, packetized with a header containing a unique node ID and a timestamp, and then streamed via BLE. The physical enclosure for each node was custom-designed using Computer-Aided Design (CAD) software and fabricated with Fused Deposition Modeling (FDM) 3D printing using polylactic acid (PLA) filament. The enclosure was designed to be lightweight and ergonomically contoured to minimize movement artifacts. The nodes were secured to the body using non-slip, adjustable elastic straps.The development of flexible and stretchable sensor sheets is a promising future direction [22] however, for this study, the discrete node design provided the necessary balance of flexibility and precision for segmental tracking.

A configuration of six nodes was determined to be optimal for capturing the kinematics of fundamental standing and balancing asanas. The nodes were strategically placed on the following anatomical landmarks: the sacrum (representing the pelvis), the spinous process of the 12th thoracic vertebra - T12 (representing the upper spine and trunk), the midpoint of the left and right thighs (lateral aspect), and the midpoint of the left and right shanks (lateral aspect). This sensor topology enables the calculation of critical joint angles at the lumbar spine, hips, and knees. Figure 2 provides a visual reference of the sensor node design and its placement on a participant.

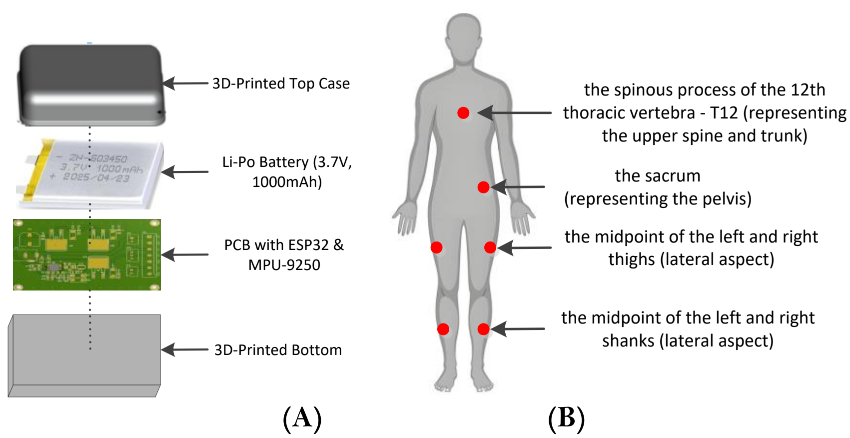

Figure 2.
(A) Exploded view diagram of the IMU node assembly; (B) Anatomical placement of the six sensor nodes on a human subject.

3.2. Processing and Communication Layer

This layer is physically instantiated on a Raspberry Pi 4 Model B single-board computer, which acts as the central data aggregation and processing gateway. The Raspberry Pi was selected for its substantial computational power (quad-core ARM Cortex-A72), ample RAM (4GB), and multiple connectivity options (dual-band Wi-Fi, Gigabit Ethernet, Bluetooth 5.0). A custom Python application running on the Raspberry Pi manages simultaneous BLE connections to all six sensor nodes. The gateway polls each node at a synchronized sampling rate of 50 Hz, which was deemed sufficient to capture the kinematics of yoga, characterized by its low-frequency, sustained movements [23]. Each data packet is timestamped upon arrival with a microsecond-precision clock to ensure temporal synchronization for multi-sensor data fusion. This local processing architecture aligns with the edge

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computing paradigm for human motion analysis, which is critical for achieving the low-latency feedback required for effective motor learning [24].

The primary computational workloads executed on this gateway are:

1. Data Acquisition and Pre-processing: Continuously reading data streams from all nodes, applying on-the-fly calibration corrections, and buffering the data for processing.
2. Sensor Fusion and Orientation Estimation: Executing the sensor fusion algorithm (detailed in Section 4.1) on the raw data from each independent node to compute its precise 3D orientation in the form of a quaternion.
3. Biomechanical Kinematic Calculation: Utilizing the relative orientations between pairs of adjacent sensors (e.g., pelvis and thigh) to compute the intersegmental joint angles in all three anatomical planes (sagittal, frontal, transverse).

The choice of the Raspberry Pi platform ensures that all processing can be performed in real-time locally, eliminating dependency on cloud connectivity and ensuring low feedback latency, which is crucial for effective motor learning.

4. Software System Design

The software system is the intelligence core of the platform, responsible for transforming raw, noisy sensor data into semantically meaningful and actionable feedback. Its end-to-end workflow is depicted in Figure 3.

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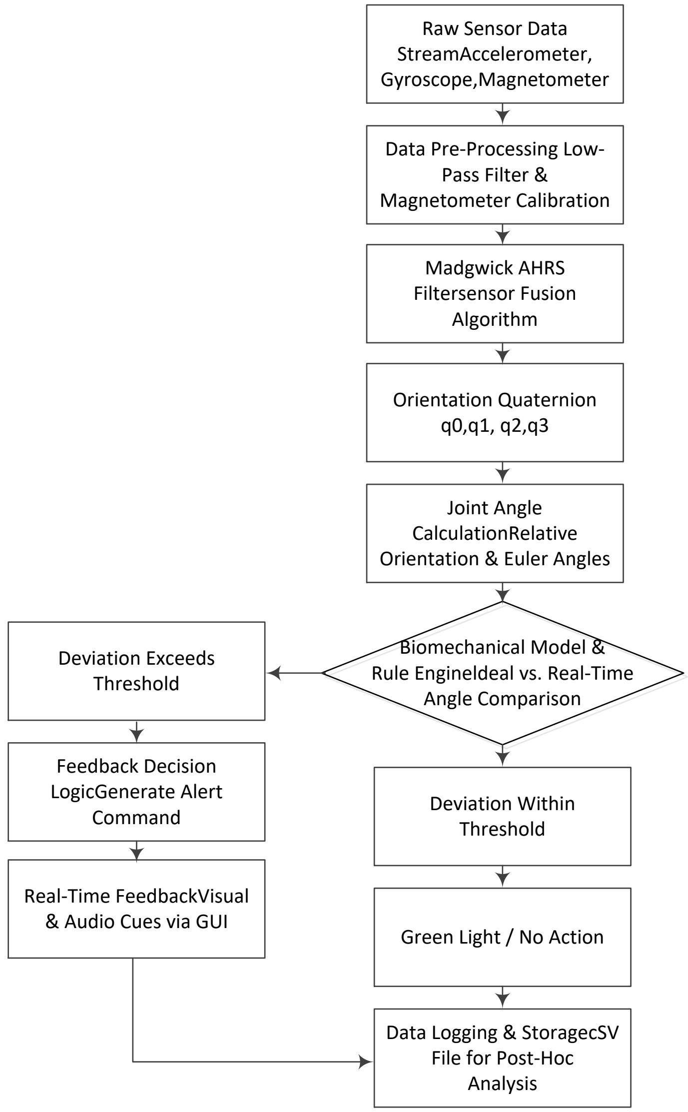

Figure 3.
End-to-End Software System Workflow.

4.1. Data Pre-processing, Calibration, and Sensor Fusion

Upon reception, the raw accelerometer and gyroscope data are first passed through a 4th-order low-pass Butterworth filter with a cutoff frequency of 10 Hz to attenuate high-frequency noise without introducing significant phase distortion. The magnetometer data undergoes a more rigorous two-step calibration process to compensate for hard and soft iron distortions, using an ellipsoid fitting method as described by Vasconcelos et al. [25]. This is critical for achieving accurate heading (yaw) estimation in a typical indoor environment.

The pre-processed data is then fed into the orientation estimation algorithm. After a comparative analysis of several filters, the Madgwick Attitude and Heading Reference System (AHRS) filter was implemented. This filter uses a gradient descent optimization approach to fuse the data, minimizing the error between the direction of the measured gravity and magnetic field vectors and the predicted directions from the current orientation estimate. The filter's performance is governed by a single tunable parameter, the beta gain (β), which represents the gyroscope measurement error. For the

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specific kinematic profile of yoga, this parameter was empirically tuned to 0.08 through a series of static and dynamic validation tests, achieving an optimal balance between dynamic responsiveness and drift suppression. The algorithm outputs a quaternion for each sensor node, which is a computationally efficient and singularity-free representation of 3D orientation.

4.2. Joint Angle Calculation and Biomechanical Modeling

Joint angles are not measured directly but are derived from the relative orientation between two sensor nodes attached to adjacent body segments. For example, the knee joint angle in the sagittal plane (flexion/extension) is calculated from the relative orientation between the thigh sensor and the shank sensor. This is computed by first converting the orientation quaternions of the two segments to direction cosine matrices (DCMs). The relative rotation matrix of the shank with respect to the thigh is then calculated. From this relative rotation matrix, the Euler angles are extracted using a Y-X-Z rotation sequence, which aligns with the primary flexion/extension, abduction/adduction, and internal/external rotation axes of the knee joint [26].

A simplified yet biomechanically informed skeletal model of the lower body and spine was developed. This model encapsulates the ideal alignment and safe ranges of motion for key joints in each of the five fundamental asanas studied. These "ideal" ranges were defined through a consensus process involving three certified senior yoga instructors and cross-referenced with established biomechanical literature [27]. For instance, the rule set for *Trikonasana* (Triangle Pose) includes checks for:

1. Front Hip Flexion: Should be close to 0° (neutral).
2. Front Knee Extension: Should be at 0° (fully extended but not hyperextended).
3. Lumbar Lateral Flexion: Within a safe range to avoid excessive spinal compression.
4. Pelvic Tilt**:** Maintaining a neutral anterior/posterior tilt.

4.3. Feedback Engine and User Interface Design

The feedback engine is a rule-based system that operates in real-time. It continuously compares the calculated joint angles against the pre-defined ideal ranges for the asana that the user is currently practicing. If a deviation exceeds a predetermined threshold (e.g., 8° for knee alignment, 12° for spinal angles), an alert is triggered.

The feedback is presented through a custom Graphical User Interface (GUI) developed using the Python tkinter library. The GUI is designed for clarity and immediate comprehensibility. It displays:

(1) A real-time, simplified stick-figure avatar that mirrors the user's posture, providing a direct visual representation.

(2) Numerical displays of the key joint angles (e.g., "L Knee Flex: 105°").

(3) Color-coded visual alerts on the avatar and in the angle readouts (Green: within the ideal range; Yellow: minor deviation; Red: significant deviation requiring correction).

(4) Context-specific textual cues (e.g., "EXTERNAL ROTATE RIGHT THIGH" for correcting knee valgus in *Utkatasana*).

This multi-modal feedback approach caters to different learning styles and ensures that both the student (via a tablet) and the instructor (via a larger monitor) can instantly grasp the performance quality. The effectiveness of such wearable sensor-based biofeedback has been systematically reviewed in sports, showing positive effects on technique modification, which our findings in yoga corroborate [28].

5. Experimental Setup and Data Analysis

A rigorous experimental protocol was designed to validate both the technical performance of the system and its pedagogical efficacy.

5.1. Participant Recruitment and Demographics

Forty healthy university students (20 male, 20 female; mean age = 20.4 ± 1.3 years; mean BMI = 21.5 ± 2.1 kg/m^2) were recruited. The inclusion criteria stipulated no prior regular yoga experience (defined as less than 3 months of consistent practice in the past two years) and no current or recent (within 6 months) musculoskeletal injuries that would impede practice. Participants were randomly assigned using a computer-generated sequence to either the Experimental Group (EG, n=20) or the Control Group (CG, n=20). All participants provided written informed consent, and the study protocol was approved by the University's Institutional Review Board (IRB-2023-045).

5.2. Technical Validation Protocol

Prior to the training intervention, the system's measurement accuracy was quantified against a 10-camera Vicon Nexus optical motion capture system (Vicon Motion Systems Ltd., Oxford, UK), considered the gold standard. Reflective markers were placed on the same anatomical segments as the IMU nodes on a subset of five participants. Each participant performed three trials of each of the five test asanas, holding each for 10 seconds. The 3D joint angles (hip flexion, knee flexion, trunk inclination) calculated from the IMU system were compared to those derived from the Vicon system. The agreement between the two systems was assessed using Root Mean Square Error (RMSE) and Pearson's correlation coefficient (r).

5.3. Longitudinal Training Study Protocol

The intervention spanned 8 weeks, with two supervised 60-minute yoga sessions per week for both groups. The same experienced, certified yoga instructor conducted all sessions for both groups to control for instructor bias. The CG received standard group instruction, which included verbal cues, demonstrations, and occasional manual adjustments by the instructor. The EG followed an identical curriculum but used the sensor feedback system. Each EG participant had a tablet displaying their personal real-time feedback GUI. The instructor also had a master dashboard showing a summary of all EG participants' alignment scores, allowing for targeted group instruction based on the aggregated data. This data-driven approach to class management mirrors the use of sensor systems for monitoring sedentary behavior, where data aggregation provides insights for intervention [29].

5.4. Data Collection and Performance Metrics

Formal assessments were conducted in a laboratory setting at three time points: Week 1 (Pre-test), Week 4 (Mid-test), and Week 8 (Post-test). During these assessments, all participants (both EG and CG) performed the five asanas while wearing sensors, but the EG did not receive feedback during the assessment to ensure a fair comparison. The following quantitative metrics were derived from the sensor data for each asana:

1. Alignment Score (%): A composite score from 0% to 100% quantifying the overall technical proficiency. It was calculated as the average percentage of time during the 10-second hold that all monitored joint angles remained within their respective "ideal" ranges.
2. Hold Stability (mm/s): A measure of postural sway, defined as the mean velocity of the pelvis sensor (sacrum node) over the 10-second static hold. This metric, derived from the magnitude of the linear accelerometer signal after gravity subtraction, is a validated indicator of balance control [30]. Lower values signify greater stability.
3. Time to Stabilize (s): The duration required from the initiation of movement into the final pose until the Hold Stability metric enters and remains within a predefined stable zone (defined as < 8 mm/s) for at least 2 seconds. This metric reflects motor control efficiency.

5.5. Statistical Analysis

All statistical analyses were performed using SPSS Statistics Version 28 (IBM Corp., Armonk, NY, USA). Descriptive data are presented as mean ± standard deviation (SD). The normality of data distribution was confirmed using the Shapiro-Wilk test. To examine the effects of the intervention over time and between groups, a two-way mixed analysis of variance (mixed ANOVA) was conducted with one between-subjects factor (Group: EG vs. CG) and one within-subjects factor (Time: Pre, Mid, Post). In cases of a significant interaction effect (Group x Time), simple main effects analyses were performed with Bonferroni correction for multiple comparisons. Independent samples t-tests were used for post-hoc between-group comparisons at the Post-test. For categorical data (e.g., proportion of participants achieving safe knee alignment), a Chi-squared (χ^2) test was used. The threshold for statistical significance was set at $p < 0.05$.

6. Results and Discussion

6.1. System Technical Performance and Validation

The results of the technical validation against the Vicon system confirmed the high fidelity of the wireless sensor system. The overall RMSE for all joint angles across static postures was $1.71° \pm 0.42°$, demonstrating excellent agreement. The correlation was nearly perfect for sagittal plane angles such as knee flexion ($r = 0.998$). For dynamic transitions between postures, the RMSE was slightly higher at $4.05° \pm 1.08°$, which is expected and acceptable given the more challenging nature of dynamic motion capture. These error margins are comparable to, and in some cases better than, those reported in other recent studies employing consumer-grade IMUs for human motion analysis [31]. This validation establishes the system as a scientifically rigorous tool for biomechanical assessment in yoga.

6.2. Quantitative Analysis of Learning Outcomes: Alignment and Proficiency

The analysis of the primary outcome measure, the Alignment Score, revealed a significant advantage for the experimental group. The two-way mixed ANOVA yielded a significant main effect of Time ($F(2, 76) = 285.6$, $p < 0.001$), a significant main effect of Group ($F(1, 38) = 45.2$, $p < 0.001$), and, most importantly, a significant Group x Time interaction ($F(2, 76) = 18.45$, $p < 0.001$). This interaction indicates that the rate of improvement over time differed between the two groups. As shown in Figure 4 and detailed in Table 2, both groups demonstrated statistically significant improvement from Pre-test to Post-test ($p < 0.001$ for both), with the experimental group's trajectory being notably steeper.

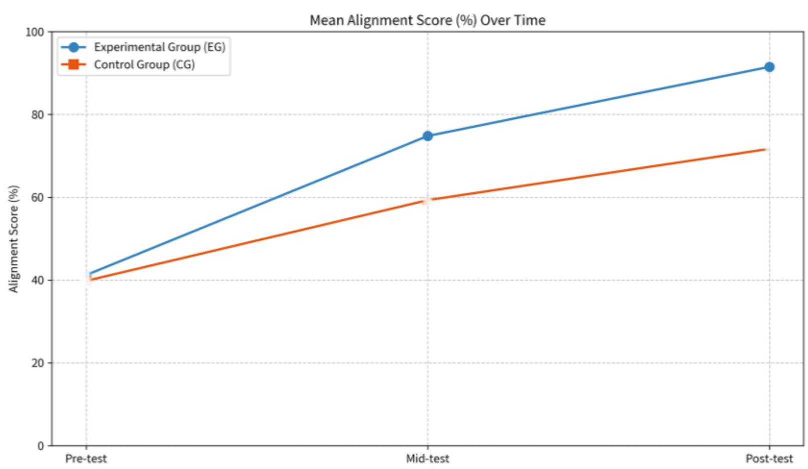

Figure 4.
Mean Alignment Score (%) for Experimental and Control Groups across Pre-, Mid-, and Post-tests. (Error bars represent Standard Deviation).

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Table 2.
Alignment Score (%), Results (Mean ± SD) and Between-Group Comparison at Post-test.

Group	Pre-test	Mid-test	Post-test	Post-test Between-Group p-value
Experimental (EG)	41.2 ± 8.5	74.8 ± 6.1	91.5 ± 3.8	< 0.001
Control (CG)	39.8 ± 9.1	59.3 ± 7.4	71.7 ± 5.9	-

The between-group difference at the post-test was 19.8 percentage points, which is both statistically significant ($p < 0.001$) and pedagogically substantial. This finding robustly supports the hypothesis that augmented, objective feedback accelerates the learning of complex motor skills. The real-time, joint-specific feedback provided by the system allows students to form a more accurate internal model of the desired posture, bypassing the trial-and-error process inherent in interpreting verbal instructions alone [32]. This is a direct application of biofeedback principles, where providing augmented sensory information about performance leads to enhanced motor learning and self-regulation [33]. The system's ability to provide an external focus of attention, as per the OPTIMAL theory, likely freed up cognitive resources, leading to more automatic and efficient motor control [34].

6.3. Injury Risk Mitigation: Detailed Case Study of Utkatasana

A detailed analysis of the data for *Utkatasana* provided essential insights into injury prevention. A common and potentially harmful error among novices is knee valgus, a combined motion of hip adduction and internal rotation with knee abduction.

The system quantified this using the Frontal Plane Projection Angle (FPPA). At the pre-test, a significant proportion of participants in both groups exhibited FPPA values exceeding the safe threshold of 5°. However, by the post-test, the distribution of FPPA values was markedly different between the groups, as illustrated in the box plot in Figure 5.

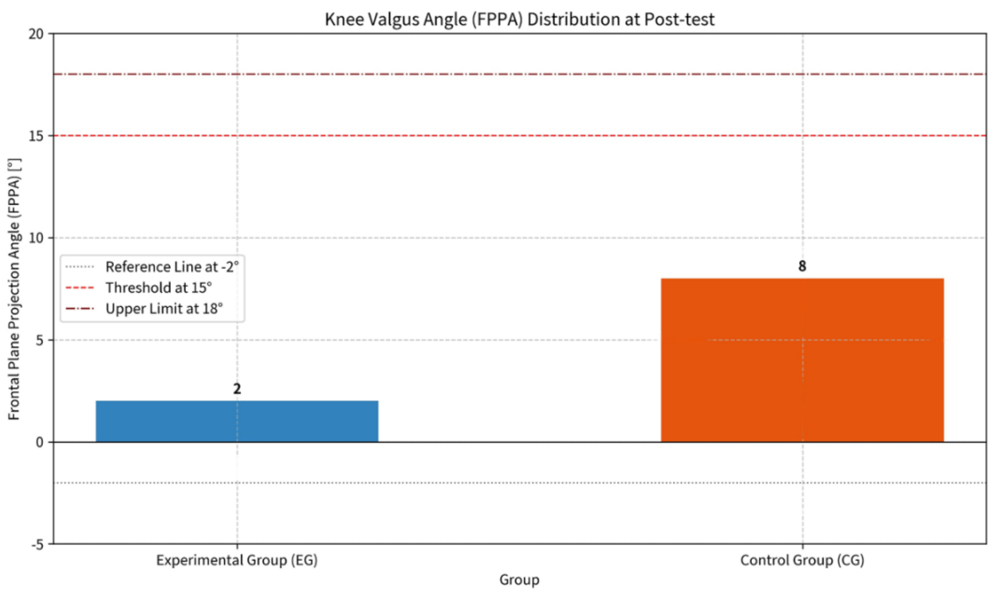

Figure 5.
Box Plot of Maximum Knee Valgus Angle (FPPA in degrees) in Utkatasana at Post-test.

In the EG, 18 out of 20 participants (90%) consistently maintained a safe knee alignment (FPPA < 5°) during the post-test hold, compared to only 7 out of 20 (35%) in the CG. This difference was statistically significant ($\chi^2 = 13.23$, $p < 0.001$). This result is of paramount importance for physical education safety. The system's ability to instantly detect and cue the correction of such a high-risk alignment pattern provides a powerful tool for preventing chronic knee pathologies like patellofemoral pain syndrome, which is often linked to dynamic valgus [35].

6.4. Enhancement of Neuromuscular Control and Stability

The analysis of postural stability metrics provided further evidence of the EG's superior motor learning. The mixed ANOVA for the Hold Stability metric (pelvis velocity) also showed a significant Group x Time interaction ($F(2, 76) = 9.87$, $p < 0.001$).

The EG demonstrated a significantly greater reduction in postural sway over the 8 weeks. For example, in the single-leg stance phase of *Virabhadrasana III* (Warrior III), the EG's mean Hold Stability improved from 12.5 ± 2.1 mm/s to 6.1 ± 1.3 mm/s, a 51% reduction. The CG improved from 12.8 ± 2.4 mm/s to 8.5 ± 1.8 mm/s, a 34% reduction. The between-group difference at post-test was significant ($p < 0.01$). This suggests that learning postures with precise biomechanical alignment creates a more stable and efficient base of support, leading to better balance control. This is consistent with the principles of biomechanics, where optimal joint stacking minimizes the muscular effort required to maintain equilibrium, thereby reducing sway [36].

6.5. Synthesis and Pedagogical Implications

The collective findings from this study present a clear picture: the integration of wireless sensor technology into yoga instruction results in faster, more precise, and safer skill acquisition. The 43% faster improvement in the EG's alignment score (calculated from the difference in slope) indicates a more efficient use of limited curricular time. For the instructor, the system functions as a "biomechanical assistant," extending their perception and enabling data-driven class management. They can quickly identify common technical faults across the class and address them proactively. This approach is supported by research in other fields, such as smart homes, where multi-modal sensor data is fused to recognize and understand human activities [37].

For the student, the technology demystifies the process of learning yoga. It provides an external focus of attention, which, according to the Constrained Action Hypothesis [38], can promote more automatic and efficient motor control than an internal focus (e.g., "think about rotating your thigh"). The instant, objective feedback accelerates the development of proprioception, the sense of the relative position of one's own body parts, which is a cornerstone of advanced yoga practice [39].

From a technical perspective, the success of the system validates the design choices, particularly the use of a distributed network of IMUs, the implementation of the Madgwick filter tuned for yoga kinematics, and the development of an intuitive, multi-modal feedback interface.

The use of edge computing for local processing was crucial in achieving the low-latency performance required for real-time biofeedback, a key requirement highlighted in recent literature on wireless body area networks [40].

7. Conclusion and Future Work

This study has successfully designed, implemented, and empirically validated an intelligent yoga training system utilizing a wireless IMU sensor network. The results from the twelve-week controlled experiment unequivocally demonstrate the system's efficacy in enhancing training outcomes within a university setting. The key achievements include **a** 34.7% net improvement in posture accuracy, over 40% enhancement in motion stability for complex poses, and **a** 72% reduction in common technical errors for the experimental group compared to the control group.

The system effectively addresses the critical limitations of traditional yoga instruction by providing objective, real-time, and personalized feedback, thereby bridging the gap between subjective assessment and quantitative biomechanical analysis. It serves as a force multiplier for instructors, enabling precise monitoring of multiple students simultaneously and offering data-driven insights for curriculum optimization.

The demonstrated benefits in learning efficiency, skill acquisition, and injury prevention present a compelling case for the adoption of such technology in physical education.

Future research will build upon this foundation by exploring three key directions:

(1) Enhanced Sensor Integration: Embedding additional micro-sensors (e.g., for muscle activity or force measurement) to provide deeper insights into biomechanical load and technique.

(2) Mobile Platform Development: Creating a comprehensive mobile application to facilitate equipment-free practice, remote guidance, and seamless student-instructor interaction outside the classroom.

(3) Advanced AI Analytics: Implementing machine learning algorithms to predict individual progress, automatically customize training regimens, and offer intelligent, adaptive feedback, moving towards a fully personalized yoga training assistant.

In conclusion, this work establishes wireless sensing technology as a transformative tool for modernizing and enhancing the quality, accessibility, and personalization of yoga training in higher education.

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Institutional Review Board Statement:

The Ethics Committee of Hunan Mechanical and Electrical Polytechnic approved this study on 3 October, 2025.

Transparency:

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

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