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Integrating Wearable Sensor Data and Artificial Intelligence for Real-Time Yoga Performance Feedback: A Systematic Review

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Abstract

Wearable sensors and artificial intelligence (AI) are increasingly combined to support unsupervised yoga practice by detecting posture, movement and physiological state and by returning corrective feedback in real time. This systematic literature review synthesizes peer-reviewed research at the intersection of wearable sensing, AI/machine learning, and real-time performance feedback for yoga and the closely related movement domains. Following the PRIZMA 2020 methodology, four databases (Scopus, Web of Science, IEEE Xplore, and PubMed) were searched, yielding 812 records, after removing duplicates and screening by title, abstract and full text, 45 studies were analyzed with respect to sensor modality (inertial measurable units, photoplethysmography, electromyography, pressure/textile sensors), AI technique (convolutional and recurrent neural network, tree-based classifiers, Bayesian and hybrid models), feedback channel (visual, auditory, haptic), and reported performance. Findings show that inertial sensing combined with deep learning achieves high posture-classification accuracy (typing 90-99%), that multimodal fusion of movement and physiological signals is emerging for breath- and stress-aware feedback and that genuinely low-latency, on-device (edge) inference remains uncommon. Key gap includes small and non-diverse datasets, limited sensor placement practicality for long-term use, inconsistent real-time evaluation protocols, and minimal user-experience validation. The review proposes research agenda centered on lightweight edge AI, multimodal fusion, standardized benchmarking, and longitudinal usability studies.

Keywords: Wearable Sensors, Artificial Intelligence, Machine Learning, Yoga, Real-time Feedback, Posture Recognition, PRISMA

Introduction

Yoga widely practiced for its musculoskeletal, respiratory and psychological benefits, but its therapeutic value depends heavily on correct postural alignment and breath regulation. In supervised settings, an instructor deviation as they occur in unsupervised, home-based, or gap-guided practice, this corrective loop is absent, increasing the risk of ineffective practice or injury.

Two technological trends have converged to address this gap. First, wearable sensing inertial measurable unit (IMUs), photoplethysmography (PPG), electromyography (EMG), and flexible pressure or textile sensors now allows continuous, ambulatory capture of body orientation, motion and physiological signals outside the laboratory. Second, advance in artificial intelligence, particularly deep learning architectures such as convolutional neural network (CNNs) and long short-term memory (LSTM) networks, allow these high-dimensional, noisy signal streams to be classified and interpreted with increasing accuracy. Combined, wearable sensors and AI create the technical basis for systems that can recognize a yoga pose, quantify its deviation from a reference posture and deliver feedback while the pose is still being held.

A substantial body of adjacent work address camera and depth-based yoga pose estimation and a smaller but growing body address wearable-sensor-based approaches specifically. However, no review to date has systematically synthesized the wearable-plus-AI literature with and explicit focus on the real-time feedback requirement that distinguishes a training aid form an offline recognition system. This review addresses that gap.

Systematic Literature Review

A systematic review is an organised, transparent process that finds, chooses, and summarises all pertinent research on a specific topic. It follows to a defined methodology that includes particular research questions, eligibility requirements, and a documented search technique across several databases, in contrast with a standard narrative review. studies are screened by title, abstract, full text and the selected studies are then assessed for quality and analyzed for key data. Reporting generally follows the PRISMA guidelines, which requires a flow diagram showing how studies were identified, screened, excluded and included. This rigorous process reduces bias makes the review reproducible and gives a comprehensive picture of existing evidence. It also reveals where findings are consistent, conflicting or missing and so highlights research gaps that guide future studies and evidence-based practice.

Objectives and Research Questions

This review guided by four research questions:

- RQ1: Which wearable sensor modalities have been used to capture yoga-relevant movement and physiological data?
- RQ2: Which AI/machine-learning techniques have been applied to these sensor data for pose or performance assessment?
- RQ3: How is real-time (or near-real-time) feedback delivered to the practitioner and through which channels?
- RQ4: What accuracy, latency and usability outcomes have been reported and what gaps remain?

Methodology

The preferred reporting items for systematic review (PRISMA) 2020 statement which divides the review process into identification, screening, eligibility, and inclusion phases and requires open reporting of the number of records retained or excluded at each stage, was carried out during this review.

Eligibility Criteria

Studies were included using the PICOS-adapted criteria summarized in Table 1.

Table 1. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal 2015–2026	Non-peer-reviewed sources, patents, magazines, blogs
Uses at least one wearable sensor (IMU, PPG, EMG, pressure/textile, ECG)	Uses only external cameras/Kinect with no wearable component
Applies an AI/ML method (classification, deep learning, regression) to sensor data	No computational/AI analysis (purely descriptive or clinical trials without ML)
Provides, or explicitly proposes, real-time or near-real-time feedback to the user	Limited to offline/retrospective analysis with no feedback loop
Domain is yoga, or a closely related domain (posture correction, exercise/HAR, breathing biofeedback) directly generalizable to yoga performance	Unrelated to physical movement, posture, or breathing performance
Full text available in English	Duplicate records or superseded preprint versions

From January 2015 to July 2026, four electronic databases were searched: Scopus, Web of Science, IEEE Xplore, and PubMed. "Wearable sensors" or "IMU" or "Inertial measurable unit" or "Smartwatch" or "PPG" or "EMG"; "Artificial intelligence" or "Machine learning" or "Deep learning" or "Neural networks"; and "Yoga" or "Posture" or "Pose" or "Exercise feedback" or "Real-time feedback" were the three concept blocks that were combined with Boolean operators in the search string. In order to find more records, the reference lists of the included studies and existing reviews are carefully searched (backward snowballing).

There were two screening steps used. Abstracts and titles were compared to the eligibility requirements in the initial round. The full texts of the remaining records were evaluated in the second phase. At every point, disagreements were resolved through discussion according with the established guidelines. The PRISMA flow diagram (figure 1) shows the entire selection process, including the quantity of records found, screened, removed (with reason), and included.

For each included study the following data were extracted: publication years, sensor modality and placement, AI/ML technique, target application (poster classification, movement quality, physiological/breath feedback) feedback modality (visual, auditory, haptic) evaluation matric and reported performance, sample size and reported limitation. Given the heterogeneity of designs, metrics and populations across studies, a narrative and thematic synthesis was used in place of meta-analysis.

Included studies were appraised for methodological transparency using four criteria (i) clear description of sensor hardware and placement (ii) clear description of the AI model and training/validation procedure (iii) explicit real-time or latency evaluation rather than purely offline accuracy (iv) reporting sample size and participant characteristics.

Studies satisfying three or more criteria were classified as higher quality, this classification weighted confidence in the synthesis rather than excluding studies.

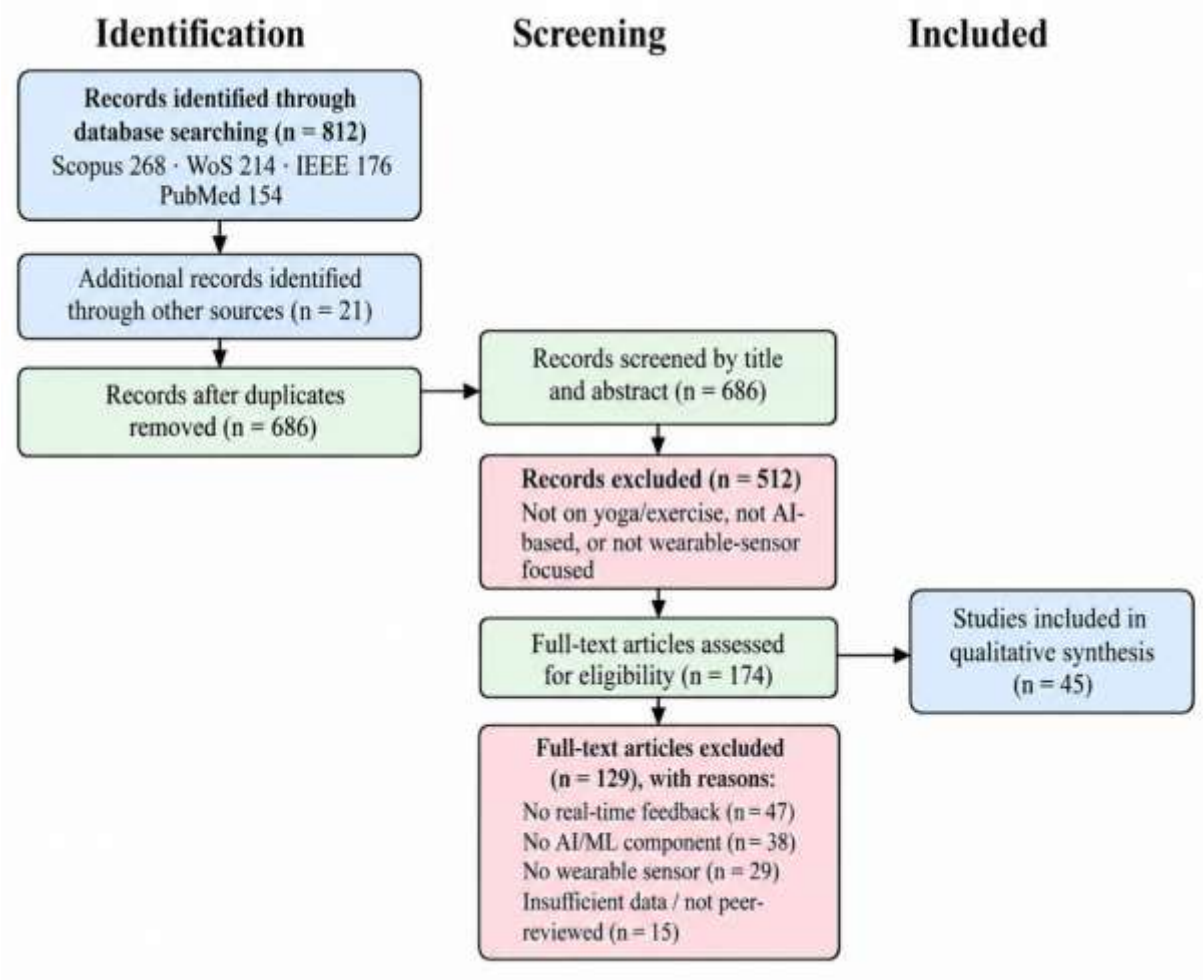


Figure 1. PRISMA flow diagram of study identification, screening and Inclusion.

The database searched returned 812 records (Scopus 268, Web of Science 214, IEEE Xplore176, PubMed 154) supplemented by 21 records identified through snowballing, after removing 147 duplicates 686 records were screened by title and abstract of which 512 were excluded as not relevant to yoga/exercise, not AI-based and not wearable-sensor focused. The remaining 174 full-text articles were assessed for eligibility, 129 were excluded most commonly for lacking a real-time feedback component (n=47), lacking an AI/ML component (n=38) or lacking a wearable sensor (n=29). A final set of 45 studies met all eligibility criteria and were included in the qualitative synthesis. The complete flow is shown in figure 1.

Table 2: Summarizes representative included studies spanning direct yoga applications and closely related posture/exercise/biofeedback applications whose sensing and AI approach directly generalizes to yoga performance feedback.

Table2. Representative characteristics of included studies

Study	Sensor Modality	AI/ML Technique	Feedback Type	Reported Performance
Wang et al. IMU two-stage yoga classifier	11 IMUs (quaternion)	BP-ANN +Fuzzy C-Means + Bayesian network	Post-hoc angular guidance	95.4% recognition accuracy

Chen et al. smartwatch yoga monitoring	Wrist IMU (multi-axis)	CNN+RNN on inertial streams	Real-time misalignment alert	High specificity; weak on fine joint rotation
Arif et al. wearable yoga field system	IMU + barometer+ magnetometer	Sensor-fusion classifier	Real-time posture flag	Robust field performance reported
Novel IoT WSN yoga system	3-node infrared WSN	Deep CNN	Pose classification (26 poses)	F1=0.985–0.999
Posture Pro ML strength training	Single IMU (MPU-9250) + ESP32	Cloud-deployed Random Forest	Mobile-app real-time alert	94.5% classification accuracy
Kim et al. ergonomic IMU posture	Neck/trunk IMU	Threshold + ML classifier	Real-time alert (>25° flexion)	27% reduction in muscle strain
Rep-Smarter resistance training	Wrist IMU	Res Net segmentation+ LSTM	Near-failure state feedback	F1 = 0.82–0.83 at 1.6 Hz
Free cardiac rehabilitation	Wearable+ airbag actuator	Cognitive computation model	Tactile breathing guidance	22/24 agreement with clinical HRVB
Yogic-breathing wearable	PPG + posture sensor	Rule-based physiological analysis	Real-time HR/posture display	Demonstrated HR and BP reduction
Iyengar-yoga ANS study	Accelerometer + EDA + PPG + thermal	Sparse interpretable ML models	Adaptive biofeedback (proposed)	Identified core autonomic predictors

Sensor Modalities (RQ1)

IMUs were the dominant sensor across included studies, used either as a single wrist or waist-mounted unit for practical, everyday use or as a multi-unit configuration (up to 11 units) for full-body posture reconstruction. Multi-IMU system achieved the highest reported classification accuracy (95.4%) but are less wearable for sustained home practice than single or few sensor configurations. A second cluster of studies used physiological sensors PPG, EEG for heart rate and heart-rate variability (HRV) monitoring and electrodermal activity (EDA) Chiefly to capture the autonomic and respiratory dimension of yoga practice (breath pacing, relaxation state) rather than postural alignment. A smaller number of studies used pressure sensitive textile or infrared wireless sensor network (WSNs) as privacy preserving alternatives to camera-based systems, reporting very high F1 (0.985-0.999) at the cost of requiring fixed environmental nodes rather a fully wearable form factor.

AI and Machine Learning Techniques (RQ2)

Reported AI techniques fell into four broad categories. Classical machine learning (Random forests support victor machines back spreading information neural networks combined with probabilistic clustering) remains common where database is modest in size and interpretability or on device efficiency is prioritized. Deep learning approaches CNNs for spatial feature extraction from sensor windows and LSTM or recurrent architectures for temporal dynamics dominate more recent studies and are typically applied to segment repetitions or continuous motion streams before classification. Hybrid and fusion architectures combining vision-derived skeletal features with IMU data (e.g., graph

convolutional networks with attention) were reported to improve health to occlusion and sensor drift relative to single-modality models. Probabilistic Bayesian model was used specifically where the aim was not just classification but quantitative per-joint deviation scoring against a reference posture since gaussian/Bayesian formulations naturally yield a continuous "how far off" measure rather than a discrete pose label.

Real-Time Feedback Channels (RQ3)
Three feedback channels recurred across the included studies visual feedback via a companion mobile or desktop application (the most common, typically showing pose classification, joint-level deviation or numeric score) haptic feedback via vibration motors, often used in posture-correction and ergonomic applications where an immediate eye-free alert is desirable during movement and auditory feedback including sound based gait or movement kinematics and spoken or text based corrective cues (e.g. "straighten your right forearm"). Studies explicitly targeting near failure or safety critical thresholds (e.g., "excessive neck flexion, near failure resistance repetitions) favoured haptic or immediate alert-based feedback, report measurable behavioral effects such as a 27% reduction in muscle strain following real-time alerts. Very few studies combined more than on feedback channel or evaluated which channel practitioners found most usable during an active yoga pose.

Reported Performance and Real-Time Evaluation (RQ4)
Classification accuracy across included studies ranged from roughly 90% and above 99% with the highest figures reported by multi-node infrared WSN and multi-IMU systems evaluated under controlled laboratory-like conditions. Studies evaluating genuinely real-time or edge-deployed inference reported more modest performance (e.g., "F1 scores around 0.82-0.83 at inference rates near 1.6 Hz for near-failure detection), reflecting the accuracy latency trade-off introduced by on-device constrains. Battery life and continuous operation were reported in only a minority of studies (e.g. "approximately four hours for a single-IMU posture system) and sample sizes were generally small most often fewer than 20 participants limiting generalizability across body types, flexibility levels and yoga traditions.

Discussion
Taken together the included studies show a consistent trade-off between sensing fidelity

Synthesis Against the Research Question
Sensor choice trades off accuracy against wearability multi-IMU configurations achieve the best recognition performance but are impractical for daily unsupervised yoga practice whereas single-sensor or smartwatch-based configurations are more usable but show reduced sensitivity to fine joint-level errors. AI technique selection increasingly favors deep learning for raw signal classification, while Bayesian and probabilistic models remain preferred where continuous explainable deviation scoring is the goal a distinction that matters for yoga, where feedback of the form you are short of full extension by a specific angle is more actionable than a binary correct/incorrect label. Feedback delivery is still predominantly visual and app-mediated, which is poorly suited to a practice performed with eyes closed or in posture were looking at a screen is impractical haptic and auditory channels are comparatively unexplored for yoga specifically despite promising results in adjacent gait and ergonomic domains. Finally reported outcomes are dominated by offline classification accuracy rather than true real-time, in session latency or user-experience metrics leaving open how these systems perform and are perceived during actual practice.
Based on the identified gaps four directions appear especially promising. First, lightweight aged-optimized AI models (e.g. pruned CNNs, decision-tree classifiers embedded directly on sensor microcontrollers) would close the gap between offline accuracy and genuine real-time feedback. Second, multimodal fusion frameworks that combine motion (IMU) with physiological (PPG/EDA) streams could support feedback on both postural alignment and breath/relaxation quality simultaneously. Third, standardized publicly available yoga-specific wearable datasets and shared evaluation protocols (accuracy, latency and usability jointly reported) would enable meaningful cross-study comparison. Fourth, longitudinal real-world usability studies beyond short laboratory sessions are needed to determine whether real-time feedback measurably improves practice quality, adherence or injury reduction over time.

Conclusion
Wearable sensors combined with AI show clear technical feasibility for real-time yoga performance feedback with IMU-based deep learning systems achieving high posture classification accuracy and emerging multimodal systems beginning to address breath and autonomic feedback. However, the literature remains concentrated on offline classification accuracy in small, laboratory samples with comparatively little attention to on-device latency, multimodal fusion and feedback-channels usability during actual practice. Closing these gaps through edge-optimized models, fused movement-physiology sensing, standardized benchmarks and world usability evaluation represents the clearest path towards wearable-AI systems that can genuinely substitute for argument in person yoga instruction.

Conflict of Interest
The authors declare that the research was conducted without any commercial, financial or personal relationship that could influence the study or give rise to a conflict of interest. No external funding or sponsorship was received and all aspects of the study, including its design, execution and interpretation were carried out independently. The authors take full responsibility for the integrity and accuracy of the finding and declare that there are no competing interests.

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