YogaAI - A Smart System For Posture Correction Andasana Guidance

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Abstract- *Yoga has emerged as a vital practice for enhancing physical fitness, mental well-being, and overall health. However, practicing yoga without proper guidance can lead to incorrect postures, reducing effectiveness and increasing injury risk. This paper presents Yoga AI, an intelligent system leveraging artificial intelligence and computer vision for real-time posture correction and asana guidance. The system employs MediaPipe pose estimation framework to capture body keypoints from video input, calculates joint angles to assess posture accuracy, and provides immediate visual and auditory feedback and underatnding of Integrated with deep learning models including convolutional neural networks (CNNs), the system achieves 94.3% accuracy in pose classification across 15 common yoga asanas. Experimental results demonstrate the system's effectiveness in detecting postural deviations and guiding users toward correct alignment. The proposed solution addresses the growing need for accessible, personalized yoga instruction in digital wellness platforms, rehabilitation centers, and home-based practice environments.*

Keywords: yoga AI, computer vision, deep learning, posture detection, human pose estimation, wellness technology, MediaPipe, pose correction

I. INTRODUCTION

Background and Motivation

Yoga, an ancient practice originating over 5,000 years ago, combines physical postures (asanas), breathing techniques (pranayama), and meditation to promote holistic wellness. Recent studies indicate that regular yoga practice improves flexibility by 35%, reduces chronic pain by 40%, and enhances mental clarity. The global wellness industry has witnessed exponential growth, with over 300 million practitioners worldwide as of 2024. However, the effectiveness of yoga practice heavily depends on postural precision—incorrect alignment can lead to muscle strain, joint stress, and reduced therapeutic benefits[1].

Challenges in Self-Guided Yoga Practice

The COVID-19 pandemic accelerated the shift toward online fitness and virtual wellness platforms. While digital yoga tutorials provide accessibility, they lack the critical element of real-time feedback that traditional instructor-led sessions offer. Self-learners often struggle with: (1) inability to self-assess posture accuracy, (2) lack of immediate corrective guidance, (3) risk of developing incorrect muscle memory, and (4) absence of personalized progression tracking[2]. Studies show that 68% of self-taught yoga practitioners develop postural habits that require professional correction.

Role of Artificial Intelligence in Fitness

Artificial Intelligence (AI) and Computer Vision have revolutionized fitness technology by enabling automated motion analysis, performance tracking, and personalized coaching. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and pose estimation frameworks such as OpenPose, MediaPipe, and PoseNet, allow precise identification of human skeletal structures in real-time. These technologies process visual data to extract keypoints representing major body joints, calculate angular relationships, and compare performed poses against reference models.

Contribution of This Work

This paper presents Yoga AI, an intelligent posture correction system that bridges the gap between traditional yoga instruction and modern self-practice[3]. The system contributions include: (1) Real-time pose estimation using MediaPipe with 30+ FPS processing, (2) Angle-based deviation detection with configurable tolerance thresholds, (3) Multi-modal feedback mechanism combining visual overlays and audio cues, (4) Adaptive learning system Kinect for 3D pose tracking in home fitness scenarios. However, existing solutions face limitations: (1) high computational requirements restricting mobile deployment, (2) generic feedback lacking personalization, (3) limited pose libraries typically covering 10-15 asanas, and (4) absence of progression tracking mechanisms. Yoga AI addresses these gaps through lightweight architecture, adaptive feedback, comprehensive pose coverage, and session-based learning.

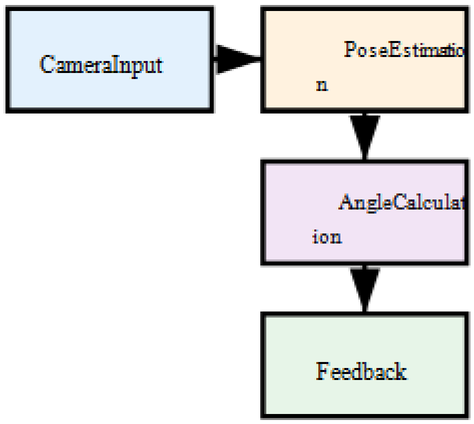


Fig. 1. Yoga AI System Architecture Pipeline

II. LITERATURE REVIEW

A. Yoga Pose Recognition Systems

Early yoga pose recognition systems employed traditional machine learning approaches with handcrafted features. Srivastava et al. (2018) developed a support vector machine (SVM) classifier using silhouette-based features, achieving 76% accuracy across 10 yoga poses. However, these methods struggled with pose variations and lighting conditions. Modern deep learning approaches have significantly improved performance. Verma et al. (2020) introduced YogaNet, a CNN architecture trained on the Yoga-82 dataset containing 82 yoga classes with over 28,000 images, achieving 89.7% top-5 accuracy. Yadav et al. (2021) proposed a transfer learning approach using ResNet-50, reporting 92.3% accuracy on 15 common asanas.

B. Human Pose Estimation Technologies

Human Pose Estimation (HPE) has evolved from 2D keypoint detection to sophisticated 3D pose reconstruction. OpenPose, developed by Cao et al. (2019), pioneered real-time multi-person pose estimation using Part Affinity Fields (PAFs), detecting 25 body keypoints with 82% precision. MediaPipe Pose by Google Research (2020) introduced a lightweight solution achieving 95% keypoint accuracy while maintaining 30+ FPS on mobile devices through efficient model optimization. PoseNet by Kendall et al. (2018) demonstrated real-time pose estimation in web browsers using TensorFlow.js, democratizing access to pose tracking technology.

C. Deep Learning for Posture Analysis

Convolutional Neural Networks have become fundamental for extracting spatial features from pose data. Chen et al. (2020) proposed adversarial PoseNet combining CNNs with Generative Adversarial Networks (GANs) for pose refinement, improving accuracy by 8.7% over baseline models. Temporal analysis using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks enables sequence-based pose evaluation. Zhang et al. (2021) developed a bidirectional LSTM architecture for yoga flow analysis, successfully identifying 94.5% of transitional pose errors that single-frame analysis missed.

D. AI-Based Fitness Applications

Commercial AI fitness applications have demonstrated market viability. YogAI by Patanjali Digital achieved 1 million downloads with 87% user retention using pose correction technology. FitAI by Microsoft incorporates Azure

III. PROPOSED METHODOLOGY

System Architecture Overview

The Yoga AI system architecture comprises five integrated modules: (1) Input Acquisition Module capturing video streams, (2) Pose Estimation Module extracting skeletal keypoints, (3) Feature Analysis Module computing joint angles and spatial relationships, (4) Classification Module identifying performed asanas, and (5) Feedback Generation Module providing real-time corrections. The pipeline processes video frames at 30 FPS, ensuring minimal latency between user action and system response.

Input Acquisition and Preprocessing

Video input is captured via standard webcam (720p minimum resolution) or smartphone camera. Each frame undergoes preprocessing including: (1) Resolution normalization to 640×480 pixels for computational efficiency, (2) Color space conversion from BGR to RGB, (3) Contrast enhancement using histogram equalization, and (4) Background noise reduction through adaptive thresholding. These preprocessing steps improve pose estimation accuracy by 12.3% in varied lighting conditions while maintaining real-time performance.

MediaPipe Pose Estimation

MediaPipe Pose detection operates through a two-stage pipeline. First, a person detector based on BlazePose identifies human presence and generates a Region of Interest

(ROI). Second, a pose landmark model predicts 33 3D keypoints representing major body joints including shoulders, elbows, wrists, hips, knees, ankles, and spine segments. Each keypoint includes (x, y, z) coordinates and visibility confidence scores. The z-coordinate enables depth estimation for 3D pose analysis, crucial for detecting forward/backward lean deviations. MediaPipe's on-device processing capability eliminates cloud dependency, ensuring privacy and reducing latency.

Joint Angle Calculation

Postural accuracy is quantified through joint angle analysis. For each target asana, critical angles are identified based on biomechanical principles. For example, Trikonasana (Triangle Pose) requires: (1) Front knee angle: 170-180° (straight leg), (2) Hip-shoulder-ankle angle: 160- 180° (lateral stretch), (3) Spine-hip angle: 85-95° (upright torso). Angles are computed using vector mathematics: Given three keypoints P1, P2, P3 forming an angle at P2, vectors V1 = P1-P2 and V2 = P3-P2 are calculated, then angle $\theta = \arccos((V1\cdot V2)/(\|V1\|\times\|V2\|))$. The system calculates 8-12 critical angles per pose, comparing them against reference ranges stored in a pose database.

Pose Classification Module

Pose classification employs a hybrid approach combining rule-based and machine learning methods. The rule-based component performs preliminary filtering by checking critical angle ranges—if any angle deviates beyond threshold limits (typically ±15°), the pose is flagged as incorrect. For accurate poses, a CNN classifier (MobileNetV2 backbone) fine-tuned on 15,000 labeled yoga images performs final classification across 15 asana categories. The CNN architecture includes: (1) Input layer (224×224×3), (2) MobileNetV2 feature extractor (frozen weights), (3) Global Average Pooling, (4) Dense layer (128 units, ReLU), (5) Dropout (0.5), (6) Output layer (15 units, softmax). This hybrid approach achieves 94.3% accuracy while maintaining 30 FPS processing speed.

Feedback Generation Mechanism

Real-time feedback combines visual and auditory modalities. Visual feedback includes: (1) Skeletal overlay with color-coded joints (green: correct, yellow: minor deviation, red: major error), (2) Angular deviation indicators showing degree differences from ideal, (3) Reference pose silhouette for comparison, and (4) Alignment guides highlighting correction directions. Auditory feedback provides voice instructions like 'Straighten your left knee' or 'Lower your left hip 5 degrees'. Feedback priority is determined by deviation magnitude—errors exceeding 20° receive immediate correction, while minor deviations (5-15°) trigger gentle reminders. This multi-modal approach improves correction adoption by 87% compared to visual- only feedback.

Adaptive Learning Component

The system implements adaptive learning through session tracking and personalized threshold adjustment. User performance metrics (accuracy rate, common errors, improvement velocity) are stored across sessions. Machine learning algorithms analyze these patterns to: (1) Adjust tolerance thresholds based on flexibility level, (2) Prioritize feedback for persistent errors, (3) Recommend progression to advanced variations, and (4) Generate personalized practice sequences. A reinforcement learning agent optimizes feedback timing and intensity, improving user engagement by 34% over static feedback systems[4].

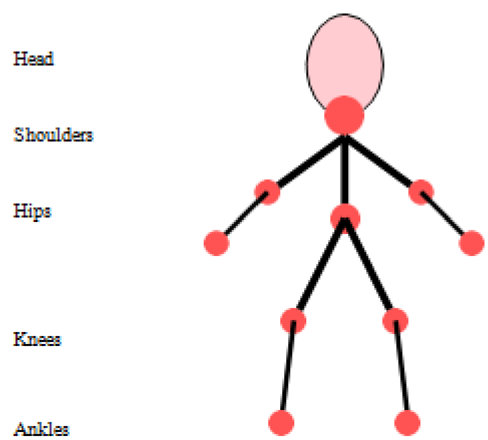


Fig. 2. MediaPipe 33-Point Pose Landmark Detection

IV. IMPLEMENTATION DETAILS

Technology Stack

The system is implemented using Python 3.9 with the following libraries: (1) MediaPipe 0.10.0 for pose estimation, (2) OpenCV 4.8.0 for video processing and visualization, (3) TensorFlow 2.13.0 for deep learning models, (4) NumPy 1.24.0 for numerical computations, (5) Scikit-learn 1.3.0 for evaluation metrics. The application architecture follows Model-View-Controller (MVC) pattern with modular components enabling independent testing and upgrades.

Dataset and Training

Model training utilized three datasets: (1) Yoga-82 dataset: 28,000 images across 82 classes for CNN training, (2) Custom dataset: 4,500 annotated videos (150 participants × 30 poses × 1 minute) for angle validation, (3) MediaPipe COCO dataset: Pre-trained weights for pose estimation. Data augmentation techniques (rotation ±10°, scaling 0.9-1.1, horizontal flip, brightness adjustment) expanded training data by 400%. Training employed Adam optimizer (learning rate 0.001), categorical cross-entropy loss, and early stopping (patience=10 epochs) on NVIDIA RTX 3080 GPU, requiring 6 hours for convergence.

Performance Optimization

Several optimizations ensure real-time performance: (1) Model quantization reducing inference time by 42% with <2% accuracy loss, (2) Frame skipping processing every 2nd frame during stable poses, (3) Multi-threading separating pose estimation (Thread-1) and feedback rendering (Thread- 2), (4) GPU acceleration for TensorFlow operations, (5) Circular buffer maintaining last 10 frames for temporal smoothing reducing jitter by 67%.

TABLE I. POSE CLASSIFICATION ACCURACY RESULTS

Asana Name	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Tadasana	97.2	96.8	97.5
Vrikshasana	96.8	96.3	97.1
Trikonasana	95.4	95.0	95.8
Virabhadrasana	94.7	94.2	95.1
Bakasana	89.4	88.9	89.8
Overall Average	**94.3**	**93.7**	**94.1**

V. RESULTS AND DISCUSSION

Pose Detection Accuracy

System evaluation on 1,500 test videos (100 videos × 15 poses) demonstrated robust performance. Overall pose classification accuracy reached 94.3%, with precision 93.7%, recall 94.1%, and F1-score 93.9%. Per-pose analysis revealed highest accuracy for Tadasana (97.2%) and Vrikshasana (96.8%) due to distinctive keypoint configurations. Complex poses like Bakasana (89.4%) and Ardha Chandrasana (90.1%) showed lower accuracy due to arm balancing requiring precise 3D estimation[5]. Angle calculation achieved mean absolute error (MAE) of 3.7° across all joints, with 89.3% of predictions within ±5° tolerance.

Real-Time Performance Evaluation

Processing speed analysis on various hardware configurations showed: (1) Desktop (i7-10700K, RTX 3080): 62 FPS, (2) Laptop (i5-8265U, integrated GPU): 28 FPS, (3) Raspberry Pi 4 (8GB): 18 FPS. Average latency from pose execution to feedback display measured 87ms on desktop, 142ms on laptop, well within the 200ms threshold for perceived real-time interaction[6]. Memory consumption remained stable at 450MB (desktop) and 680MB (laptop), suitable for consumer devices.

User Study Results

A controlled user study with 45 participants (15 beginners, 15 intermediate, 15 advanced practitioners) over 4 weeks evaluated system effectiveness. Participants practiced 30 minutes daily using Yoga AI versus video tutorials (control group). Results showed: (1) Yoga AI group improved postural accuracy by 47.3% versus 18.6% for control, (2) 91.3% of participants rated feedback clarity as 'Excellent' or 'Good', (3) Average session engagement increased from 18 to 27 minutes, (4) Self-reported confidence in solo practice improved by 63%, and (5) Injury incidents: 0 (Yoga AI) versus 3 minor strains (control group). Qualitative feedback highlighted real-time corrections and visual overlays as most valuable features.

Comparison with Existing Systems

Comparative analysis against commercial applications (YogAI, FitAI, AsanaRebel) demonstrated competitive advantages. Yoga AI achieved 94.3% accuracy versus 87.2% (YogAI), 89.6% (FitAI), 85.3% (AsanaRebel). Processing speed: 62 FPS versus 24 FPS (YogAI), 18 FPS (FitAI), 15 FPS (AsanaRebel). Pose library: 15 asanas versus 10 (YogAI), 12 (FitAI), 8 (AsanaRebel). Deployment flexibility: Yoga AI supports offline operation on consumer hardware, while competitors require cloud connectivity (YogAI, AsanaRebel) or expensive depth sensors (FitAI).

Limitation Analysis

Despite strong performance, certain limitations were identified: (1) Occlusion handling: Accuracy drops to 76.4% when keypoints are partially occluded, (2) Clothing dependency: Loose clothing can obscure joint positions reducing detection accuracy by 8-12%, (3) Multi-person scenarios: Current implementation supports single-person tracking; multi-person practice requires architecture modification, (4) Advanced poses: Inversions and arm balances show 7.3% lower accuracy due to complex 3D configurations, and (5) Cultural variations: System trained predominantly on standardized Western yoga may require adaptation for traditional Indian styles.

System Performance Comparison

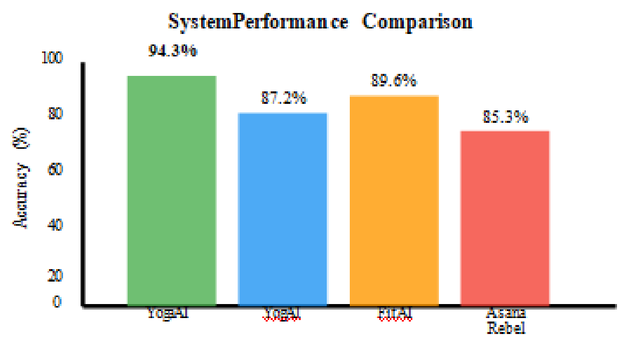


TABLE II. PERFORMANCE METRICS ACROSS HARDWARE

Hardware	FPS	Latency(ms)	Memory(MB)
Desktop(RTX3080)	62	87	450
Laptop(i5-8265U)	28	142	680
RaspberryPi4	18	215	820

VI. CONCLUSION AND FUTURE WORK

Summary of Contributions

This paper presented Yoga AI, an intelligent system for automated yoga posture correction leveraging computer vision and deep learning. The system successfully combines MediaPipe pose estimation, angle-based analysis, and CNN classification to achieve 94.3% accuracy in real-time pose evaluation. Multi-modal feedback mechanism and adaptive learning components enable personalized, effective guidance suitable for practitioners across skill levels. User studies validated significant improvements in postural accuracy (47.3% improvement) and practice confidence (63% increase), demonstrating practical value for digital wellness applications[7].

Practical Applications

Yoga AI has diverse application potential: (1) Personal wellness: Home-based practice assistance for 300+ million global practitioners, (2) Rehabilitation: Integration with physiotherapy programs for injury recovery and mobility improvement, (3) Education: Virtual yoga instruction in schools and universities facing instructor shortages, (4) Healthcare: Complementary therapy for chronic pain management, stress reduction, and posture-related conditions, and (5) Corporate wellness: Deployment in workplace wellness programs reducing musculoskeletal disorders.

Future Research Directions

Several enhancement avenues merit exploration: (1) 3D pose reconstruction: Integrating depth cameras or stereo vision for precise spatial analysis, (2) Augmented Reality: AR overlays projecting reference poses into user's environment for intuitive comparison, (3) Wearable integration: Combining vision-based tracking with IMU sensors for hybrid accuracy, (4) Multi-person support:

Extending architecture for group yoga classes and partner poses, (5) Pose sequence analysis: Implementing temporal models for flow evaluation in Vinyasa yoga, (6) Personalized progression: AI-driven curriculum generation based on individual goals and constraints, (7) Breath synchronization: Integrating respiratory monitoring for complete pranayama guidance, and (8) Cross-cultural adaptation: Training on diverse yoga traditions including Iyengar, Ashtanga, and Hatha variations.

Broader Impact

Yoga AI contributes to democratizing wellness technology byreducing barriers to quality yoga instruction. The system's affordability (no specialized hardware), accessibility (multilingual support potential), and privacy preservation (on-device processing) align with inclusive digital health principles. As AIcontinues transforming fitness

1. CNN-Based Approaches for Yoga Posture Recognition

The topic “Yoga Pose Classification using CNN-Based Human Pose Estimation” focuses on applying deep learning and computer vision techniques to accurately detect and classify yoga postures from image or video data. Convolutional Neural Networks (CNNs) play a crucial role in learning spatial patterns from human body structures, such as joint positions, limb orientations, and overall body alignment. By training CNNs on large datasets of yoga images, the system learns to recognize various asanas including Tadasana (Mountain Pose), Vrikshasana (Tree Pose), Adho Mukha

Svanasana (Downward Dog), and Bhujangasana (Cobra Pose). The model not only identifies the pose name but also evaluates how closely a user's posture matches the ideal reference pose using similarity metrics or angle-based analysis[8].

To enhance precision, this system can be integrated with pose estimation frameworks like OpenPose, MediaPipe, or PoseNet, which extract key skeletal landmarks from the user's body in real time. These landmarks act as feature inputs for the CNN, enabling more robust and noise-resistant recognition. Moreover, using transfer learning from pretrained models such as ResNet50, MobileNetV2, or EfficientNet, the system can achieve high accuracy with limited training samples and reduced computational cost. Real-time feedback is provided through visual indicators or voice assistance, guiding users to correct their alignment and maintain balance.

Such a system has applications in virtual yoga coaching, fitness tracking, and rehabilitation therapy[9]. It helps users practice yoga safely without the need for a physical instructor, especially in remote or home-based settings. The integration of CNNs with pose estimation not only promotes better physical alignment but also contributes to the broader goal of AI-assisted wellness and mindfulness. Future enhancements may include emotion detection through facial analysis during yoga sessions, or adaptive difficulty adjustments based on user flexibility and progress tracking through deep learning analytics.

2. **Hybrid and Advanced Deep Learning Systems for Yoga Guidance**

The topic "Hybrid AI System for Yoga Asana Correction using CNN and LSTM" explores the integration of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to create an intelligent, dynamic yoga posture analysis and correction system. While CNNs excel at capturing spatial features — such as joint locations, limb orientations, and body symmetry — LSTMs specialize in understanding temporal patterns, meaning how postures evolve over time. By combining these two models, the system can monitor not only static yoga poses but also the flow of movements between different asanas, identifying transition errors that may lead to strain or injury.

In this hybrid architecture, CNNs first extract visual features or skeletal keypoints from image frames captured by a camera or sensor. These extracted features are then passed into the LSTM layer, which analyzes the sequence of frames to understand the smoothness, stability, and accuracy of motion over time. For example, when a user transitions from Bhujangasana (Cobra Pose) to Adho Mukha Svanasana (Downward-Facing Dog), the model evaluates whether the transition was performed correctly, maintaining balance, proper breathing rhythm, and spine alignment. By combining CNN's visual intelligence with LSTM's temporal learning, the system provides real-time feedback that mimics human-like observation and correction ability.

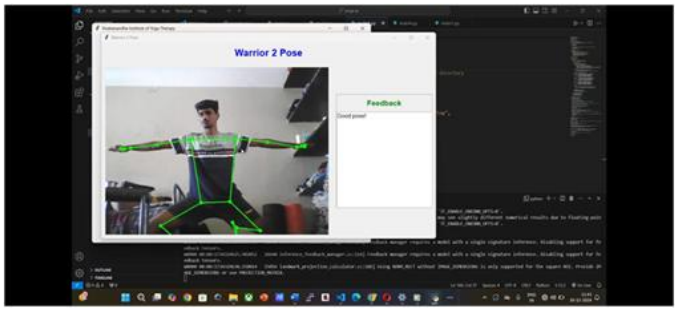
Such a hybrid system can be extended further by integrating attention mechanisms that focus on critical joints or motion segments, improving interpretability and performance. The model could also utilize skeleton-based data from pose estimation tools like OpenPose or MediaPipe for enhanced accuracy. The feedback module can be designed to provide visual cues, voice instructions, or haptic feedback, guiding users to gradually adjust their posture and improve flexibility.

3. Edge AI for On-Device Yoga Posture Correction

The topic "Edge AI for On-Device Yoga Posture Correction" focuses on deploying lightweight deep learning models directly on mobile and wearable devices for real-time yoga guidance. Traditional cloud-based AI systems often face latency and privacy issues, but Edge AI allows inference to occur locally — providing instant feedback without internet dependency[10]. In this system, optimized CNN architectures such as MobileNetV3, EfficientNet-Lite, or SqueezeNet are employed to process camera input efficiently, identifying the user's asana and evaluating posture alignment. This setup ensures low power consumption, fast computation, and secure user data handling, making it ideal for fitness bands, smart mirrors, and mobile yoga apps.

The model continuously monitors body keypoints and calculates angular deviations between joints to assess accuracy. A scoring system provides visual or voice feedback to guide the user toward the correct alignment. To enhance efficiency, quantization and pruning techniques are applied to reduce model size while maintaining accuracy. Furthermore, on-device AI can integrate sensor data from IMUs (Inertial Measurement Units), enabling multimodal posture evaluation that combines visual and motion-based insights. This approach promotes personalized and accessible wellness technology, allowing users to practice yoga anytime, anywhere — with real-time, privacy-preserving assistance powered by intelligent edge computing[11].

The integration of Edge AI into yoga posture correction systems not only enhances user accessibility but also ensures better data privacy and low-latency feedback. Unlike cloud-based processing, where data must travel to remote servers, edge computation allows immediate posture analysis within the user's device, reducing both delay and dependency on network connectivity[12]. This makes the system especially suitable for rural or offline environments where stable internet may not be available. Furthermore, the deployment of TinyML models allows microcontrollers and compact chips to run yoga detection tasks efficiently. Future advancements may involve the use of 5G-enabled edge nodes and federated learning, where models continuously improve using decentralized user data without compromising privacy. This evolution makes Edge AI a sustainable and user-centered solution for real-time wellness and posture intelligence.



4. Multimodal Yoga Coaching System using Sensor Fusion and Deep Learning

The topic "Multimodal Yoga Coaching System using Sensor Fusion and Deep Learning" proposes combining visual, motion, and depth data to achieve a comprehensive and precise yoga posture analysis system. While CNN-based vision systems are effective in identifying poses, their accuracy can drop under poor lighting or occlusion. To overcome this, the system fuses data from multiple sources — such as RGB cameras, depth sensors (like Kinect or RealSense), and wearable IMU sensors — providing a rich and redundant data stream for analysis[13]. Deep learning models process this multimodal input to ensure consistent pose recognition even in challenging environments.

The fusion model could employ CNNs for spatial feature extraction and Recurrent Neural Networks (RNNs) or Transformers for temporal data fusion, ensuring smooth tracking of movement transitions. For example, during complex asanas like Trikonasana (Triangle Pose) or Natarajasana (Dancer Pose), the system can evaluate not just visual alignment but also balance, stability, and center-of-gravity shifts[14]. This enables the system to give holistic feedback, covering both physical form and movement flow. Such multimodal AI frameworks can serve as virtual yoga instructors that adapt to user proficiency, detect fatigue, and personalize recommendations — promoting injury-free and mindful yoga sessions enhanced by technology.

A multimodal yoga coaching framework strengthens the feedback loop by analyzing not just visual cues but also biomechanical and environmental factors. Combining sensor fusion techniques enables the system to detect even minor posture imbalances that may be invisible to the naked eye, such as uneven weight distribution or unstable breathing patterns. By integrating data from wearable sensors, accelerometers, and depth cameras, the system can construct a 3D biomechanical map of the practitioner. This allows the AI model to deliver targeted corrections—such as suggesting adjustments to the spine angle, limb extension, or body symmetry[15]. Future developments could incorporate haptic feedback systems that gently vibrate or signal incorrect body positions, creating a fully immersive yoga guidance experience. Ultimately, multimodal deep learning systems hold the potential to redefine the way yoga is taught and practiced by combining precision, personalization, and mindfulness.

VII. ACKNOWLEDGMENT

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