International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN (Online): 2347-5552, Volume-14, Issue-1, January 2026
DOI: https://doi.org/10.55524/ijircst.2026.14.1.6
Article ID IRP-1707, Pages 43-54
www.ijircst.org

Artificial Intelligence Powered Yoga Posture Detection and Correction with Personalized Wellness Insights

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Received: 24 November 2025 Revised: 10 December 2025 Accepted: 24 December 2025

ABSTRACT- Yoga is a practice that promotes overall physical fitness, mental clarity, and balancing of the mind. But, with technological advancements in the area of Artificial Intelligence, smarter, accurate, and easier yoga practices are now a reality with intelligent systems. This research proposes a posture detection and correction system for yoga practice, which uses MediaPipe for human pose detection in images, with XGBoost as a classification algorithm. The system identifies necessary body points from MediaPipe to validate posture alignment. The research has trained and tested the system on a yoga posture dataset, which showed high accuracy in identifying and classifying yoga poses. The result clearly indicates that combining MediaPipe with XGBoost results in a fast and efficient posture assessment system.

KEYWORDS- Digital Wellness, Human pose estimation, Posture Correction, Real-time Feedback, Yoga Pose Detection.

I. INTRODUCTION

Yoga is an Indian practice that encourages bodily fitness, mental steadiness and emotional harmony. Due to its established health advantages yoga has become globally popular as a way to enhance flexibility, posture and general health. However, executing yoga poses improperly can cause muscle tension, imbalance or harm. Since access to instructors is not always possible for everyone, beginners frequently find it challenging to hold proper postures while practicing alone.

The modern yoga practice has been evolving by the use of Artificial Intelligence (AI) and Computer Vision (CV). Camera-based pose detection helps observe a practitioner’s posture and body alignment, allowing timely suggestions that guide them toward performing poses correctly. Such smart systems aid users in executing poses by detecting improper alignments and recommending corrections. Consequently AI-enabled yoga assistants are now being considered as a cost- efficient digital substitute, for human trainers.

A yoga pose recognition system generally employs a camera to record images or video footage of an executing yoga posture. The collected frames undergo processing through pose estimation techniques that identify body points, like shoulders, hips, knees and elbows. These points are subsequently evaluated by a machine learning model to determine the specific pose being executed. Achieving pose identification is vital since incorrect posture alignment can greatly diminish the benefits of the asana and elevate the chance of bodily harm.

Earlier investigations have utilized deep learning techniques like Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) to classify yoga poses. Although these approaches can reach levels of accuracy, they generally need extensive labeled datasets along with robust hardware, for real-time processing. Conventional machine learning models, combined with feature extraction can deliver similar results but with significantly reduced computational demands.

In this project we created an AI-powered Yoga Posture Detection and Correction System that combines MediaPipe for pose estimation with Extreme Gradient Boosting (XGBoost), for pose classification. MediaPipe developed by Google is an open-source platform that detects poses in real-time by locating 33 key body landmarks. These landmarks are obtained from every image or video frame. Transformed into numerical coordinates, which the XGBoost classifier then analyzes to precisely recognize yoga poses.

The main goal of this system is to help practitioners keep alignment and lower the chance of injury by offering instant corrective feedback. Additionally, the system includes a Surya Namaskara module that can identify and assess all twelve positions in the Sun Salutation series. This allows for monitoring of flowing movements instead of just static postures thereby enhancing the model’s applicability, for entire yoga practices. In addition, the system provides personalized wellness insights by suggesting suitable yoga poses based on individual health conditions and posture performance.

A. MediaPipe

MediaPipe is an open-source platform designed for developing real-time computer vision application. It offers built solutions for pose estimation, hand tracking face detection and more. In this project the Pose module of MediaPipe is utilized to detect 33 human body landmarks covering joints such, as shoulders, elbows, hips and knees.

These points are detected as (x, y) coordinate pairs, acting as the main input attributes for processing. MediaPipe efficiently handles both static images and live video feeds making it suitable for real-time yoga session tracking. Figure 1 shows the landmark detection results with MediaPipe.

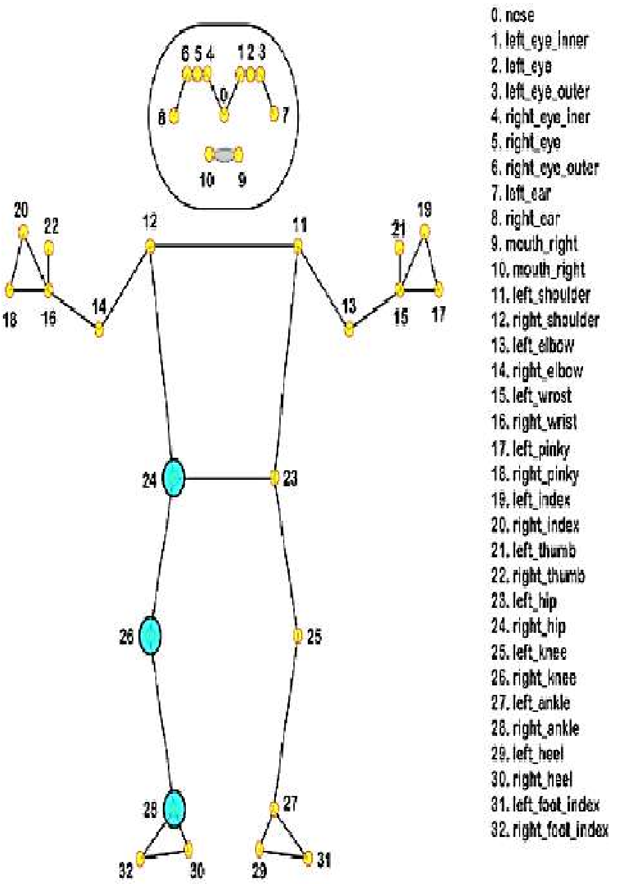

Figure 1: Human Body coordination using Mediapipe [21]

B. Extreme Gradient Boosting (XGBoost)

XGBoost is a gradient boosting technique commonly applied to supervised learning problems including classification and regression. It builds a collection of decision trees with each new tree focusing on the mistakes made by ones thereby enhancing the model's accuracy. XGBoost is known for its speed, scalability and reduced tendency to overfit relative, to classifiers.

This study utilizes XGBoost to categorize yoga poses based on features derived from MediaPipe. The model receives as input the 33 landmark positions along with calculated attributes that depict the user's posture. Throughout training the model establishes the relationship, between these features and the corresponding yoga pose categories. When testing it forecasts the pose and offers feedback if any discrepancies are noticed.

C. Objectives of the Study

The main objectives of this research work are:

- To develop an AI-based yoga posture detection and correction system using MediaPipe and XGBoost that accurately identifies yoga poses performed by practitioners.
- To implement a pose correction module that compares user poses with ideal reference postures and provides real-time feedback.
- To evaluate the system's accuracy, efficiency, and real-time responsiveness across multiple yoga postures and sequential movements.
- To design and test a Surya Namaskara module that recognizes and tracks the twelve-step Sun Salutation sequence for complete flow analysis.

II. LITERATURE REVIEW AND ANALYSIS

A. Review of Related Work

Archana Kedar et al. [1] developed a real-time yoga pose detection system using the MoveNet architecture. The accuracy of MoveNet was enhanced by integrating an initial convolutional neural network layer. The system has been incorporated into a React web interface, where it provides live feedback to assist users in maintaining accurate yoga postures.

Maan Veer et al. [2] proposed a system that combines Computer Vision, Random Forest Classification, and Transfer Learning (TL) techniques to rapidly recognize important skeletal points and body landmarks, resulting in accurate and reliable pose estimations in various situations.

Krupali Dhawale, et al. [3] developed a system that employs PoseNet along with the Yoga-82 dataset to classify yoga poses as correct or incorrect by extracting key body points through a webcam. In addition, the researchers upgraded PoseNet by adding hierarchical labels to its architecture, achieving improved accuracy over standard classification methods.

M. Akash et al. [4] introduced a deep-learning approach for classifying yoga poses using transfer learning. They employed models such as VGG-16, ResNet-50, and DenseNet 121 to classify yoga postures more accurately. The experimental results showed that DenseNet-121 performed better than the other models and was the most accurate for yoga pose classification.

Vivek Anand Thoutam, et al. [5] proposed a deep learning-based system that identifies incorrect yoga postures and offers real-time feedback for correction. This method applies a Multilayer Perceptron (MLP), using the calculated angles between key body joints as input.

Mansoor Hussain D et al. [6] created a web platform designed to facilitate the practice of Surya Namaskar as well as other exercises. They used algorithms like ml5.js and PoseNet for pose detection and feedback. In order to handle dynamic movements like Surya Namaskar smoothly, they used a mutex lock to coordinate feature extraction and pose detection efficiently.

Rutuja Gajbhiye et al. [7] developed a real-time system for yoga pose detection and correction, employing OpenPose to extract keypoints and a hybrid CNN-SVM approach for pose classification. The system analyzes five personalized yoga poses, checking the user's posture against target poses to offer feedback. It employs a time-distributed CNN to understand spatial keypoint patterns in each frame and a Long Short-Term Memory (LSTM) to learn how poses change over time.

Yash Agrawal et al. [8] used a machine learning method to recognize yoga poses with the YOGI dataset containing over 5500 images. They used tf-pose estimation to compute joint angles and tested multiple models, ultimately determining that the Random Forest algorithm yielded the most accurate results.

Kushal Ganesh and Amar Ramudhin [9] proposed an application that leverages computer vision techniques like OpenPose or MoveNet, combined with a CNN trained on yoga pose datasets, to detect joints and monitor posture in real-time. The system further integrates reinforcement learning to tailor practice routines for individual users and provide visual feedback on enhancements in posture alignment and movement.

Deepak Mane et al. [10] created a model using MediaPipe to track body keypoints and measure joint angles, helping users accurately assess and correct their yoga poses. A Support Vector Machine with a Radial Basis Function (RBF) classifier was trained using normalized joint angle data to detect poses and guide users in improving their posture.

Abhishek Sharma et al. [11] proposed a self-help-based system for real-time detection and correction of yoga posture and hand mudra. Features were extracted using MediaPipe and joint angles are computed from coordinates. These features were tested on various machine learning and deep learning models, with XGBoost, fine-tuned using RandomSearchCV, delivering the best accuracy.

Jothika Sunney [12] worked on building a real-time yoga pose detection system that makes use of MediaPipe's BlazePose and OpenCV to track 33 body landmarks in 3D. The system was developed and tested using machine learning models such as XGBoost, Random Forest, SVM, and Decision Tree. Among these, XGBoost stood out as the most efficient, providing high accuracy along with faster performance and a smaller model size.

Anuradha T, N. Krishnamoorthy, C. S. Pavan Kumar, L. V. Narasimha Prasad, Chunduru Anilkumar, and Usha Moorthy[13] proposed a system that takes input images through a webcam, skeletonizes them, and classifies the poses using deep learning models such as VGG16, VGG19, and CNN architectures. Their approach also combines CNN and LSTM algorithms with data from the OpenPose library for yoga action recognition, showing promising results.

Deepak Kumar and Anurag Sinha [14] developed a system that allows users to upload photos of their yoga posture for real-time feedback on posture accuracy using deep learning techniques. This research uses OpenPose for keypoint detection and CNN and LSTM for posture classification. The combination of CNN and LSTM models has been highly effective in classifying of all six yoga postures. Even a simple CNN with SVM also produced results that exceeded expectations.

L. Jaba Sheela et al. [15] proposed a real-time yoga pose evaluation system with MediaPipe BlazePose to detect body landmarks. These landmarks are converted into a stick-figure representation and processed using a Sequential CNN model. The model, built with Keras, is trained using categorical cross-entropy as the loss function and the Adam optimizer.

Sweta Mishra et al. [16] have suggested a system that integrates PoseNet and K-Nearest Neighbours (KNN) algorithms to examine user posture through webcam input and give personalized advice for correct alignment. The suggested system extends the pose detection with other features like a BMI calculator, calorie counter, meditation tracker and exercise planning module.

Debabrata Swain et al. [17] proposed a system that uses MediaPipe to extract keypoints. The extracted body keypoints are then processed by a CNN+LSTM model for pose classification. The CNN component captures spatial features while the LSTM learns temporal patterns, and a Softmax layer predicts the most probable yoga pose.

Preeti Garg et al. [18] developed a deep learning approach to identify yoga poses, estimate body posture, and provide feedback on pose accuracy. With Keras multi-person pose estimation, 12 joint key points are discarded from video frames, and their angles with respect to the x-axis are determined. The model was tested on a set of 70 videos with 350 instances, MLP being the best with a maximum accuracy.

Roli Bansal et al. [19] proposed DeepYoga, a real-time yoga pose recognition system using a CNN model trained on five poses. It captures live webcam input, uses MediaPipe to extract body landmarks, and classifies poses without relying on angle-based calculations, making the system faster and more efficient.

Vildan Atalay Aydın [20] proposed a deep learning model that applies wavelet transforms to classify various yoga postures. By processing wavelet subbands separately through multiple CNNs, the model achieves higher precision and provides better feedback for users to monitor their poses. Future research could explore adding real-time guidance and leveraging advanced learning techniques to further enhance the accuracy of yoga posture recognition.

B. Critical Analysis of Reviewed Literature

The reviewed literature indicates rapid progress in AI based yoga posture recognition, with most systems relying on pose estimation tools such as MediaPipe, OpenPose, and PoseNet. These models detect joints effectively in real-time, yet their performance is often influenced by environmental factors like lighting and camera angle. Many existing approaches use machine learning algorithms such as SVM and KNN based on handcrafted features, which limits their ability to capture temporal changes in dynamic yoga sequences. Deep learning architectures, particularly CNN - LSTM hybrids, provide better accuracy by utilizing both spatial and temporal information, but such models are not widely implemented due to computational demands.

Many systems provide only basic visual cues and do not include voice feedback or detailed corrective explanations, which reduces accessibility for beginners. Furthermore, a significant number of studies rely on limited or custom datasets that cover only a small set of poses, leading to reduced generalization. Very few systems incorporate personalized guidance based on user-specific factors such as flexibility levels, posture history, or wellness needs, and most do not offer tailored health insights connected to each pose.

Overall, this analysis underlines the trade-offs between model complexity, computational requirements, feedback quality, and user accessibility.

III. PROPOSED ARCHITECTURE

In this paper, an AI-powered Yoga Posture Detection and Correction System is proposed that integrates MediaPipe for feature extraction and the XGBoost algorithm for classification. The system identifies yoga postures in real-time, compares them with reference poses, and provides corrective feedback to the practitioner. The proposed architecture is capable of detecting and correcting static yoga poses as well as analyzing sequential movements such as Surya Namaskara.

The model leverages computer vision to extract human body landmarks from input images or live video feeds and applies machine learning to classify postures accurately. The proposed approach is computationally efficient, provides high accuracy, and ensures fast real-time response suitable for practical wellness applications. The overall system architecture is shown in Figure 2.

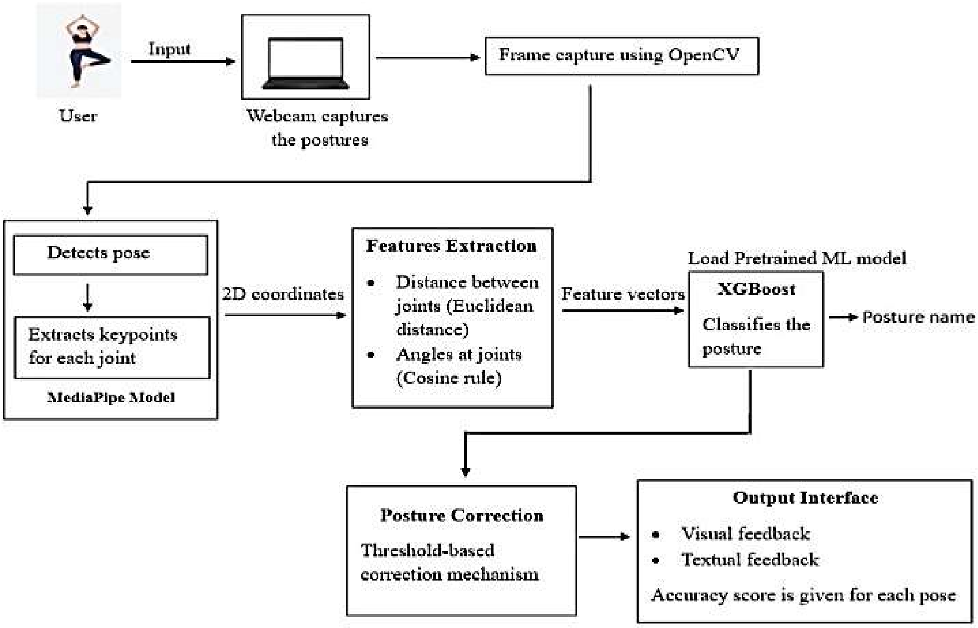

Figure 2: System Architecture of the Proposed AI-based Yoga Posture Detection and Correction System

IV. SYSTEM FLOWCHART

Figure 3 illustrates the operational workflow of the Intelligent Yoga Posture Assessment system. The process begins with system initialization and activation of the webcam to capture live video frames. Each frame is analyzed to detect the presence of a human body using pose estimation algorithms. If no human is detected, the system continuously monitors the incoming frames until a valid input is available. When a human is detected, the system generates a skeletal representation by identifying key joint coordinates, including the shoulders, elbows, hips and knees. These coordinates are then used to compute joint angles, distances, and relative positions, which form the basis for evaluating the user's posture.

Following feature extraction, the system compares the calculated joint parameters with predefined ideal pose configurations to assess the accuracy of the performed yoga posture. Based on this comparison, the system provides real-time corrective feedback that guides the user to adjust overall posture. Upon completion, the system stops monitoring, thereby concluding the assessment. This workflow enables precise, real-time posture evaluation, supporting users in improving yoga practice with personalized guidance.

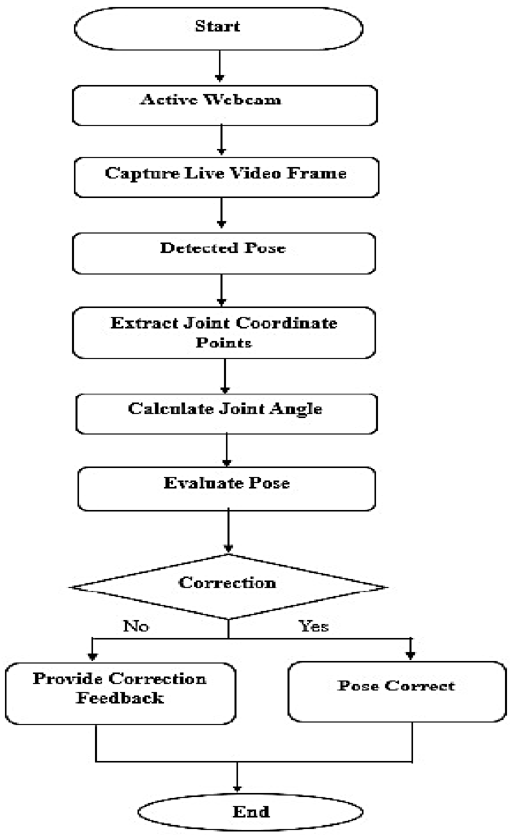

Figure 3: System Flowchart of the Proposed AI-based Yoga Posture Detection and Correction System

V. METHODOLOGY

A. Dataset Overview

The dataset used in this study was created by combining manually captured yoga pose data and publicly available datasets from sources such as Kaggle and Google.
The dataset used in this system consists of two parts:

- Yoga Pose Dataset (50 poses): Containing around 4,880 images of 50 distinct yoga postures.
- Surya Namaskara Dataset (12 poses): Containing 1,279 images representing the 12 sequential steps of the Sun Salutation cycle.

Figure 4 shows sample images from the Yoga Dataset used in this study. Each image was processed using MediaPipe Pose estimation library. This library detects 33 body landmarks, including shoulders, elbows, wrists, hips, knees, and ankles. From these landmark coordinates, joint angles were computed using below trigonometric formula.

$$angle = |arctan2(c_y - b_y, c_x - b_x) - arctan2(a_y - b_y, a_x - b_x) \times \left(\frac{180}{\pi}\right)|$$

These derived features represent the body's orientation and were used as input for the XGBoost classifier. The computed angle data and corresponding labels were stored in a CSV file for training and testing. Each record contained the pose label in the first column and 8 angular features in the remaining columns.

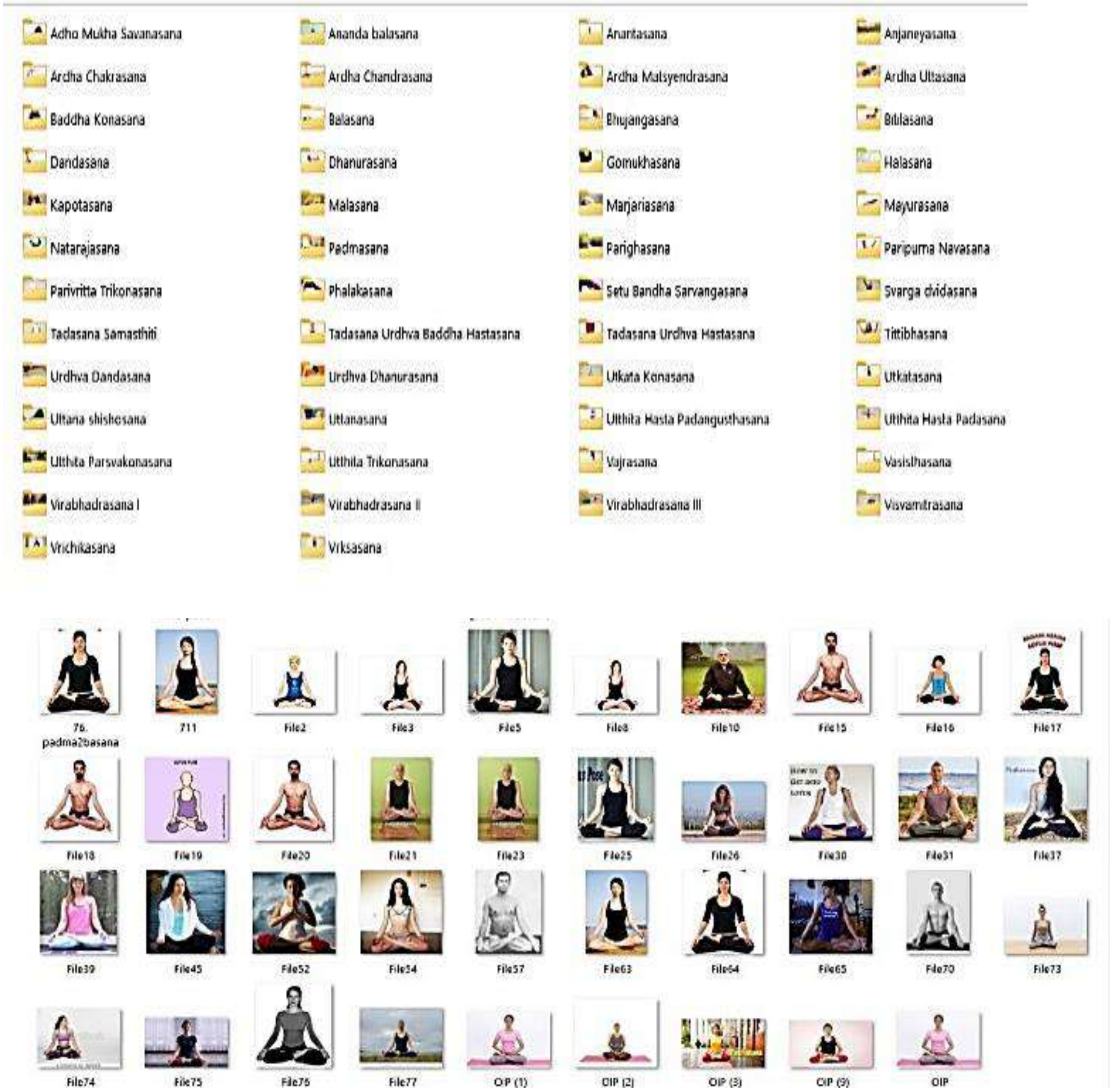

Figure 4: Yoga Dataset

B. Preprocessing

Before training the model, several preprocessing steps were performed to ensure data consistency and improve model performance. Figure 5 illustrates the joint angles extracted from the image dataset, which were used as input features, and the key preprocessing operations include:

- Normalization: All landmark coordinates and joint angles were normalized to have zero mean and unit variance to prevent scale dominance.
- Augmentation: To increase the diversity and richness of the dataset, we implemented several data augmentation techniques. These included rotating, horizontally flipping, adjusting the brightness of, and zooming in on the images to ensure a wider range of variations for model training.
- Splitting: The dataset was divided into training and testing subsets in multiple ratios to evaluate the model's robustness.

- Balancing: Each class (yoga pose) was ensured to have an equal number of samples to avoid bias in training.

These preprocessing steps ensured that the XGBoost model received clean, well-distributed data for efficient training and accurate classification.

left_elbow	right_elbow	left_shoulder	right_shoulder	left_knee	right_knee	left_hip	right_hip	pose_label
165.8414763	167.1613425	172.7505445	175.8895301	175.6355773	175.9947936	52.9366869	51.71459812	Adho Mukha Savanasana
159.4814724	166.5691813	178.3654651	178.7628672	178.9874209	175.5131003	56.69907394	54.46072519	Adho Mukha Savanasana
169.4756187	167.9557129	171.1745372	170.9778399	176.665337	176.0118606	67.46683995	65.40733822	Adho Mukha Savanasana
168.2494638	172.5438889	174.933136	172.4657492	179.0779419	179.7788547	52.37061817	49.78460789	Adho Mukha Savanasana
167.7799476	171.4729635	170.3982849	170.7678996	175.4210688	179.6485105	55.86811045	54.55817004	Adho Mukha Savanasana
174.1322029	176.0361258	157.6941485	159.8438359	174.4402519	175.299597	64.09354441	63.25366585	Adho Mukha Savanasana
170.2819196	171.795029	172.0948492	172.3397959	177.8239456	178.8708807	53.64965929	52.71117102	Adho Mukha Savanasana
173.0983233	167.874293	174.3064358	175.8867292	178.3688899	176.9120146	62.11530659	61.03911172	Adho Mukha Savanasana
165.7311691	165.8981303	176.2101154	171.9110344	174.4697265	173.6827626	47.32654088	44.34432423	Adho Mukha Savanasana
159.2943412	165.9498368	170.8201238	173.2489927	175.7133323	176.4448867	57.03145512	57.85920393	Adho Mukha Savanasana
163.3597322	163.0256994	178.638526	179.1668595	178.0659058	179.3928872	47.44827773	45.26575337	Adho Mukha Savanasana
167.5647312	166.2411138	169.6951201	171.4994293	176.5971427	179.2164962	52.52301409	49.05285949	Adho Mukha Savanasana
172.9162352	179.0646262	102.8372262	173.0690805	176.1523499	173.6545662	42.38419541	59.43867264	Adho Mukha Savanasana
163.8184984	157.3044497	167.8721331	165.6291632	176.0579001	175.6485248	55.84252487	54.18814737	Adho Mukha Savanasana
174.6167746	170.0063253	164.7201583	165.9699238	178.803359	177.5268859	58.75612325	58.49288581	Adho Mukha Savanasana
169.5811885	172.9723456	174.197848	170.9937678	177.0804107	177.6944956	54.92889881	62.76927804	Adho Mukha Savanasana
163.3393559	162.0814504	165.1664137	163.3331172	179.7836442	176.2713229	58.11446379	59.07806875	Adho Mukha Savanasana
160.3377999	163.3102264	159.5385462	159.1167529	178.8874227	179.3079358	61.74846339	63.78289143	Adho Mukha Savanasana
165.7404107	165.1039444	167.7675221	169.9298835	176.9627904	179.1584445	58.3979561	56.05773875	Adho Mukha Savanasana
156.126373	165.6905708	147.5365035	149.855223	178.6305201	169.6403755	78.18236773	75.72095801	Adho Mukha Savanasana
170.7630486	167.4587158	174.4861546	175.4921002	179.4027724	178.844364	54.260382	54.02104655	Adho Mukha Savanasana
167.9022716	175.4328638	177.4627542	174.5089132	176.9561735	178.0121704	47.98881844	54.86270502	Adho Mukha Savanasana
169.4874428	170.7374547	173.3784212	172.254878	172.5494861	173.6208627	54.81409034	55.55413999	Adho Mukha Savanasana
177.8309835	174.9420269	178.0143269	179.8538854	173.7954767	177.3225883	56.21341321	53.75204458	Adho Mukha Savanasana
164.5834811	154.3287642	164.1506605	158.0688774	174.8710641	171.6755126	66.7364327	63.11952291	Adho Mukha Savanasana

Figure 5: Angle extracted from image dataset

C. Training the XGBoost Model

The obtained feature vectors after the data preprocessing were the inputs for the XGBoost classifier training. XGBoost is a popular and powerful gradient boosting algorithm that gradually adds trees to the model, each new tree addressing the errors of the previous ones, thereby improving the overall prediction.

The training of the model was done with the help of the scikit-learn wrapper for XGBoost. The 33 landmark points (x, y) along with the calculated angular features were fed to the model as input, whereas each yoga pose label was the target variable. The model learned to identify complex, non-linear relationships between joint positions and their corresponding asanas.

The experiment was performed on a 20 train–test split, resulting in a classification accuracy of 95.73%. The proposed method was superior to traditional algorithms such as SVM, Random Forest, and KNN.

D. Pose Detection and Classification

During time execution of the program, the user performs yoga poses in front of a webcam. The system gets the video frames with the help of OpenCV and sends them to MediaPipe Pose for processing. MediaPipe Pose returns 33 keypoints and 8 joint angles. The angles are then fed to the trained XGBoost classifier for the prediction of the yoga pose label.

If the posture detected is one of the library asanas, then it gets printed on the GUI. In any other case, the system considers the pose as incorrect and activates the correction module.

E. Pose Correction Module

After pose classification, the system extracts the user's current joint angles and compares them with the true reference angles defined for the ideal posture. The differences between the user's angles and the ideal values are then analyzed to identify alignment errors, and the system provides targeted corrective feedback based on these deviations.

- Straighten left arm fully.
- Lift your left shoulder upward.
- Extend left elbow strongly.

The feedback is displayed in both textual and graphical formats. The GUI highlights incorrect joints in red and correct ones in green. Additionally, a pose accuracy score is shown to help the practitioner gauge posture precision.

F. Surya Namaskara Module

A dedicated Surya Namaskara (Sun Salutation) module was developed to evaluate sequential movements involving 12 connected poses. Using frame-by-frame tracking from MediaPipe, the system detects each transition and ensures the order of poses is maintained.

The module verifies posture correctness at every stage before allowing the user to proceed to the next step. It achieved an average sequence detection accuracy of 98.82% and provided feedback on flow smoothness and body alignment.

VI. EXPERIMENTAL RESULTS

The experimental evaluation focused on analyzing the model's accuracy, efficiency, and capability to provide real-time corrective feedback. The system was trained and tested using both the 50-pose static yoga dataset and the 12-step Surya Namaskara dataset.

A. Experimental analysis of Yoga poses

The system was evaluated using a 50-pose static yoga dataset to determine the most accurate algorithm for pose classification and feedback generation. Four models namely Random Forest**,** SVM**,** KNN**,** and XGBoost Classifier were tested with different training-to-testing ratios. As shown in Table 1, the XGBoost Classifier consistently achieved the highest accuracy and efficiency across all datasets. Its gradient boosting approach effectively captured pose variations and minimized overfitting, making it the most reliable model for real-time yoga pose recognition and corrective feedback.

The confusion matrix gives a clear picture of how well our model recognizes each posture. It shows where the predictions are correct and where the system mixes up poses, helping us understand its real-world accuracy. Additionally, precision, recall, and F1-score metrics further validated the robustness of the XGBoost model across multiple yoga poses.

Table 1: Analysis of the four algorithms

Training Size	Testing Size	Accuracy (%)			
		KNN	Decision Tree	SVM	XGBoost Classifier
80%	20%	97.25	97.64	97.64	98.82
70%	30%	97.38	97.64	97.64	98.95
60%	40%	96.85	95.02	96.85	96.07
50%	50%	97.64	96.06	97.64	97.16

B. Experimental analysis of Suryanamaskara poses

The system was further evaluated using a 12-step Surya Namaskara dataset to examine algorithm performance in recognizing sequential yoga postures and providing corrective feedback. Four machine learning models Random Forest, SVM, KNN, and XGBoost Classifier were assessed under multiple training-to-testing ratios. As presented in Table 2, the XGBoost Classifier consistently demonstrated superior performance in terms of accuracy and computational efficiency. Its gradient boosting methodology effectively managed sequential pose variations and mitigated overfitting, establishing it as the most suitable model for real-time Surya Namaskara posture recognition and feedback generation.

Table 2: Analysis of the four algorithms for Surya Namaskara

Training Size	Testing Size	Accuracy (%)			
		KNN	Decision Tree	SVM	XGBoost Classifier
80%	20%	92.6	83.14	89.07	95.73
70%	30%	92.5	82.9	89.5	93.8
60%	40%	91.8	80.7	87.71	92.03
50%	50%	91.33	82.5	87.33	91.4

C. Unit Test Cases and Results

Unit testing was performed to check the accuracy and reliability of each component of the yoga posture recognition system before integrating them into a complete system. Separate tests were conducted for modules including video input processing, pose landmark detection, feature extraction, pose classification, and feedback generation to ensure that each module functioned correctly and consistently.

For posture evaluation, the system analyzed body landmarks and joint alignments against predefined reference angles. Figure 6 illustrates Bhujangasana with corrective feedback, where joint misalignments were detected and appropriate suggestions were generated. Figure 7 shows Bitilasana performed correctly, with all joints aligned to reference angles and no feedback issued. Figure 8 presents Tadasana Urdhva Baddha Hastasana with corrections, highlighting detected deviations in arm and posture alignment. Figure 9 demonstrates Phalakasana with corrective feedback, indicating improper joint positioning. Figure 10 depicts Vajrasana in a perfect pose, correctly recognized without triggering alerts. Figure 11 shows Utkatasana with corrections, where misaligned joints prompted real-time guidance. Figure 12 represents a scenario where no valid pose was detected, confirming the system's ability to handle invalid or absent inputs.

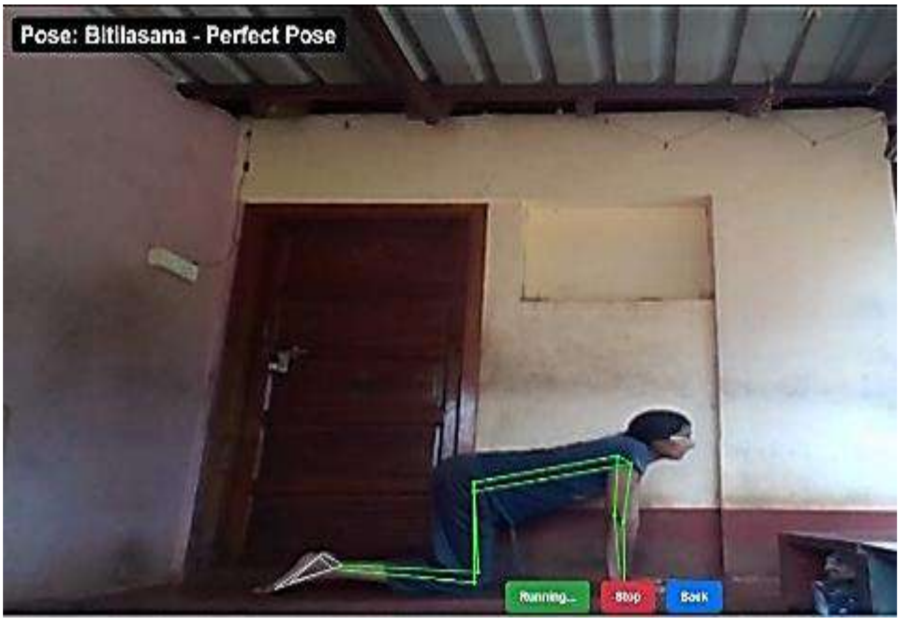

Figure 6: Bhujangasana with correction

Figure 7: Bitilasana – Perfect Pose

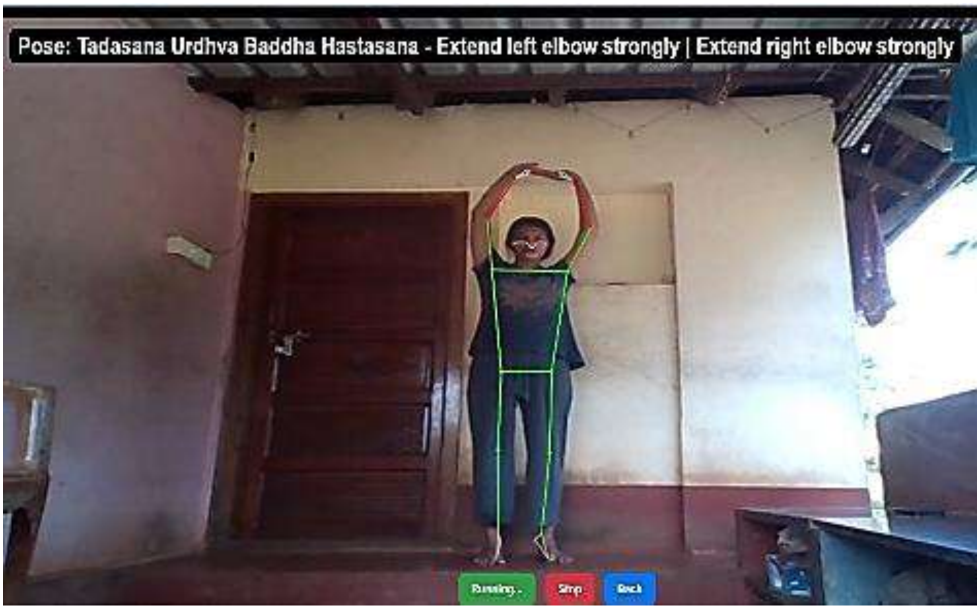

Figure 8: Tadasana Urdhva Baddha Hastasana with corrections

Figure 9: Phalakasana with corrections

Figure 10: Vajrasana – Perfect Pose

Figure 11: Utkatasana with corrections

Figure 12: No Pose Detected

Unit testing of the Surya Namaskara module was performed in order to verify that the system is able to correctly follow the sequence of poses. Surya Namaskara consists of twelve yoga poses that must be performed in a fixed order and this module is responsible for checking whether each pose is performed at the correct stage. The system continuously compared the expected pose at each step with the pose detected by the recognition model. When the detected pose matched the expected one, the system confirmed that the pose was performed correctly and smoothly moved on to the next pose in the sequence. In case the pose was different, the system stayed at the same step and instructed the user to correct the posture before continuing. Steps 1 to 12 represent the complete Surya Namaskara sequence, where each step corresponds to a specific yoga pose performed in a predefined order.


Step 1: Pranamasana


Step 2: Hasta Uttanasana


Step 3: Padahastasana


Step 4: Ashwa Sanchalasana


Step 5: Chaturanga Dandasana


Step 6: Ashtanga Namaskar


Step 7: Bhujangasana


Step 8: Adho Mukha Svanasana


Step 9: Ashwa Sanchalanasana


Step 10: Padahastasana


Step 11: Hasta Uttanasana


Step 12: Pranamasana

VII. PERSONALIZED WELLNESS INSIGHTS

In the proposed system, personalization is implemented through age-based yoga recommendations**,** disease-specific yoga routines**,** and calorie-based yoga sessions**.** This allows the system to suggest poses and sequences suited to each user's fitness level and wellness goals. For example, users with specific health conditions receive yoga routines designed to improve their condition safely, while those aiming for calorie reduction are guided toward higher-intensity postures.

VIII. CHALLENGES AND LIMITATIONS

While the AI-based Yoga Posture Detection and Correction System is effective in numerous aspects; it still has difficulty with several problems. The deficiency that is mostly prominent is the system dependency on the quality of the input data. Variations in lighting, background and clothing can result in a lower accuracy of the detected pose. In the case of complicated or transitional poses in a sequence like Surya Namaskara, the system may wrongly identify the gesture because the move is too fast or some parts of the body are blocked. Furthermore, a lot of computing power is needed to provide feedback on the spot, so it may not be possible to use a device of low specifications. Lack of representation of various body types, different levels of flexibility, and yoga styles in the dataset may cause the system to be less generalized.

IX. FUTURE SCOPE

The device is packed with potential to broaden its horizon as a solution that would not only have a deep impact but also become more advanced. Incorporating wearable sensors or depth cameras could enable the device to provide the user with the most accurate 3D pose estimation, joint tracking, and posture alignment. Moreover, the model can be extended to identify not only a wide range of yoga poses but also advanced transitions and even breathe monitoring like count, rhythm, and breath–movement coordination which can be very helpful in wellness. Apart from that, having the system available on a mobile or cloud platform would be attractive, as it would be more accessible to users.

X. CONCLUSION

The AI-driven Yoga Posture Detection and Correction System is a major breakthrough in using technology to improve traditional methods of wellness. With MediaPipe used for real-time pose estimation and XGBoost used for accurate pose identification and correction, this system successfully analyzes and provides users with accurate mirror corrections for yoga posture, making yoga safe for beginners and improving yoga performance for advanced yoga practitioners. Moreover, this system can be considered a remote yoga assistance tool because it eliminates the need for a yoga instructor, thus making yoga accessible to people all over the world, despite geographic and financial considerations. Although issues such as the need for more dataset samples, working in different environments, and computational requirements exist in this project, this research work exemplifies how AI systems can fill the gap between traditional yoga instruction and technology-driven health assistance systems. In future studies, using more advanced AI systems, such as AI-driven yoga pose recognition using wearable devices and mobile apps, may improve this project in terms of accuracy, effectiveness, and usability.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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