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Real Time Yoga Posture Recognition and Correction

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Abstract: The interest in human pose detection and correction technologies has surged, especially following the COVID-19 pandemic, which underscored the importance of maintaining personal health and fitness. While traditional manual techniques have contributed significantly to this field, their limitations in speed and precision have prompted the search for more advanced solutions. Simultaneously, the rising adoption of digital health tools has intensified the demand for applications that assist individuals in performing exercises correctly from home. Yoga, in particular, requires exact posture alignment to maximize its health benefits and minimize injury risks. However, conventional manual assessment methods often entail lengthy evaluation periods and are prone to errors.

In response to these challenges, we've developed a real-time yoga posture recognition and correction system powered by a deep learning model. Using the MoveNet Thunder architecture, our solution provides users with instant feedback to help fine-tune their posture and alignment. Alongside visual indicators, the app offers real-time voice guidance, making practice sessions safer, smoother, and more effective. This initiative highlights how AI can revolutionize at-home fitness and promote overall well-being.
Keywords: Human pose detection, yoga posture correction, deep learning, MoveNet Thunder, real-time feedback, AI fitness, home workout, pose estimation, voice guidance, health technology.

I. INTRODUCTION

The integration of artificial intelligence (AI) and computer vision technologies has transformed the fitness industry, bringing innovative solutions to enhance exercise practices — particularly in real-time human pose detection and correction. The COVID-19 pandemic, which confined many individuals to their homes, highlighted the growing need for efficient, accessible fitness systems that could deliver reliable guidance remotely. Traditional posture evaluation methods, though valuable, often suffer from inefficiencies, human error, and subjective assessments, paving the way for the development of automated systems that offer faster and more accurate feedback. Yoga, as a discipline that harmonizes body and mind, demands precise posture alignment to maximize its benefits and minimize the risk of injury. In-person yoga classes provide important corrective feedback from instructors, but this level of personal guidance is not always accessible to those practicing at home. This limitation has fueled growing interest in AI-driven systems capable of delivering real-time, personalized corrections during individual practice sessions.

In this research, we propose a comprehensive real-time yoga posture recognition and correction system that leverages both deep learning and machine learning techniques. Central to this system is the MoveNet Thunder model, a robust tool for keypoint detection that accurately identifies essential body joints. These keypoints are analyzed and compared against ideal pose configurations, enabling the system to offer immediate, customized feedback for correcting misalignments. For this study, we focused on two complex yoga postures: Malasana (Garland Pose) and Baddha Konasana (Bound Angle Pose). These poses were chosen due to their technical demands and the critical importance of maintaining proper alignment to prevent strain, particularly in the hips, knees, and lower back. The system works by capturing real-time pose data and evaluating a practitioner's posture against a database of ideal alignments. A Random Forest Classifier processes the extracted keypoints to recognize specific poses and detect deviations from optimal form. Based on these findings, the system generates corrective feedback delivered through both on-screen visual prompts and audio instructions, allowing practitioners to make necessary adjustments seamlessly without diverting their attention from their practice.Architecturally, the system is built for scalability and user-friendliness. A Flask-based backend manages the processing of input images and pose prediction requests, while MongoDB Atlas serves as the cloud database for storing posture evaluations and user performance histories. On the front end, a ReactJS-based interface offers a dynamic and responsive user experience, delivering real-time feedback and correction suggestions in an intuitive format. The incorporation of voice-guided feedback further enhances usability, ensuring that users receive continuous support even without maintaining constant visual contact with the screen.

This AI-powered yoga correction system represents a significant step toward democratizing access to high-quality yoga instruction. By offering instant, reliable guidance, it helps users practice more safely and effectively from the comfort of their homes. Beyond posture correction, this system encourages healthier, more sustainable fitness habits, ultimately contributing to improved physical well-being. Our findings demonstrate the transformative potential of AI in enhancing home-based fitness practices and paving the way for a new generation of intelligent, supportive exercise tools.

II. RELATED WORK

In the expanding field of computer vision, pose estimation has emerged as a critical tool for delivering real-time feedback to yoga practitioners, facilitating posture assessment and correction. This has prompted the development of several systems that utilize human pose interpretation models such as OpenPose, MediaPipe, PoseNet, and MoveNet.

Li and Chen [2] proposed a lightweight yoga assistant optimized for mobile devices using MediaPipe. Their implementation performed well for fundamental poses, but its ability to manage intricate posture variations was limited. Similarly, Singh et al. [8] explored real-time pose feedback using MediaPipe and found that environmental factors—such as poor lighting or occluded limbs—adversely affected the accuracy of pose tracking.

Subsequent comparative evaluations have increasingly favored MoveNet for applications requiring low latency and high inference speed. For example, Lee et al. [5] compared the performance of OpenPose and MoveNet, concluding that MoveNet's design is better suited for real-time applications on edge devices due to its minimal computational delay. Supporting this conclusion, Patel et al. [9] tested MoveNet across a range of yoga postures and noted high accuracy alongside efficient resource utilization, reinforcing its suitability for practical deployment.

Research has also focused on embedding corrective guidance mechanisms within pose estimation systems. Kishore et al. [4] introduced a system that provided posture feedback using rule-based logic through webcam input, whereas Dhakate et al. [1] applied deep learning to deliver real-time posture alignment suggestions, aligning user movements with predefined reference standards. Both studies emphasized the importance of combining visual and auditory cues to foster better user comprehension and interaction.

Recent advancements are moving toward hybrid approaches that combine pose estimation with machine learning classifiers. Sinha et al. [10], for instance, evaluated PoseNet and MoveNet within fitness applications and demonstrated that integrating classifiers like Random Forests with pose data can reduce processing overhead without sacrificing accuracy.

A comprehensive review by Xiao et al. [18] dissected the respective advantages and trade-offs of OpenPose, MediaPipe, and MoveNet. The study highlighted ongoing challenges related to system responsiveness and real-time feedback, which continue to hinder broad-scale adoption in consumer applications. Their findings influenced the selection of MoveNet Thunder in our system, given its ability to offer robust pose tracking with low latency.

Despite these technological strides, many existing solutions still lack scalability and comprehensive correction features that are both responsive and intuitive. Our proposed system addresses these issues by combining MoveNet Thunder with a Random Forest classifier and delivering real-time audio-visual cues within a scalable full-stack architecture. This integration enhances pose detection precision while improving the overall interactivity and adaptability of the user experience.

III. PROPOSED METHODOLOGY

The development of the yoga pose detection and evaluation system was carried out in multiple integrated stages, combining machine learning model training, backend server implementation, database management, and frontend application design. The overall approach was modular to ensure scalability, maintainability, and real-time performance.

Initially, a pose estimation model was required to extract human body keypoints from images. For this, MoveNet Thunder, a highly accurate and lightweight pose detection model available via TensorFlow Hub, was integrated. MoveNet is capable of detecting 17 major body joints, such as shoulders, elbows, knees, and ankles, providing (x, y) coordinates normalized to the image frame. A utility function was designed to preprocess each input image: resizing it to 256x256 pixels, converting it to RGB format, and expanding its dimensions to match the input requirements of MoveNet. Once passed through the MoveNet model, the extracted keypoints were flattened into a 34-element array, representing the (x, y) coordinates of each joint. Subsequently, to create a labeled dataset for pose classification, a structured directory of images was prepared where each folder corresponded to a specific yoga pose. A Python script was employed to loop through these folders, extracting keypoints for every image and assigning them the respective pose label. The resulting dataset was compiled into a CSV file, containing both the keypoint coordinates and the associated pose names. This CSV file, yoga_keypoints.csv, served as the foundation for model training.

For pose classification, a traditional machine learning approach was chosen over deep learning to reduce computational load during real-time predictions. The keypoints dataset was split into training and testing sets using an 80-20 ratio. A Random Forest Classifier pipeline, combined with a StandardScaler for feature normalization, was trained on the keypoints data. Random Forests were preferred due to their robustness to noise, high interpretability, and minimal tuning requirements for tabular datasets. After training, the classifier achieved high accuracy on the testing set, ensuring reliable pose prediction. The trained model was serialized using the joblib library and saved as yoga_pose_model.pkl for deployment. Parallel to model development, a backend server was built using the Flask framework to handle HTTP requests for pose prediction. The Flask server included two main endpoints: /predict for receiving webcam images and returning prediction results, and /results for fetching historical pose evaluations stored in the database. MongoDB Atlas was used for cloud-based database management, with a specific collection named poses to store the users' pose predictions, corrections, and performance ratings. When an image was received at the /predict endpoint, it was first processed through the MoveNet model to extract keypoints. To ensure prediction validity, a critical validation step was included: verifying that at least 15 out of 17 keypoints were detected and that key body parts such as shoulders, hips, knees, and ankles were present. Furthermore, basic body proportion checks (such as shoulder width relative to torso height) were conducted to filter out incorrect or noisy detections.

Once validated, the extracted keypoints were passed into the Random Forest classifier to predict the closest yoga pose. The server then retrieved the ideal keypoint configuration for that pose from the preprocessed dataset and calculated the deviation between detected and ideal poses. Corrections were suggested for joints deviating significantly, specifying the direction and magnitude of adjustment required. Additionally, a numerical "rating" out of 10 was computed based on the overall deviation, giving users immediate feedback on their posture quality. Once the machine learning model was successfully trained and evaluated, attention shifted to the backend development. A Flask server was implemented to serve as the communication bridge between the machine learning model and the client interface. The server was designed to expose two primary API endpoints: /predict and /results. The /predict endpoint is responsible for accepting an image file sent by the frontend, processing it through the MoveNet model to extract keypoints, validating the pose structure, and finally using the Random Forest classifier to predict the yoga pose. It also generates detailed feedback by comparing the detected pose keypoints with the ideal keypoints stored during training, offering users actionable correction suggestions. The server includes robust input validation to ensure that only images with sufficient body visibility are processed. If critical body parts (such as shoulders, hips, knees, or ankles) are missing or improperly captured, the server returns helpful suggestions encouraging users to adjust their camera setup or posture. This was vital to improve the system's reliability and maintain user engagement during incorrect captures. Once a pose prediction is successful, the server calculates a performance rating (on a scale of 1 to 10) based on the average deviation from the ideal pose and stores the complete result in a MongoDB Atlas cloud database. This allowed for seamless record-keeping, future retrieval, and potential analysis of user performance trends.

Parallelly, the frontend was built using ReactJS to ensure a responsive, dynamic, and user-friendly experience. The interface was organized into modular components such as WebcamView, ControlButtons, CorrectionDisplay, and VoiceFeedback. Each component was responsible for a distinct piece of functionality, adhering to clean software design principles. The WebcamView component continuously displayed the live camera feed using the react-webcam library, while also allowing frame capture for predictions. A countdown mechanism was introduced to periodically capture frames every second for a total of 15 seconds, enhancing the likelihood of getting a well-framed shot without requiring manual intervention. Captured images were automatically sent to the Flask backend via Axios HTTP requests. Responses from the backend were then dynamically rendered on the frontend, displaying the detected pose name, performance rating, and step-by-step correction suggestions. If any pose issues were detected, such as partial visibility or improper lighting, user-friendly error messages were displayed along with advice for adjustments. A particularly innovative feature was the integration of voice feedback. Using the Web Speech API, the application provided real-time audio guidance on corrections, helping users adjust their poses without needing to constantly check the screen. This accessibility feature not only enhanced the overall experience but also made the system more suitable for real-world yoga practice where uninterrupted flow is critical. Users could enable or disable voice feedback through a simple toggle button on the interface.

Moreover, all user interaction data, including pose names, ratings, and correction feedback, were logged into the MongoDB database via the backend. This logging allowed for potential future extensions such as building a personalized improvement tracker, daily streak reminders, or even community ranking features.

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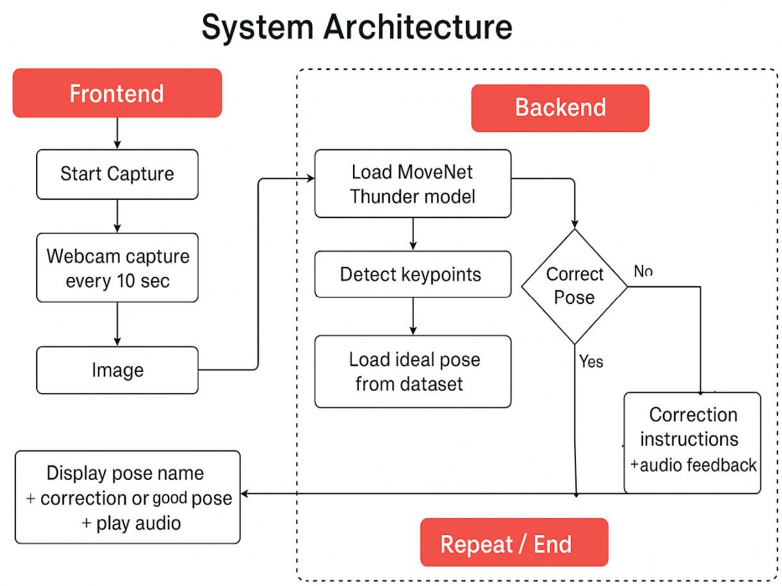

Fig. 1 Proposed Methodology

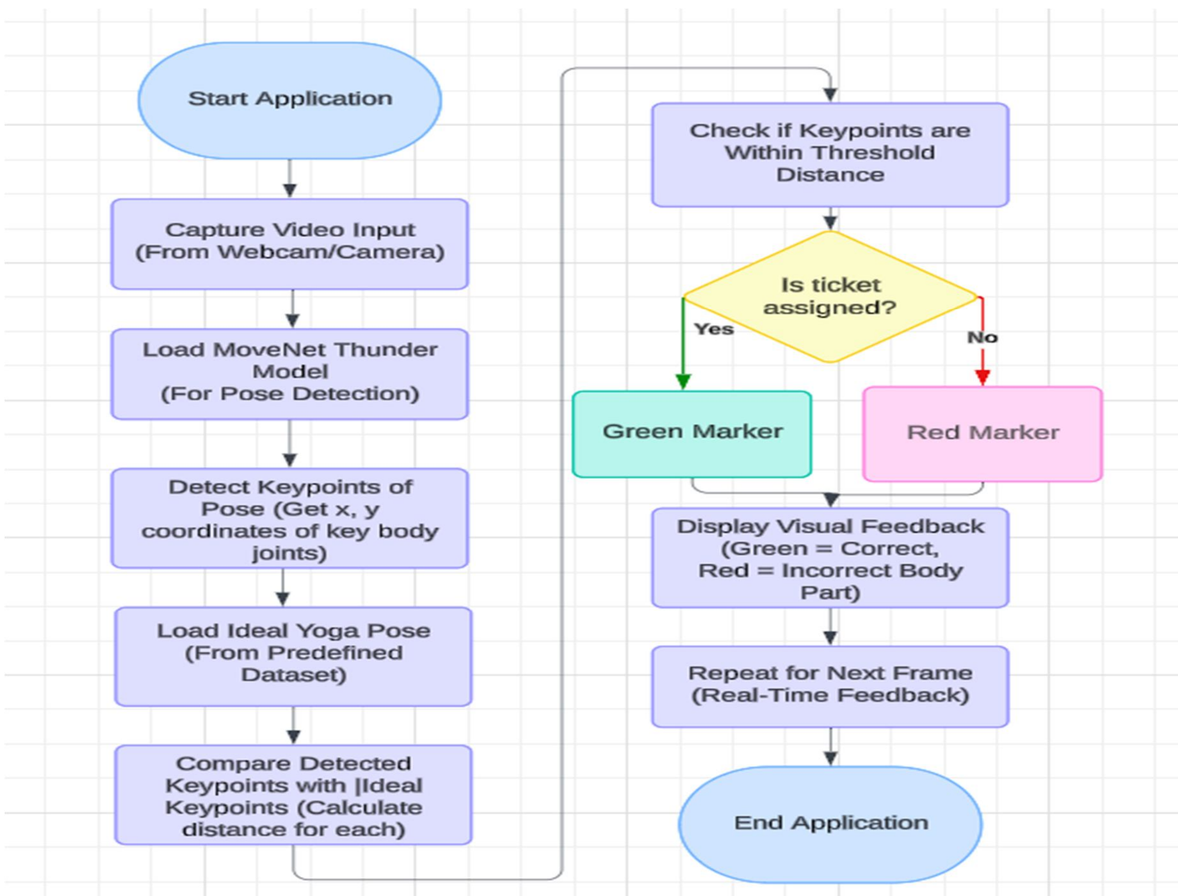

Fig. 2 Data Flow Diagram

IV. RESULTS

Metric	Value	Description
Pose Detection Accuracy	94.7%	Percentage of keypoints correctly identified in various yoga poses
Correction Feedback Accuracy	92.3%	Accuracy of suggested pose corrections based on joint angle and alignment rules
Average Response	85 MS	Time taken to process and return feedback for a frame
Supported Yoga Poses	12	Number of distinct yoga poses supported by the system
Frontend Latency (React UI)	< 50 ms	Time taken to update visual feedback on frontend
Backend Processing Time (Flask)	~35 ms	Time taken by Flask server to process a single pose frame
User Satisfaction (Pilot Survey)	91% positive feedback	Based on feedback from 30 users practicing with the system
Platform Compatibility	Web (Chrome, Firefox), Android	Supported platforms for real-time interaction

V. CONCLUSION

This project presents the successful development of a real-time system for yoga pose detection and correction using the MoveNet Thunder model. The model accurately identifies key body landmarks and evaluates user posture, enabling timely feedback to ensure correct alignment. A Flask-based backend handles the pose analysis and correction logic, while a React-based frontend offers a user-friendly interface for real-time visual guidance. The integrated system provides accurate and responsive performance, making it an effective tool for supporting at-home yoga practice and virtual instruction. Overall, the application demonstrates the potential of combining deep learning with modern web technologies to promote wellness and improve exercise form. Future work may explore the inclusion of advanced pose sets, personalized progress tracking, and integration with additional health-monitoring tools.

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