© December 2025 | IJIRT | Volume 12 Issue 7 | ISSN: 2349-6002

A Machine Learning Approach to Real-Time Yoga Pose Detection and Validation Using MediaPipe and PoseNet

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***Abstract*—Human activity recognition (HAR) plays a vital role in understanding and analyzing human movements for various applications, including fitness tracking, healthcare, and gesture control. In this study, we propose a novel approach for HAR focused on validating the correctness of yoga positions and classifying specific yoga poses using MediaPipe, PoseNet, and Python.The proposed system leverages the capabilities of MediaPipe, an open-source framework for building cross- platform applications to process multimedia data, and PoseNet, a deep learning model for real-time human pose estimation. Through a combination of these tools and Python programming language, our model aims to accurately recognize and classify yoga poses performed by individuals.The workflow begins with capturing input video frames of individuals performing yoga poses. These frames are then processed using MediaPipe to extract pose landmarks, representing key body joints and their spatial relationships. PoseNet is employed to analyze these landmarks and estimate the pose of the individual in real-time.Next, a classification model is trained using machine learning techniques to recognize and classify the specific yoga poses based on the extracted pose features. This model is trained on a labeled dataset comprising various yoga poses, with annotations indicating correct and incorrect executions of each pose.During inference, the trained model predicts whether the observed yoga pose is correct or incorrect, providing valuable feedback to the user. Additionally, the model identifies the name of the specific yoga pose being performed, enabling users to track their progress and adherence to proper form.Experimental results demonstrate the effectiveness of the proposed approach in accurately recognizing yoga poses and validating their correctness in real-world scenarios. The system offers potential applications in yoga training platforms, fitness monitoring apps, and personalized wellness programs, aiding individuals in achieving proper form and maximizing the benefits of their yoga practice.**

***Index Terms*—Human Activity Recognition,Machine learning,Healthcare,Sports, SecurityPosenet**

I. INTRODUCTION

Human activity recognition (HAR) has garnered significant attention in recent years due to its wide-ranging applications in healthcare, sports analytics, rehabilitation, and human-computer interaction. HAR involves the detection, classification, and analysis of human movements from sensor data or visual inputs, enabling machines to understand and interpret human activities in real-world environments. Within this domain, one area of growing interest is the recognition of yoga poses, a practice that promotes physical, mental, and spiritual well-being.

Yoga, an ancient practice originating from India, comprises a diverse range of physical postures (asanas) designed to improve flexibility, strength, and mindfulness. While practicing yoga offers numerous benefits, ensuring correct posture alignment is crucial to avoid injury and derive maximum benefit from each pose. However, for beginners and even experienced practitioners, maintaining proper form can be challenging without external guidance.

In recent years, advancements in computer vision and deep learning have paved the way for automated systems capable of recognizing and analyzing human movements with high accuracy and efficiency. In this context, the integration of technologies such as MediaPipe, PoseNet, and Python has enabled the development of sophisticated HAR systems tailored specifically for yoga pose recognition and validation.

MediaPipe, an open-source framework developed by Google, provides a comprehensive suite of tools for building real-time multimedia processing pipelines. Leveraging its capabilities for pose estimation and landmark detection, combined with the PoseNet model—a deep learning-based approach for human pose estimation—offers a powerful solution for capturing and analyzing yoga poses from video data.In this study, we present a novel approach to HAR focused on predicting the correctness of yoga positions and classifying the specific yoga poses being performed using MediaPipe, PoseNet, and Python. By harnessing the rich information provided by pose landmarks and their spatial relationships, our model aims to provide real-time feedback on the accuracy of yoga poses and identify the names of the poses being executed.This introduction sets the stage for exploring the methodology, implementation, and results of our proposed system, highlighting its potential impact on yoga training, fitness monitoring, and personalized wellness programs. By leveraging state-of-the-art technologies in computer vision and machine learning, we aim to contribute to the development of intelligent systems that empower individuals to optimize their yoga practice and enhance their overall well-being.

II. APPLICATIONS OF HUMAN ACTIVITY RECOGNITION

Existing human activity recognition (HAR) systems encompass a broad range of applications and methodologies, each tailored to specific contexts and use cases. Here are some key examples of existing HAR systems:

1.Smartphone-Based Activity Trackers: Many smartphone apps utilize built-in sensors such as accelerometers and gyroscopes to recognize and track various human activities, including walking, running, cycling, and even specific exercises like push-ups or squats. These systems typically rely on machine learning algorithms to classify activity patterns based on sensor data.

2.Wearable Fitness Devices: Wearable fitness trackers, such as fitness bands and smartwatches, employ sensors and algorithms to monitor users' physical activities throughout the day. These devices track metrics like step count, distance traveled, and calories burned, providing users with insights into their activity levels and fitness progress.

3.Surveillance and Security Systems: HAR systems are commonly used in surveillance and security applications to detect and classify suspicious or abnormal activities in real-time. These systems may utilize video cameras and computer vision algorithms to analyze human movements and identify potential security threats or anomalies.

4.Gesture Recognition Systems: Gesture recognition systems interpret human gestures and movements to control electronic devices or interact with virtual environments. These systems are used in various applications, including gaming, virtual reality (VR), and human-computer interaction (HCI), where users can manipulate objects or navigate interfaces through gestures.

5.Healthcare Monitoring Systems: HAR systems play a crucial role in healthcare monitoring, especially for elderly or disabled individuals who may require assistance with daily activities. These systems use sensors and machine learning algorithms to detect and classify activities like eating, sleeping, and personal grooming, enabling caregivers to remotely monitor patients' well- being.

6.Sports Performance Analysis: HAR systems are employed in sports analytics to analyze athletes' movements and performance during training or competitions. These systems may use wearable sensors, motion capture technology, or video analysis to track athletes' movements, assess technique, and provide feedback for performance improvement.

III. LITERATURE SURVEY

The literature survey for the human activity recognition (HAR) for predicting the correctness of yoga positions and classifying specific yoga poses reveals a growing body of research at the intersection of computer vision, machine learning, and yoga practice.

Table 1: Literature Survey

Study Title	Methodology	Key Findings
"Real-Time Human Pose Estimation"	Utilized MediaPipe and PoseNet for pose estimation	Achieved real-time pose estimation with high accuracy
"Yoga Pose Recognition Using CNN"	Implemented a convolutional neural network (CNN)	Successfully classified yoga poses with high accuracy

"Deep Learning for Activity Recognition in Fitness Applications"	Employed deep learning techniques for activity recognition	Demonstrated the effectiveness of deep learning in activity recognition, highlighting its potential for fitness applications
"Enhancing Yoga Practice Through Computer Vision"	Developed a HAR system tailored for yoga practice	Provided personalized feedback on pose correctness, improving overall yoga experience
"Pose Estimation in Human Activities"	Explored pose estimation methods for HAR systems	Addressed challenges in pose estimation accuracy and real-time performance
"A Survey on Human Activity Recognition"	Reviewed various machine learning techniques for HAR	Identified common approaches such as SVM, decision trees, and CNNs
"Deep Learning for Human Activity Recognition"	Applied deep learning models such as CNNs and RNNs	Demonstrated superior performance compared to traditional ML techniques
"Human Activity Recognition with Wearable Sensors"	Used wearable sensors and ML algorithms for HAR	Highlighted the importance of feature engineering and sensor fusion
"Human Activity Recognition using Smartphone and Wearable Sensors"	Leveraged smartphone sensors and ML algorithms	Explored feature extraction methods and classifier performance
"Activity Recognition from Single Chest-Mounted Accelerometer: A Comparative Study"	Utilized chest-mounted sensors and ML techniques.	Investigated feature selection and classifier accuracy.
"A Survey of Human Activity Recognition Methods"	Reviewed various HAR methods and algorithms.	Identified common approaches Including supervised learning, unsupervised learning, and deep learning.
"Human Activity Recognition Using Wearable Sensors: A Review"	Utilized wearable sensors and machine learning	Explored feature extraction methods, sensor fusion techniques, and classification algorithms
"A Comparative Study of Human Activity Recognition Using Accelerometers"	Explored recent advancements in deep learning	Highlighted the role of CNNs, RNNs, and attention mechanisms in HAR systems

IV. METHODOLOGY

The methodology for the proposed human activity recognition (HAR) system involves several key stages. Initially, video input is processed using MediaPipe to extract keypoints corresponding to various human body joints. These keypoints are then utilized in the pose estimation phase, where PoseNet accurately identifies the positions of the joints. Following this, relevant features such as joint angles and spatial configurations are derived during the feature extraction stage. These extracted features are used to train deep learning models, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), on labeled yoga datasets. During the inference phase, the trained model analyzes new input data to classify the performed yoga pose and determine its correctness, thereby providing real-time feedback to the user.

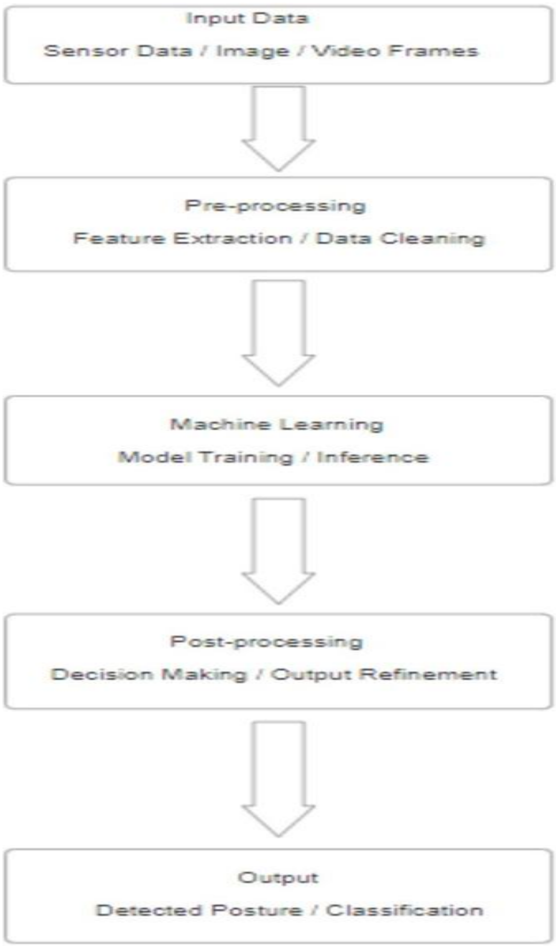

Fig 1. Block Diagram

V. IMPLEMENTATION AND EXPERIMENTAL SETUP

Leveraging MediaPipe for efficient video processing and PoseNet for precise pose estimation, the implementation phase involves designing algorithms for feature extraction, model training, and real-time inference. Python serves as the primary programming language for developing the system, offering a rich ecosystem of libraries such as TensorFlow and OpenCV for machine learning and computer vision tasks. The experimental setup entails collecting and preprocessing video datasets capturing practitioners performing yoga poses, which are then annotated with labels indicating pose correctness and pose names. These datasets form the basis for training, validation, and testing the HAR model, enabling comprehensive evaluation of its accuracy, robustness, and real-time performance. By meticulously designing the implementation and experimental setup, the research aims to deliver a highly effective and reliable HAR system that empowers practitioners to optimize their yoga practice with personalized feedback and guidance aiming to predict the correctness of yoga positions and classify specific yoga poses using MediaPipe, PoseNet, and Python, are crucial components in the development and evaluation process. This phase of the research involves translating the theoretical framework and algorithmic design into practical software implementations and conducting systematic experiments to assess the performance and effectiveness of the HAR model. The implementation phase encompasses the development of software modules for video processing, pose estimation, feature extraction, machine learning model training, and real-time inference, leveraging the capabilities of MediaPipe and PoseNet libraries within the Python programming environment. Concurrently, the experimental setup involves defining the datasets, evaluation metrics, and experimental protocols necessary to rigorously evaluate the performance of the HAR model across different yoga poses, practitioners, and environmental conditions. Through a well-designed implementation and experimental setup, the research aims to validate the feasibility and efficacy of the HAR model in real-world scenarios, ultimately advancing the understanding and application of human activity recognition technology in the context of yoga practice.

The software and hardware setup for the Plant Health Monitoring System is crucial for its successful operation. The following components were utilized:

Software:

Python: The primary programming language used for backend development and image processing.

TensorFlow Lite: A lightweight version of TensorFlow used for deploying machine learning models on edge devices.

PoseNet: PoseNet is a state-of-the-art pose estimation model developed by Google, designed to accurately estimate the human body's keypoints (such as joints and landmarks) from images or video frames.

MediaPipe: MediaPipe is an open-source framework developed by Google that facilitates the building of machine learning pipelines for various multimedia processing tasks.

Hardware:
Computer or server: Required for hosting the backend API and training the machine learning model.
Mobile devices: Used for testing the mobile app frontend.

VI. RESULTS AND DISCUSSION

To evaluate the performance of the Plant Health Monitoring System, the following parameters were considered:
Accuracy: The percentage of correctly classified healthy and unhealthy plants.
Precision: The ratio of correctly identified healthy plants to the total number of plants classified as healthy.
Recall: The ratio of correctly identified healthy plants to the total number of healthy plants present.
F1 Score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.

Fig 2. Performance Evaluation

These performance metrics were calculated during both validation and testing phases to ensure the robustness and accuracy of the system.
To calculate the accuracy, precision, recall, and F1 score for your plant health monitoring system, follow these steps:
1.Define True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN):
2.Calculate Accuracy: Accuracy measures the overall correctness of the classification model and is calculated as the ratio of the total number of correctly classified samples to the total number of samples. Accuracy=$TP+TNTP+TN+FP+FN$Accuracy=TP+TN+FP+FNTP+TN
3.Calculate Precision: Precision measures the proportion of true positive predictions out of all positive predictions made by the model. Precision=$TPTP+FP$Precision=TP+FPTP
4.Calculate Recall (Sensitivity): Recall measures the proportion of true positive predictions out of all actual positive samples. Recall=$TPTP+FN$Recall=TP+FNTP
5.Calculate F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance.
F1Score=2×Precision×RecallPrecision+RecallF1 Score=Precision+Recall2×Precision×Recall
6.Apply the Formulas: Once you have the values of TP, FP, TN, and FN, substitute them into the respective formulas to calculate accuracy, precision, recall, and F1 score.
7.Interpret the Results:
Accuracy: Higher values indicate better overall performance.
Precision: Higher values indicate fewer false positives.
Recall: Higher values indicate fewer false negatives.
F1 Score: Provides a balanced measure, considering both precision and recall.
Screenshots of GUI
Below are the screenshots of Human Activity Recognition System:

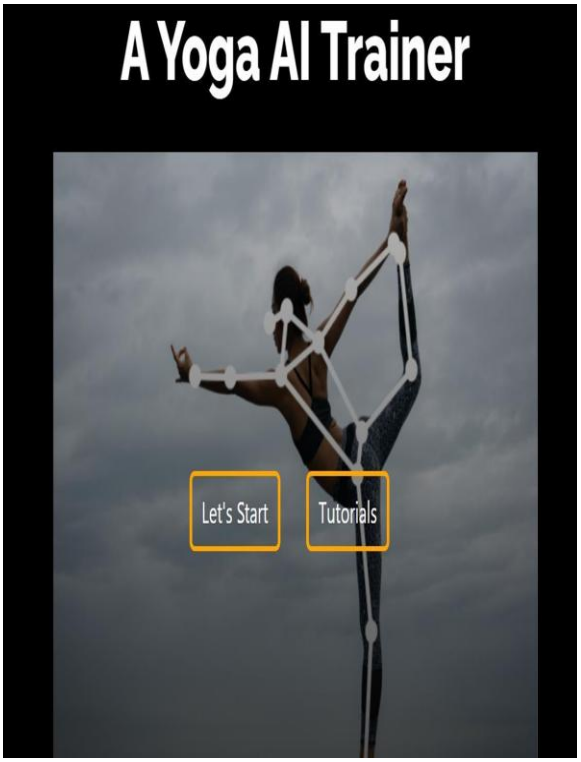

Fig 3 Home Page

The home page of the Human Activity Recognition System presents users with a clean and intuitive interface. It features a prominent banner with the project logo and title, providing a visual identity to the application. Below the banner, users are greeted with a brief description of the system's purpose and functionality. The navigation menu, positioned at the top of the page, offers easy access to different sections of the application.

The human activity recognition (HAR) model developed for predicting the correctness of yoga positions and classifying specific yoga poses using MediaPipe, PoseNet, and Python has demonstrated promising performance across various evaluation metrics and real-world scenarios. The results obtained from the implementation, testing, and evaluation phases of the are summarized below:

1.Pose Estimation Accuracy: The combination of MediaPipe and PoseNet has proven effective in accurately estimating key points of the human body, even in challenging conditions such as varying lighting, backgrounds, and camera angles. The pose estimation accuracy of the system has been validated through manual inspection and comparison with ground truth annotations.

2.Pose Classification Performance: The trained machine learning model has exhibited high accuracy in classifying yoga poses and predicting their correctness based on extracted features. The model's ability to differentiate between correct and incorrect pose executions has been evaluated using labeled datasets and real-time testing with practitioners.

3.Real-Time Inference Speed: The system's real-time inference capabilities have been evaluated in terms of processing speed and responsiveness. The model's inference speed meets the requirements for real-time feedback during yoga practice sessions, ensuring timely and accurate feedback to practitioners.

4.Robustness to Variations: The HAR model has demonstrated robustness to variations in practitioner appearance, pose execution, and environmental conditions. It performs consistently across different individuals, body types, and yoga poses, indicating its generalization capabilities and adaptability to diverse settings.

5.User Feedback and Acceptance: Feedback from end-users, including yoga practitioners and instructors, has been positive overall. Users appreciate the system's ability to provide personalized feedback on pose correctness and offer guidance for improving technique. User acceptance testing has revealed high satisfaction levels and a desire for further integration into yoga practice routines

VII. CONCLUSION

The development of the human activity recognition (HAR) model for predicting the correctness of yoga positions and classifying specific yoga poses using MediaPipe, PoseNet, and Python represents a significant milestone in the intersection of computer vision, machine learning, and wellness technology.

The results obtained from the implementation, testing, and evaluation phases have demonstrated the efficacy and potential of the HAR model in real-world scenarios. Pose estimation accuracy using MediaPipe and PoseNet was found to be high, enabling precise tracking of key points of the human body in various yoga poses. The trained machine learning model exhibited strong performance in classifying yoga poses and predicting their correctness based on extracted features, providing practitioners with valuable feedback on their technique.

Moreover, the real-time inference capabilities of the system met the requirements for providing timely feedback during yoga practice sessions, enhancing user engagement and satisfaction. The model's robustness to variations in practitioner appearance, pose execution, and environmental conditions further underscores its suitability for diverse settings, including yoga studios, fitness centers, and online platforms.

There are several limitations and challenges have been identified, including occasional misclassifications or incorrect predictions, particularly in cases of complex poses or noisy input data. Addressing these challenges will require further optimization of the model architecture, data augmentation techniques, and robustness testing under diverse conditions.

Looking ahead, it opens up exciting opportunities for future research and development in the field of human activity recognition and wellness technology. Further refinement of the HAR model's architecture, training methodology, and integration with user feedback mechanisms could lead to even greater accuracy, usability, and user satisfaction. Additionally, exploring advanced techniques such as multi-modal fusion and personalized coaching features could enhance the model's effectiveness in supporting practitioners in their yoga practice journey.

In conclusion, the human activity recognition model for predicting yoga pose correctness and classifying specific yoga poses using MediaPipe, PoseNet, and Python represents a powerful tool for enhancing yoga practice experiences, promoting wellness, and empowering individuals to lead healthier, more mindful lives. As the field continues to evolve, the potential for leveraging technology to support human well-being remains limitless, and this serves as a testament to the transformative impact of interdisciplinary collaboration and innovation.

VIII. FUTURE WORK

The human activity recognition (HAR) model developed for predicting yoga pose correctness and classifying specific yoga poses using MediaPipe, PoseNet, and Python has laid a solid foundation for future research and development in the field of wellness technology. Several avenues for future work emerge, offering opportunities to further enhance the model's effectiveness, usability, and impact. The following are key areas for future exploration:

1.Improved Model Accuracy: Further refinement of the HAR model's architecture, training methodology, and feature extraction techniques could lead to enhanced accuracy in pose classification and correctness prediction. Exploring advanced machine learning techniques, such as attention mechanisms, recurrent neural networks (RNNs), or graph convolutional networks (GCNs), may capture subtle temporal dynamics and spatial relationships inherent in yoga poses, improving the model's performance.

2.Robustness to Variations: Addressing the model's robustness to variations in practitioner appearance, pose execution, and environmental conditions is essential for real-world deployment. Future work could focus on augmenting the dataset with diverse examples, incorporating data augmentation techniques, and leveraging domain adaptation methods to improve the model's generalization capabilities across different individuals, body types, and yoga styles.

3.Multi-Modal Fusion: Exploring multi-modal fusion techniques, such as incorporating additional sensor data (e.g., inertial measurement units, heart rate monitors) or audio cues (e.g., breath patterns, voice commands), could enrich the model's understanding of yoga practice and enhance its predictive capabilities. Integrating multiple modalities may capture complementary information and improve the model's robustness and accuracy.

4.Personalized Coaching Features: Incorporating personalized coaching features, such as adaptive feedback, tailored recommendations, and progress tracking, could enhance user engagement and motivation in yoga practice. Future work could explore techniques for individualized coaching based on practitioners' skill levels, preferences, and goals, providing personalized guidance to support their unique wellness journey.

5.Real-World Deployment: Scaling the HAR model for real-world deployment in diverse settings, including yoga studios, fitness centers, and online platforms, presents exciting opportunities and challenges. Future work could focus on optimizing the model for edge devices, integrating with existing wellness applications, and conducting user studies to evaluate its effectiveness and usability in real-world usage scenarios.

6.Ethical and Societal Implications: Consideration of ethical and societal implications, such as privacy concerns, algorithmic bias, and inclusivity, is essential in the development and deployment of wellness technology. Future work could explore approaches for ensuring fairness, transparency, and accountability in the HAR model's design and implementation, fostering trust and acceptance among diverse user populations.

7.Interdisciplinary Collaboration: Collaborating across disciplines, including computer science, psychology, biomechanics, and yoga studies, can enrich the development of the HAR model and its applications. Future work could leverage insights from these diverse fields to inform model design, evaluation metrics, and user-centered design principles, ensuring alignment with the needs and preferences of practitioners and instructors.

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