Real-time machine learning-based posture correction for enhanced exercise performance

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Article Info

Article history:

Received Jul 18, 2024
Revised Apr 12, 2025
Accepted May 24, 2025

Keywords:

Human pose estimation
Machine learning
MediaPipe
OpenCV
Tensorflow

ABSTRACT

Poor posture and associated physical health problems have grown more common as technology use increases, especially during workout sessions. Maintaining proper posture is essential to increasing the efficacy of your workouts and avoiding injuries. The research paper presents the development of a machine-learning model designed to provide real-time posture correction and feedback for exercises such as squats and planks. The model uses MediaPipe for precise real-time posture estimation and OpenCV for analyzing video frames. It detects poor posture and provides users with instant corrective feedback on their posture by examining the angles between important body parts, such as the arms, knees, back, and hips. This innovative method enables a thorough evaluation of form without requiring face-to-face supervision, opening it up to a wider audience. The model is trained on real-world workout datasets of people performing exercises in different positions and postures to ensure that posture detection is reliable under various user circumstances. The system utilizes cutting-edge machine-learning algorithms to demonstrate scalability and adaptability for future training types beyond squats and planks. The main goal is to provide users with a model that increases the efficacy of workouts, lowers the risk of injury, and encourages better exercise habits. The model's emphasis on usability and accessibility makes it potentially a vital tool for anyone looking to enhance their posture and general fitness levels.

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1. INTRODUCTION

Maintaining a proper posture when exercising is crucial for maximizing physical performance and lowering the chance of injury [1]. Regular physical activity is beneficial for cardiovascular health, muscular strength, and general well-being, according to several studies. According to the World Health Organization, nearly 31% of the world's adult population, amounting to over 1.8 billion adults, are physically inactive [2]. However, especially for those who are new to exercising, poor exercise practices can result in a variety of difficulties, such as acute injuries and long-term musculoskeletal concerns. This emphasizes how crucial it is to maintain proper form, particularly while performing basic exercises like planks and squats.

Technological developments have made it easier to develop technology for tracking and adjusting posture while exercising. Recent studies have proposed machine learning and computer vision techniques such as convolutional neural networks (CNN), support vector machines (SVM), MediaPipe pose, and DeepPose are used to develop models for analyzing and examining human body posture. Many of the current solutions, however, need modern technology or skilled personnel, which may restrict accessibility for people in Tier 2 and Tier 3 cities where these resources might not be easily accessible [3]–[5].

Even with great advancements, there are still difficulties in developing real-time feedback systems that let users examine their body posture during workouts on their own without expert supervision. For those who want to get fitter in distant or disadvantaged locations, traditional training techniques sometimes need in-person instruction, which can be a barrier. Recent research shows that one of the main reasons people are hesitant to work out or engage in weight training living in Tier 2 or Tier 3 cities is the high cost associated with the trainer fee, in addition to the expensive gym membership fees.

In our model to solve these challenges, pose estimation techniques such as MediaPipe are used which detect up to 33 key points such as left hip, right hip left knee, and right knee in the human body for analyzing the human body posture [6], [7]. To train our model, a custom dataset was compiled which consisted of people performing exercises such as squats and planks in different positions in video format. The model analyzes the angles between various human body joint points to examine the correctness of posture during a workout. The model narrows the gap between the need for professional training and the economic challenges that are faced by people living in remote areas where such professional training services are not available.

2. RESEARCH METHOD

2.1. Related work

Yang *et al.* [8] proposed a system which helps in analyzing human body posture while performing exercise. The proposed system examines the human body posture by analyzing the captured video of the user using OpenCV. The system helps in generating suggestions for the users to perform the exercise correctly by analyzing the coordinate location of key points of the human body. It uses OpenPose for performing pose estimation for exercises such as squats and push-ups.

Flores *et al.* [9] presented an application, which records users working out using the cameras on their smartphones and uses a fuzzy inference system (FIS) to classify workout performance after skeletonizing the user and extracting joint angles. Ajay *et al.* [10] presented a deep learning model that makes use of MediaPipe, a machine learning and computer vision solution, and BlazePose, a real-time pose estimation model that analyzes exercise movements and gives users immediate feedback, making at-home workouts safer and more productive by confirming posture and providing recommendations for correction. Moreover, it lowers the expense of hiring qualified personal trainers and improves accessibility. Dsouza *et al.* [11] highlighted the development of a smart gym trainer program that uses computer vision and machine learning to estimate human position. The technology offers real-time feedback using deep learning and CNNs by comparing a user's activity with that of a professional athlete, making at-home workouts safer and more efficient.

Lovanshi and Tiwari [12] assessed deep learning-based human posture estimate methods, including OpenPose, ViTPose-B, HRNet, AlphaPose, DenseNet, EfficientPose, DensePose, and Hourglass using the COCO and MPII datasets. Metrics such as average accuracy (AP) and probability of accurate key points (PCK) are the main focus of the assessment. On the COCO dataset, ViTPose-B performs better in AP, and Hourglass performs better in PCK on MPII.

Agrawal *et al.* [13] used machine learning to identify yoga poses. For 10 poses, YOGI had 5459 pictures. The tf-pose-estimation algorithm generated the skeleton of the practitioner to get 12 angles for the pose detection and correction algorithm. Six classification models achieved an accuracy of 94.28%.

Zhong *et al.* [14] presented DSPNet, a deep supervision pyramid network with a minimal computational cost that is intended for human posture estimation. It tackles the problem of existing posture estimation algorithms' high computing burden, which renders them unsuitable for devices with low resources. The suggested DSPNet enhances multi-scale getting capabilities without adding more parameters by combining a deep supervision pyramid design with a lightweight upsampling unit.

Wang *et al.* [15] proposed deep learning-based methods for 3D human pose estimation that take into account a variety of input formats, including one or more views, one or more photos, and one or more individuals. It talks about body form representation using parametric models such as SCAPE, SMPL, and DensePose, and it divides 3D pose estimation techniques into single-stage, two-stage (top-down and bottom-up), and direct estimation methods. Munea *et al.* [16] proposed that 2D human pose estimation divides 2D human posture estimate into two categories: single-person and multi-person. It covers many methods, uses, difficulties, and significant studies conducted in this area. By analyzing current approaches and their shortcomings, the review seeks to provide novices with basic knowledge and direct researchers in creating better models.

Bin *et al.* [17] explained a study on human pose estimation, to further enhance localization performance, it is desirable to represent the structural linkages between body key points because they are interconnected. In this study, a novel model is offered called posture graph convolutional network (PGCN), to leverage these significant associations for posture estimation. It is built on original graph convolutional networks.

Chen *et al.* [18] presented a study that deals with one of the most basic and difficult issues in computer vision is vision-based monocular human pose estimation, which seeks to determine the human body's posture from input pictures or video sequences. The deep learning-based 2D and 3D human posture estimation techniques released since 2014 are reviewed in-depth in this study. The difficulties, key frameworks, benchmark datasets, assessment measures, performance comparison, and some exciting prospects for future study are outlined in this paper.

Srijan *et al.* [19] provided an analysis of an individual's everyday posture and how it impacts their bone health. This article assembled a study on posture. To better understand how to prevent various musculoskeletal diseases in the general population, this study conducts a pilot review and analyzes several previous research studies on posture detection and correction using machine learning and deep learning approaches.

Kim *et al.* [20] suggested a real-time Pilates posture detection system on a smartphone for workout monitoring. The eight Pilates exercises that we were trying to identify were the Bridge, Head roll-up, Hundred, Roll-up, Teaser, Plank, Thigh stretch, and Swan. Initially, body joint characteristics are extracted using the Blazepose model. Next, using the body traits that were retrieved, we created a deep neural network model that can identify Pilates.

Aonty *et al.* [21] presented a group-based convolutional neural network model used to present a human posture estimation technique. The suggested technique uses a bottom-up parsing approach to provide characteristics for the extraction of the human body's skeletal important points. Furthermore, it uses the non-parametric description for the key point association vector field to group anatomical key points for each person.

Supanich *et al.* [22] presented a machine learning-based posture classifier system that can identify different types of workout postures. The objective of this research is to develop an automated model that can accurately evaluate workout posture instead of hiring a personal trainer. We use the MediaPipe pose estimation framework to extract body skeleton sequences from a video data source that was captured by a fitness specialist using a basic web camera.

Kanchanapaetnukul *et al.* [23] explained a study whose purpose is to provide a method for detecting and evaluating Tai Chi exercise postures to assist the elderly in practicing on their own at home. The graphical user interface (GUI) on the system records the movements of senior citizens performing Tai Chi, and Tai Chi video clips are available for presentation. Using two Kinect cameras, the system will identify and evaluate the old person's movement to determine if it is right or not.

Hande *et al.* [24] aimed to investigate how recent advancements in pose estimation, correction, and recognition are applicable to calculate exercise postures and offer insightful feedback on methods to identify particular approach issues linked to a significant likelihood of injury for common exercises. Action recognition will be in charge of gathering, categorizing, and organizing the data in addition to training and combining it with real-time data to give feedback to the user.

Singhal *et al.* [25] suggested a model providing the user with real-time, lightweight fault point identification. To assist the user in making the necessary corrections, the wrong location is shown in real time on top of their video stream. The user receives the necessary information by being informed when they are sitting in an improper posture and by seeing the total amount of time spent in an improper posture during the session and addresses the prevalent problem of privacy concerns by enhancing the hand gesture recognition function with federated learning and personalization, while still enabling users to tailor their experience. Negi *et al.* [26] explained a study whose purpose is to develop a machine learning model which analyses real-time human posture using OpenPose focussing on body joint predictions in different poses like T-pose, Warrior pose, Tree-pose.

2.2. Proposed work

The approach for the posture analysis begins with constructing a custom dataset by combining multiple public datasets. Key body landmarks are extracted during preprocessing, labelled, and stored for model training. After labelling, the landmarks are transformed into feature vectors to classify poses. Finally, the model provides real-time feedback by comparing user poses to predefined exercises, aiding in accurate exercise performance.

2.2.1. Data collection

A new dataset was created by combining multiple data sources specifically designed for exercise pose detection, with an emphasis on squats and planks—two activities that need exact posture for proper execution. Exercise videos were recorded in a variety of settings to capture a wide range of body types and movement variations. Key pose features, represented as floating-point values representing joint coordinates and limb angles, were collected from each movie and combined into structured CSV files that comprised input vectors (flattened pose parameters) and output vectors (labels indicating correct posture). The dataset was thoroughly checked to ensure that the input and output items were aligned, and then divided into training (80%) and testing (20%) sets.

2.2.2. Preprocessing

The pre-processing phase entailed standardizing the video data to a uniform frame rate of 12 frames per second and scaling it to 720×1280 pixels to ensure pose detection accuracy. The MediaPipe library was used to recognize major body landmarks inside each frame, allowing essential position information to be extracted quickly. The landmarks were organized into NumPy arrays and saved as CSV files for quick access during model training.

2.2.3. Labeling

The labelling step is necessary for training the posture estimation model. Each frame retrieved from the training films was painstakingly evaluated by certified fitness specialists, who labelled the posture as correct or incorrect. This expert annotation approach guarantees that the dataset appropriately represents suitable workout techniques, laying a good foundation for model training.

In addition to the primary labels, metadata for each stance was documented, such as posture category, intensity level, and variants. This contextual information improves the dataset's usability by enabling more detailed analysis and understanding of outcomes. Consistency checks were done throughout the labelling process to ensure high data integrity, and any anomalies were addressed swiftly. This thorough labelling approach is critical for generating a dependable machine-learning model capable of accurate posture recognition and correction.

2.2.4. Pose estimation

A TensorFlow model is used to estimate pose and classify workout postures based on landmark coordinates from the MediaPipe framework. The procedure starts with transforming landmark data into a Feature Vector, which is accomplished by centering the posture at the origin, scaling it to a standard scale, and flattening the coordinates into a one-dimensional array. The MediaPipe library detects poses in real time, extracting essential body landmarks from pictures or video frames. The neural network architecture includes an input layer with 34 neurons which correspond to the flattened coordinates, two hidden layers with 128 and 64 neurons (both using the ReLU6 activation function), and a dropout layer with a 0.5 dropout rate to reduce overfitting. The output layer uses the SoftMax activation function to divide the pose into several categories. Training is carried out using an appropriately labelled dataset loaded with the data divided into batches for optimum processing. To reduce errors in classification, the model utilizes a categorical entropy cross as a loss function, which is iterated numerous times over. Performance evaluation includes parameters such as accuracy, precision, recall, and training process visualization, as well as the creation of a confusion matrix to provide a full assessment of the model's classification performance.

2.2.5. Error estimation and feedback

The feedback mechanism is an essential component of the application, giving users real-time assistance to adjust their posture during exercise. After gathering key points from the user's video feed, the model compares them to a preset list of key points for optimal posture. This comparison gives an error score, which measures the user's posture deviation from the correct standard.

When large deviations are noticed, the user interface provides fast feedback. This feedback contains visual clues and correction instructions that help users alter their posture effectively. The real-time nature of this feedback motivates users to participate actively in their workout regimens, resulting in improved technique and reduced chance of injury. By offering rapid corrections, the application assists users in adopting effective workout techniques, ultimately improving performance and safety.

3. RESULTS AND DISCUSSION

The model demonstrated effectiveness in analyzing and suggesting real-time feedback during plank and squat workout exercises, achieving over 72% accuracy in identifying correct body alignment. This result validates the original theory that exercise posture correction could be improved by a machine learning-based technique. Accurate posture analysis that supports the goals of the study was made possible by the precise estimation of joint angles made possible by the integration of the MediaPipe framework.

Figure 1 shows the significant insights regarding our machine learning model's performance obtained from training it over 200 epochs. The training accuracy evolution is depicted in Figure 1, where the accuracy increases quickly from 10% to 70% in the first 25 epochs before gradually improving to 72% in the end. Accordingly, Figure 2 shows the training loss, which gradually converged to about 0.1 after dropping sharply from 1.2 to 0.2 in the first 25 epochs. These outcomes demonstrated the model's effective learning capacity, especially in the first phases of training. A final training accuracy of 72% suggests that the training data was implemented effectively.

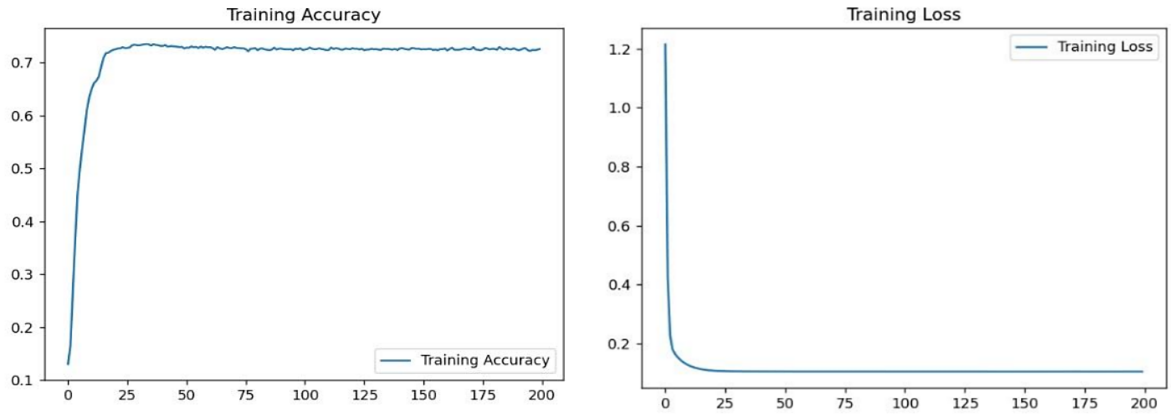

Figure 1. Training accuracy and training loss graph of the model

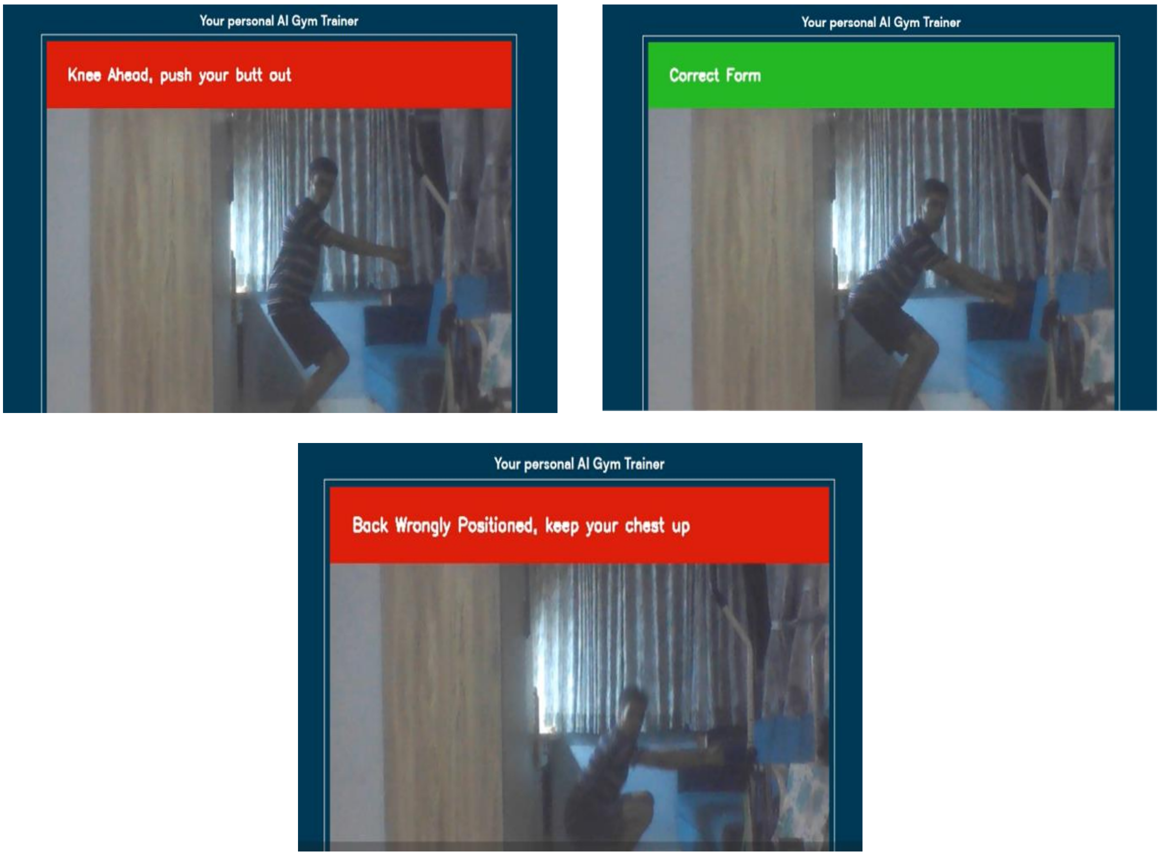

Figure 2. Models' performance on different body position

Figure 2 demonstrates the model ability to analyze the human body posture and give corrective instructions while performing exercises in different positions. Based on analysis of the body posture the model gives real time suggestions to improve it.

In contrast to earlier research, the results align with the body of literature emphasizing the benefits of employing sophisticated methods for posture correction. The efficiency of deep learning methods in real-time applications, for example, was also mentioned in previous studies. The study's strength lies in the combination of MediaPipe for landmark detection with TensorFlow for posture classification, which provides a more reliable solution than conventional techniques. However, there were several drawbacks, such as variations in user responses according on body shape and background lighting conditions. Furthermore, based on the responses given, users reported having difficulties fitting their whole-body posture, which presented an unanticipated obstacle and highlighted areas for user interface design development.

In conclusion, the study successfully showed how machine learning improves exercise performance by accurately recognizing posture. These results highlight how crucial it is to provide real-time feedback in fitness programs. To increase user engagement and efficacy, future studies should concentrate on expanding the dataset to encompass a wider variety of body shapes and postures and exploring additional feedback mechanisms.

4. CONCLUSION

With an accuracy of more than 72% in analyzing and determining the correct body posture for the user while performing exercises like squats and planks, the research has shown the effectiveness of our model for real-time correction of posture. These results demonstrate that incorporating cutting-edge machine learning methods into fitness apps can greatly improve users' capacity to maintain correct body posture. Which in turn lowers the chance of injury and boosts the efficacy of workouts overall.

These findings have significance for more than just individual fitness enthusiasts; they also show how technology-driven solutions may help communities adopt healthy exercise practices. People who do not have the means for expert training or direction can utilize it since the real-time feedback method enables users to obtain prompt remedial advice. This application can save healthcare expenses connected to exercise-related injuries and promote proper exercise practices, both of which have long-term health advantages.

Additionally, this study opens the way for several upcoming expansions and applications. Future versions of the software could include exercises other than planks and squats, making it suitable for a greater variety of physical activity. Additionally, adding functions like progress monitoring and customized exercise routines might improve user motivation and engagement. To improve the feedback systems and guarantee that the feedback given is useful and efficient, partnerships with fitness instructors and medical specialists might also be investigated. In the end, the results highlight how important technology can be to the fitness sector, especially when it comes to improving accessibility and customizing the user experience. This research opens the door for creative solutions that support physical health and well-being in a variety of groups by tackling unanswered problems about user interface design and the model's adaptation to different body types.

ACKNOWLEDGEMENTS

The authors thank our colleagues from Shah and Anchor Kutchhi Engineering College who provided insight and assistance that conspicuously assisted the research carried by us. Without their persistent support, conducting research would not have been possible.

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