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PoseTracker: Accuracy Evaluation of AI-Based Mobile Application for Exercise Posture Feedback Using MediaPipe as Human Pose Estimation Model

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Abstract—**In recent years, the rising of public health awareness has increased fitness activities participation. However, improper exercise form remains a significant contributor to injuries, particularly in unsupervised environments. To address this, PoseTracker's accuracy was evaluated as a native Android application that provides real-time feedback on exercise posture through MediaPipe based Human Pose Estimation (HPE) model. The system extracts 33 3D body landmarks, normalizes them to account for body scale, and employs cosine similarity to compare user movements against a reference dataset. Evaluations involving participants aged between 17 to 50 years old and 240 repetitions across four exercises demonstrated high detection accuracy: 88.33% for jumping jacks, 85% for squats, 83.33% for push-ups, and 82% for sit-ups. While performance can be influenced by environmental factors such as inconsistent lighting, camera positioning and incomplete body visibility, these results highlight the potential for lightweight, AI driven tools to support safe and self-guided fitness routines. Overall, the evaluations indicate that PoseTracker achieves reliable detection accuracy in distinguishing correct and incorrect exercise posture across multiple movement types under realistic conditions. Although performance variability exists due to environmental and system constraints, the accuracy levels observed demonstrate the feasibility of MediaPipe based Human Pose Estimation (HPE) for practical posture assessment in mobile fitness applications.**

Keywords—Mobile Application; Computer Vision; MediaPipe; Physical Exercise; Posture Detection

I. INTRODUCTION

A. Background

In recent years, public awareness of healthy lifestyles has risen and led to increased participation in fitness activities [1]. Regular exercise is now widely adopted for maintaining physical health, particularly with fitness training becoming more popular due to its accessibility and versatility [1]. However, despite these benefits, improper exercise form remains a common issue that increases the risk of musculoskeletal injuries, especially without proper knowledge, training or supervision [2], [3], [4].

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With the growing emphasis on fitness training, mobile applications are widely used for tracking activity [5], [6]. However, these applications are limited in providing pose-based feedback. Recent advancements in Artificial Intelligence (AI) have demonstrated significant potential for accurately detecting and analyzing complex patterns [7], [8], [9], [10], [11], [12]. Multiple studies have highlighted the capability of AI-based systems as HPE models to evaluate human body posture effectively using MediaPipe pose technology [8], [13], [14], [15].

This research aims to evaluate the accuracy of PoseTracker, a mobile fitness application that integrates a MediaPipe based pose estimation in providing appropriate feedback for exercise execution. The system is evaluated based on its ability to detect correct and incorrect forms in four exercises: push-up, sit-up, squat, and jumping jacks. Previous research titled "Comparative analysis of pose estimation models for mobile motion tracking applications" where it's focused on identifying the most suitable AI-based pose estimation model between MediaPipe, OpenPose, and MoveNet for mobile platforms. Continuing from that work, this study evaluates the accuracy of the chosen model by integrating updated algorithms to improve performance.

B. Introduction to Fitness Injuries & Posture Issues

Engaging in fitness activities is widely recognized for plenty of health benefits, including enhanced muscle strength and overall physical fitness. However, despite these positive outcomes, there is a growing concern regarding the risk of injuries associated with incorrect posture and wrong techniques, particularly during non-vised or self-guided exercise routines. Without professional supervision or proper guidance, people might unintentionally perform movements that place excessive strain on certain parts of the body, increasing the risk of injury [16].

Among the most reported injuries are those affecting the shoulders, elbows, spine, and knee [2]. These areas are especially vulnerable due to their involvement in various fitness movements. Repetitive strain injuries (RSIs) can happen when these areas are subjected to overuse without proper recovery, which can lead to pain, reduced mobility, and in some cases, long-term complications. Ultimately, proper technique and recovery are key to reducing these risks [17].

C. Traditional Approaches to Injury Prevention and Posture Correction

Traditional approaches to injury prevention and posture correction focus heavily on the quality of movement of gestures and body alignment during exercise. These methods recognize poor posture and repetitive wrong movements as primary contributors to musculoskeletal injuries. These approaches highlight the importance of executing movements with correct joint positioning to minimize excessive load on vulnerable body segments. Studies have consistently shown that improper movement patterns such as misaligned joints, unstable core posture significantly increase the risk of both acute and overuse injuries, particularly in the upper and lower extremities [18]. Although warm-up intervention programs (WIP) and dynamic stretching are integral components of traditional injury prevention strategies, their success depends on how well their capacity to facilitate correct movement gestures and sustained postural control throughout exercise execution [19]. Furthermore, dynamic warm-ups have been shown to outperform static stretching in improving performance and preventing injuries, as they better support functional movement patterns during exercise [20]. Overall, these traditional approaches underscore the significance of maintaining proper movement gestures and posture throughout physical activity is fundamental to reducing injury risk and optimizing performance [18], [19], [20].

D. Mobile Applications in Fitness & Health

Mobile technologies have significantly reshaped health and fitness practices, offering users new and accessible ways to engage with personal routine. The rapid advancement of mobile application development has played a crucial role in this transformation. Today, Mobile applications have become practical tools for exercise instruction and health monitoring making fitness support more accessible [21].

E. MediaPipe as HPE Model in Fitness

Advancements in AI and computer vision technology facilitate the ability to analyze human posture with HPE models. MediaPipe Pose is a lightweight model by Google that is supported by both mobile phones and desktops [22], [23]. It processes RGB images to estimate 33 3D body landmarks with relatively high accuracy.

HPE models also have been applied in health-related fields for many purposes like physical therapy exercises [24], detecting falls for elderly [25]. In fitness domain, HPE models have enabled applications such as virtual fitness trainer software to provide coaching and real time input [26], posture correction during multiple workout types [27], [28], [29], [30], fitness movement completeness detection[31] and pose accuracy in exercise [32], [33]. Even though pose estimation models are widely used, many current applications mainly focus on analyzing movement rather than helping users prevent injuries. This opens the chance to create AI-based systems that not only detect posture issues but also give personalized corrections based on the user's movements.

II. PROPOSED METHODS

A. System Overview

According to our previous research titled "Comparative analysis of pose estimation models for mobile motion tracking applications", MediaPipe was selected due to provide a favorable balance between estimation accuracy and real time performance. Based on these findings, the system was implemented as a native Android application using Kotlin, as its direct support with MediaPipe Integration. Jetpack Compose was used as the user interface application and follows the Model View ViewModel (MVVM) architectural pattern to strengthen scalability and maintainability.

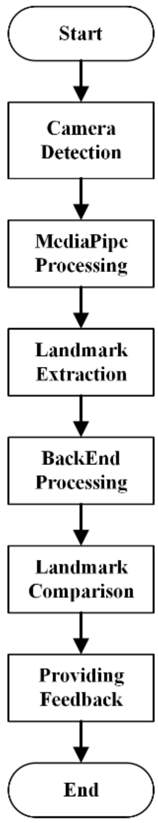
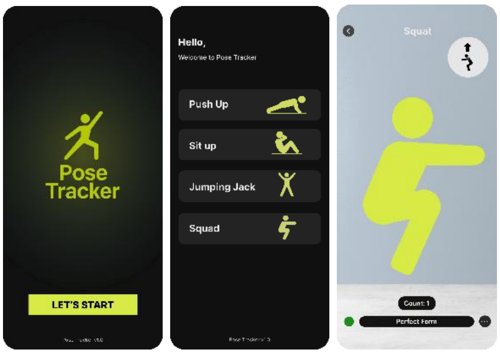


Figure 1. System Flowchart

Figure 1. illustrates the overall system workflow of the proposed fitness application. The process begins with video frames captured through camera detection with a mobile device. The frames then processed using MediaPipe to be extracted into human pose landmarks. These landmarks represented as a set of 33 MediaPipe body key points, describing the user's posture during exercise execution. The extracted landmark sequences are then sent to the backend server, where they are evaluated against a predefined reference dataset representing the correct exercise form.

Based on this comparison, the system determines whether the performed movement varies from the expected form. Finally, corrective feedback is generated and returned to the mobile application to inform the user of the evaluation result.



(a) (b) (c)

Figure 2. Design: (a) Start Page, (b) Home Page, (c) Camera Detection Page

Figure 2.a presents the initial start screen displayed upon launching the application. Figure 2.b, Depicts the home interface, which provides users with a selectable list of available exercises. Figure 2.c, Illustrates the real time detection interface, which continuously evaluates the user's movement and provide immediate feedback to ensure adherence to proper form.

B. Pose Representation and Form Evaluation

The pose landmarks dataset used in this study were taken from a training pose dataset available on Kaggle. This data set provides the coordinates of key body landmarks derived from pose estimation for several types of exercise, including push-ups, sit-ups, jumping jacks and squats that are comprised of 17.361 push-up samples, 18.898 jumping jack samples, 16.677 sit-up samples and 11.818 squat samples.

Each frame sample is represented as a 1D pose vector formed by averaging all landmark coordinates (x, y, z). To reduce the influence of body scale and camera distance, the pose vector is normalized using L2 normalization. Posture evaluation is formed by calculating the cosine similarity between the user's input pose and the normalized reference pose. For each frame, the highest similarity value to the reference pose is selected as the evaluation score.

The quality of posture at the frame level is classified based on cosine similarity, and the similarity scores are grouped into qualitative categories representing different posture quality levels. Frames classified in the higher-quality categories are considered to represent correct posture, while lower-quality categories are treated as incorrect. The categorization scheme was determined through preliminary empirical evaluation.

To improve evaluation stability, the classification results per frame are combined temporally. A training posture is considered correct if at least 80% of the frames in a movement sequence are classified as correct. If this is not achieved, the system provides corrective feedback. Cosine similarity with 80% tolerance is used to address movement variation and noise in landmark detection.

C. Exercise and Evaluation Scope

For each exercise, specific body landmarks were selected to capture common forms of deviations associated with improper execution. In push-up exercises, deviations include improper elbow flexion and misalignment between the shoulders, hips, and ankles. Sit-up evaluation emphasizes trunk inclination and hip–torso coordination. Squat analysis focuses on knee, hip, and torso coordination, as well as lower-body alignment during the downward phase. For jumping jacks, arm and leg symmetry monitored, as well as arm and leg elevation with bending to identify incorrect movement patterns.

D. Participants

The study involved 10 participants residing in Indonesia, aged between 17 and 50 years, from diverse backgrounds. No specific inclusion criteria related to gender, body weight, or fitness experience were applied. All participants reported being in good general health and free from physical impairments that could affect exercise performance. Participant characteristics were assessed based on self-reported information without detailed medical or physical evaluation.

E. Evaluation Metrics

This evaluation measures how accurately the system provides feedback appropriate to the exercise of posture. Accuracy was computed as the proportion of repetitions correctly classified by the system relative to the total number of evaluated repetitions.

$$Accuracy = \frac{Ncorrect}{Ntotal} \quad (1)$$

The system was evaluated based on its ability to provide accurate feedback regarding exercise posture. Four exercise types were considered: jumping jacks, squats, sit-ups, and push-ups. Each participant performed two attempts for each exercise, and each attempt consisted of three repetitions. This resulted in 24 repetitions per participant and 240 total repetitions across all participants, corresponding to 60 repetitions per exercise category.

III. Experimental Result

Figure 3 illustrates the results of PoseTracker posture detection as observed during user-performed exercise across four exercise types: push-up, sit-up, jumping jacks, and squat. With each posture exercise producing corresponding detection outcomes.

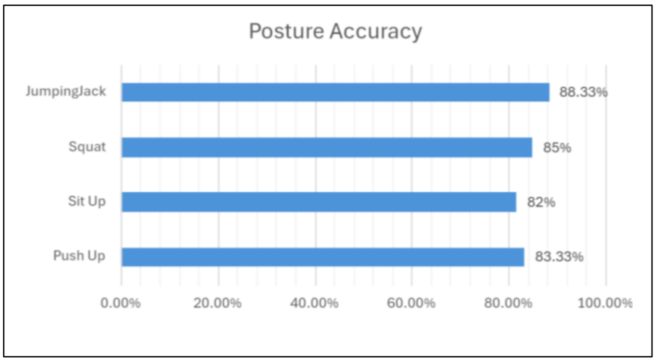


Figure 3. Posture Accuracy Chart

Figure 3 shows that the mobile application achieves high detection accuracy across all evaluated exercises with 88.33% for jumping jacks, 85% for squat, 82% for sit-up, and 83.33% for push-up. Several misclassification cases were observed during user testing. These failure cases were not primarily caused by errors in the predefined posture references, which were derived from correct form landmarks in the dataset, but rather by a combination of environmental, execution and system related factors encountered during real world usage.

The accuracy values presented in Figure 3 were obtained by calculating the average results across all participants. Each participant was given two attempts to perform each exercise, and in each attempt, the movement was repeated three times. For each execution, the system output was evaluated as follows: a score of 1 was awarded when an incorrect posture was correctly identified, and when a correct posture was accurately recognized as correct. On the other hand, a score of 0 was given when a correct posture was incorrectly classified as incorrect or when an incorrect posture was incorrectly classified as correct. The final accuracy for each exercise was then calculated as the average score across all executions and participants.

The most frequent cause of detection failure was incomplete body visibility, where the body parts moved partially or completely outside the camera frame. This reduced the posture estimation reliability and led to failed detections. Several detection failures were also triggered by incorrect exercise execution, where specific body segments did not meet the predefined form criteria for each posture. For jumping jacks, failures happened when the legs or hands were not opened symmetrically; the arms were not raised evenly, or the leg's width and arm elevation did not reach the required range. For squats, misclassification was commonly associated with insufficient hip descent, knees moving over the feet, or repetitions that were not completed through the full intended range of motion. For sit-ups, detection errors occurred due to deviations from the expected form, including inadequate or excessive knee flexion, loss of stable foot contact with the ground, and incomplete execution of the sit-up. In push-up, failure was typically linked to poor visibility and loss of proper body alignment, particularly when the torso or hips were held too low relative to the expected plank position. PoseTracker evaluates these conditions continuously across the exercise sequence. When one or more of these form-related issues persist across multiple consecutive frames and the user does not correct the movement within a given period, the repetition is classified as a failed execution. Conversely, if the user adjusts the posture such that the relevant form criteria are satisfied before this threshold is exceeded, the repetition continues to be detected as a valid execution according to the corresponding posture category.

In addition, environmental factors such as inconsistent lighting and visual background noise negatively affected landmark stability, decreasing detection of robustness under non-ideal conditions. Detection inaccuracies also increased when user performance deviated from reference motion patterns, including asymmetric movements, limited range of motion, or irregular execution timing, which caused the system to register the posture as incorrect, even when the movement was acceptable in a practical sense. Differences in system performance between devices constraints further influenced detection accuracy, as processing delays and low frame detection rates disrupt continuous tracking. Similarly, the accuracy of MediaPipe's 3D landmark estimation decreased under challenging visual conditions, such as partial occlusions or poor lighting, leading to unstable keypoint tracking. Finally, camera positioning significantly affected detection performance, as suboptimal angles or distances prevented the system from capturing complete and consistent posture information.

Overall, the findings indicate that detection errors were mainly driven by real-world environmental and operational constraints, rather than deficiencies in the posture reference model. These results also highlight the need for robust camera setup, controlled environmental settings, and device-level optimization to improve the reliability of mobile posture detection systems.

IV. Conclusion

This study evaluated the accuracy of PoseTracker as a mobile fitness application utilizing MediaPipe based HPE model to identify correct and incorrect exercise form across push-up, sit-up, squat, and jumping jack movements. The results indicate that the system can differentiate between proper and improper posture in the four fitness exercises, demonstrating consistent accuracy and ability to support safer exercise execution.

However, there are multiple factors that influence the system's accuracy including the quality of predefined pose landmarks dataset, camera visibility, lighting and position, and mobile application performance that affect form detection. Moreover, MediaPipe limitation also affects the ability to detect incorrect form with example of no keypoints to detect back hunching and limitation in detecting 3D points accurately.

Despite these limitations, the proposed approach demonstrates the potential of lightweight, AI driven fitness applications to support users in monitoring exercise form during unsupervised training. Future work will extend this study by evaluating the application's effectiveness over longer usage periods and across broader user populations, as well as investigating its potential role in supporting general health and fitness outcomes, including exercise routines and weight management.

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