Squat Assessment Using Pose Estimation: A Rule-Based Framework for Fitness Applications

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***Abstract*—This project presents a deep learning-based system for evaluating squat form using pose estimation techniques. The main goal was to develop a tool that can automatically assess the quality of squats from user-uploaded workout videos and provide real-time feedback to help improve performance and prevent injury. The system leverages MediaPipe's pose detection framework to extract key body landmarks, which are then used to compute joint angles such as the hip, knee, and ankle. Based on these angles, the system classifies posture, detects incorrect movements, and calculates metrics like total repetitions, improper repetitions, and back-angle consistency. A custom threshold-based rule engine was implemented to support two difficulty levels: beginner and pro. The system works fully through a web interface built with Streamlit and analyzes squats one frame at a time, all without requiring a GPU. Based on the results, it offers useful and reliable feedback on squat form, which makes it a good fit for personal fitness tracking or as a starting point for more advanced tools used in sports or physical therapy.**

***Index Terms*—Squat Evaluation, Pose Estimation, MediaPipe, Human Pose Analysis, Rule-Based Classification, Fitness Assessment.**

I. Introduction

A. Background and Significance

Recently, interest has been growing in how artificial intelligence (AI) can be used in sports and fitness, particularly to boost performance and help prevent injuries [1]. One key exercise, the squat, plays a major role in building lower body strength, but it's also easy to do incorrectly. Poor squat form can put unnecessary strain on joints, cause muscle imbalances, and even lead to injuries over time. While personal trainers usually help correct form, not everyone has access to that kind of support, especially when working out at home. This creates a real need for smart, automated tools that can assess exercise technique and give feedback right away. Technologies like pose estimation and video analysis are making this possible, allowing systems to track body movement in real time and suggest improvements.

B. Challenges in Current Techniques

Although human body landmarks can now be tracked with a fair degree of accuracy thanks to developments in posture estimation, there are still a number of obstacles to overcome when using these methods to assess squat form. First, joint angle identification during dynamic movements may be inaccurate due to the fact that the majority of current pose estimation methods are made for general-purpose tasks and may not be specifically optimized for exercise analysis [2]. Second, it can be challenging to adequately capture the intricacy of squatting motions when joints move in three-dimensional space since 2D pose estimation methods based on single-camera setups frequently have trouble with depth perception [3]. Furthermore, outside variables like low light, loose clothing, and uneven camera angles can add noise and reduce the precision of landmark predictions. Furthermore, the practical application of many existing systems for fitness monitoring and corrective training is limited since they mainly concentrate on detecting keypoints without offering users intelligent, real-time feedback [4].

C. Problem Statement

Although pose estimate technologies have made great strides, the majority of systems still lack real-time squat analysis that is both usable and accessible for regular users. The use of many current tools is restricted in low-resource or residential situations due to their reliance on pricey gear, such as wearables or depth sensors. However, camera-based solutions frequently only identify body landmarks without providing an interpretation that aids users in correcting their form. This makes it difficult for individuals especially beginners training at home to know whether they are performing squats correctly or risking injury due to poor posture. In addition, factors like improper camera placement, lighting conditions, and variation in user body types can affect the reliability of these systems. Therefore, there is a need for a simple, cost-effective solution that can analyze squat and interpret joint movements to provide clear, real-time feedback to support safer and more effective workouts.

D. Objectives

This research sets out to explore the development of an intelligent system for evaluating squat exercises using computer vision and deep learning techniques. The specific objectives include:

1) To investigate the use of pose estimation for capturing body posture and tracking joint movements during squats.

2) To extract meaningful biomechanical features, such as joint angles, from video input using a pretrained pose detection model.
3) To design a feedback mechanism that classifies squat performance and highlights incorrect posture based on defined movement thresholds.
4) To provide real-time feedback and performance metrics in a user-friendly interface, supporting both beginner and experienced users.
5) To implement the system in a way that is lightweight and deployable on standard hardware, enabling practical use in home or fitness environments.

E. Scope of Study

The scope of this study is limited to the evaluation of squat exercises using 2D pose estimation from single-camera video recordings. The system is designed to track specific body landmarks and compute joint angles to assess squat quality based on movement-based criteria. The analysis is restricted to single-subject videos captured from a lateral (side) perspective under normal indoor conditions. Furthermore, no new deep learning models are trained; instead, a pretrained pose estimation model is utilized to extract features required for the assessment.

II. Literature Review

A. Overview of Existing Techniques

Pose estimation has become a crucial tool in computer vision applications focused on human activity recognition, sports performance analysis, and rehabilitation. Inertial measurement units (IMUs) and depth sensors were key components of traditional exercise analysis techniques [5]. Real-time 2D pose estimation models such as OpenPose [6] and BlazePose [2] have made it feasible to precisely monitor body movements with a standard RGB camera. Without the need for sophisticated or costly equipment, these models make it simpler to compute biomechanical parameters such joint angles by identifying important spots on the body. Fitness tracking technologies that function well on common devices are now even more feasible thanks to lightweight frameworks like MediaPipe Pose [2].

B. Related Work

Pose estimate is now a widely used technique for posture assessment and activity monitoring. Hisham et al. [7] developed a system that uses MediaPipe Pose landmarks and smoothing techniques to decrease motion data noise in order to detect irregularities in squats. Their system could distinguish between normal and abnormal squats, but it only provided comprehensive feedback on glaring errors rather than joint alignment or squat quality. Gurav and Yadav [8] developed a real-time squat analysis program that provided users with immediate feedback and used joint angles to verify that the form was proper. Their approach missed subtleties like leaning forward or knee wobbling, but it performed well for simple form checks. Kwon and Kim [9] also used MediaPipe and OpenCV to design a posture correction system for squats and push-ups. They focused on making the tool accessible and fast, but their feedback was limited to simple ”correct” or ”incorrect” labels, without deeper analysis of form across squat stages. Winiarski et al. [10] used pose features with machine learning to recognize physical activities. Their approach offered more flexibility than rule-based methods, but since it relied on labeled datasets and offline training, it wasn't ideal for fast, real-time fitness apps. Madkhali et al. [11] employed OpenPose for yoga pose classification, combining rule-based thresholds and deep learning models. However, their system targeted static poses rather than dynamic exercises like squats, and it depended on higher computational resources, making it less suitable for mobile deployment. Chen et al. [12] proposed a mobile application for home exercise monitoring using pose estimation. Their system demonstrated the potential for portable fitness tracking, but they acknowledged challenges related to camera placement, lighting variability, and user clothing, which could impact pose detection reliability. Tang et al. [13] and Lee et al. [14] focused on improving exercise tracking accuracy through temporal modeling using LSTM networks. While these methods improved motion tracking across frames, they required extensive training data and more computational resources, making them less feasible for simple, real-time exercise monitoring systems. These studies demonstrate the potential of 2D pose estimation for exercise evaluation. However, most either focus on detecting only major posture errors, rely on machine learning models needing large datasets, or require computational power not suited for lightweight real-time applications highlighting the need for accessible, rule-based systems capable of providing detailed, actionable squat feedback in everyday environments.

C. Limitations in Existing Approaches

Although notable progress has been made in applying pose estimation techniques to exercise evaluation, several challenges remain. Many existing systems depend on machine learning models that require large annotated datasets and complex training processes, limiting their practicality for lightweight, real-time applications. Other solutions tend to focus only on detecting major posture deviations, without offering detailed analysis of joint behavior or movement consistency throughout the exercise. In some cases, specialized hardware or high computational resources are needed, which restricts their accessibility for everyday users. These limitations highlight the need for simple, efficient, and widely accessible solutions that can deliver precise, actionable feedback using only standard camera inputs especially for exercises like squats, where correct form is critical to safety and effectiveness.

III. Proposed Methodology

A. Existing Model and Challenges

The proposed system builds on MediaPipe Pose, a pretrained pose estimation framework capable of detecting 33 human body landmarks from 2D video input, as illustrated in Figure 1. MediaPipe Pose provides efficient and accurate skeletal tracking suitable for real-time applications on standard CPU devices. However, since it is designed for general-purpose body tracking, it does not directly evaluate exercise quality, squat depth, or posture correctness.

To make the system suitable for squat evaluation, a focused set of key body points was used, specifically the shoulders, hips, knees, ankles, and feet on both sides. These landmarks help calculate important joint angles, like the hip-knee-ankle angle to check squat depth, and the shoulder-hip-ankle alignment to assess back posture. By focusing on these points, the system keeps the analysis accurate while minimizing processing demands.

Although MediaPipe does a good job detecting joints, turning those landmarks into meaningful squat feedback isn't straightforward. The raw data needs further processing to calculate angles, track how steady the movement is, and detect common mistakes like leaning too far forward or misaligned knees. Issues like camera angle, lighting, and body shape can also impact how well the joints are tracked. To handle these problems, a rule-based method was used to convert the pose data into useful squat performance insights.

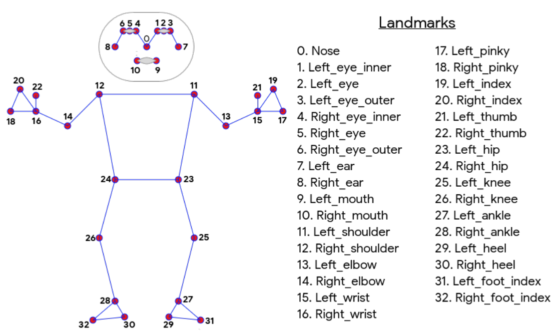

Fig. 1. The 33 anatomical landmarks detected by MediaPipe Pose.

B. Proposed Enhancements

To adapt the general-purpose output of MediaPipe Pose for squat evaluation, a rule-based analysis framework was developed. This enhancement focuses on three core tasks: joint angle calculation, squat stage classification, and posture fault detection.

The first step involves computing key joint angles from the landmarks extracted in each video frame. Specifically, the hip, knee, and ankle joints are used to calculate the hip-knee-vertical angle and ankle dorsiflexion, which are critical indicators of squat depth and alignment. Examples of these joint angles, measured during actual squat analysis using sample video frames, are shown in Figure 2. These angles are compared against predefined thresholds, tailored for two difficulty levels (Beginner and Pro), to assess whether the user achieves proper squat form.

The system then segments each squat repetition into three stages: normal, transition, and pass based on the progression of the hip-knee-vertical angle. This segmentation enables accurate detection of the start and completion of each squat, as well as the distinction between full squats and incomplete attempts.

Posture faults are identified by analyzing deviations in joint alignment. The system monitors for excessive forward lean of the torso, improper knee tracking beyond the toes, and insufficient squat depth. Faults are flagged in real time, allowing users to receive immediate corrective feedback during the exercise session.

All evaluations are performed frame-by-frame and are summarized into performance metrics, including total repetitions, improper repetitions, back angle consistency, and depth consistency. These enhancements transform raw pose landmarks into meaningful, actionable assessments of squat technique, without requiring additional sensors or specialized hardware.

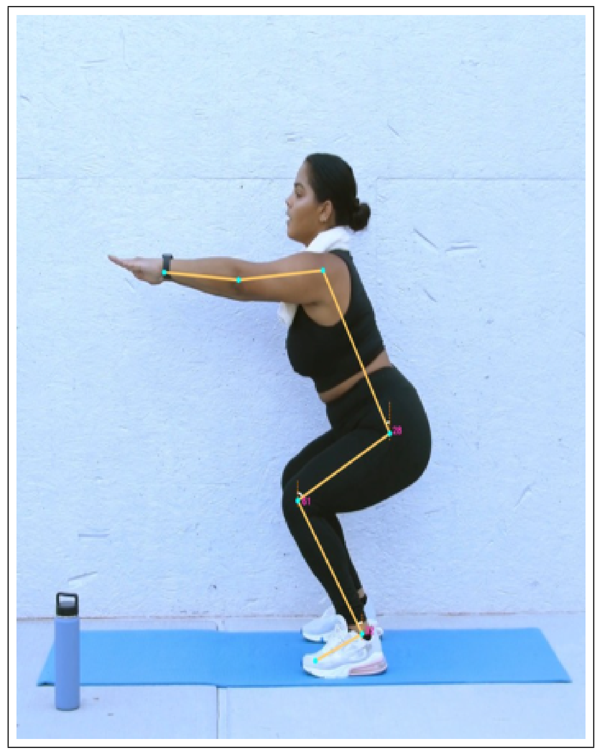

Fig. 2. Visualization of the critical joint angles measured during squat analysis, extracted from sample video frames.

C. Algorithm and Implementation

The system processes user-uploaded squat videos through a sequential pipeline. First, the video is processed frame-by-frame using MediaPipe Pose to extract 33 body landmarks. Key joints hip, knee, and ankle are selected to compute biomechanically relevant angles.

Using these angles, a rule-based evaluation system classifies each frame into squat stages (normal, transition, pass) based on predefined thresholds, adjustable for Beginner and Pro difficulty levels. The system also detects posture faults such as forward lean, improper knee alignment, and shallow squat depth.

Throughout the session, the system tracks the number of repetitions, improper movements, back angle consistency, and depth consistency. At the end of the analysis, a performance summary is generated and displayed through a web interface. A flowchart illustrating the full squat analysis pipeline, from video upload to feedback generation, is shown in Figure 3. The system is optimized for real-time performance evaluation on standard CPU devices without requiring specialized hardware.

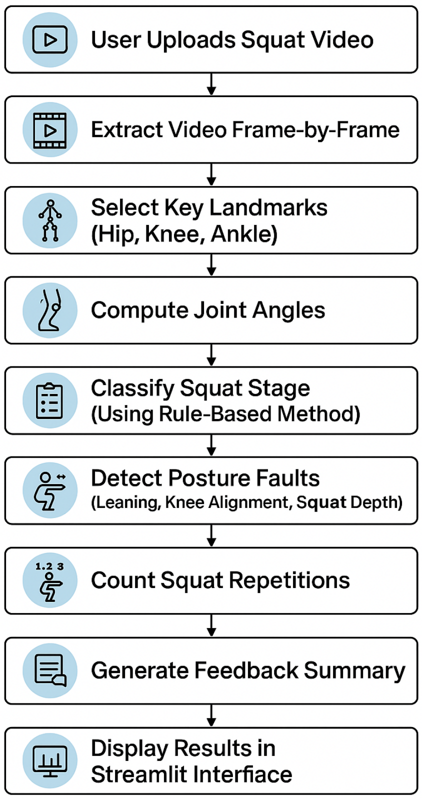

Fig. 3. Flowchart illustrating the squat analysis pipeline from video upload to feedback generation.

TABLE I
ANGLE THRESHOLDS USED FOR SQUAT EVALUATION.

Metric	Beginner Mode	Pro Mode
Hip-Knee-Vertical (Squat Depth)	10°–50°	15°–50°
Ankle Angle (Dorsiflexion)	$\geq 45°$	$\geq 30°$
Knee Angle Transition	50°–70°–95°	50°–80°–95°
Back Offset Angle (Torso Lean)	35°	35°

IV. Experimental Design and Evaluation

A. Datasets and Preprocessing

The system was tested using a set of user-recorded squat videos collected by the researcher. These videos were selected to include a variety of squat performances captured under typical indoor conditions using standard 2D cameras, such as mobile phones and webcams. Each video contained a single individual performing multiple squat repetitions from a lateral (side) viewpoint, ensuring full visibility of the hips, knees, and ankles. Preprocessing involved extracting frames sequentially from the uploaded videos. Each frame was processed through the MediaPipe Pose model to extract 33 human body landmarks. From these landmarks, the hip, knee, and ankle joints were selected as the primary points of interest. Landmark coordinates, originally provided in normalized form, were converted into pixel values relative to the frame dimensions. Additionally, frames were horizontally flipped when necessary to maintain a consistent orientation across samples. These processed joint coordinates were then used to compute the biomechanical angles necessary for squat stage classification and posture fault detection.

B. Performance Metrics

The squat evaluation system measures performance using several key metrics based on joint angle calculations:

- **Total Repetitions:** Number of correctly detected squats, identified by tracking progress through squat stages using changes in the hip-knee-vertical angle.
- **Improper Repetitions:** Squats marked as incorrect due to not meeting required angle limits or showing posture issues like forward lean or poor knee alignment.
- **Depth Consistency:** How consistently the user reaches the target depth in multiple squats, measured using the hip-knee-vertical angle. Accepted ranges vary with difficulty level.
- **Back Angle Consistency:** Checks torso stability during the squat to ensure minimal forward lean. A 35° offset is used as a reference for both beginner and pro modes.
- **Ankle Stability:** Evaluates ankle flexibility by measuring the lowest ankle angle during squats. Thresholds change depending on difficulty level.
- **Knee Movement Validation:** Verifies that knees bend and extend properly, using predefined angle ranges to check joint transitions during the squat.

The specific threshold values for depth consistency, ankle stability, and knee movement across different difficulty levels are summarized in Table I. The system tracks performance frame by frame throughout each session, and generates a final summary showing total repetitions, improper repetitions, depth consistency, and back angle stability. For evaluation, system results were compared with manual observations made by an expert trainer.

C. Experiment Setup

To evaluate how well the proposed squat analysis system works, experiments were carried out in a controlled environment using Python 3.9. The system was built using several important libraries: MediaPipe for pose estimation, OpenCV for video frame processing, and Streamlit to create the user interface. Other tools like NumPy and SciPy were used for math-related tasks. The application ran on a regular CPU-based machine, showing that it works well for local use without needing a GPU.

TABLE II
COMPARISON BETWEEN MODEL DETECTION AND EXPERT EVALUATION ACROSS 23 VIDEOS.

Video #	Total Squats	Model Detection Result	Expert Observation	Match
1	3	3 improper squats detected	Incorrect squats	Y
2	2	No reps detected (side view missing)	Slightly above parallel, forward lean	Y
3	2	2 improper squats detected	Forward lean detected	Y
4	3	3 clean reps detected	Proper clean form	Y
5	5	5 improper squats detected	Excessive depth	Y
6	2	No reps detected (wrong view)	Incomplete squats	Y
7	3	3 improper squats detected	Excessive depth	Y
8	2	No reps detected (wrong view)	Bending outward, forward lean	Y
9	8	8 good reps detected	Excellent form	Y
10	3	2 good reps, 1 improper rep detected	1 rep incomplete, rest solid	Y
11	2	2 improper squats detected	Incomplete squats	Y
12	2	No reps detected (camera misaligned)	Mild forward lean	Y
13	3	No good reps detected	3 clean squats	N
14	3	No good reps detected	3 clean squats	N
15	2	Forward lean detected	Forward lean	Y
16	4	1 good, 3 improper detected	3 deep squats, 1 correct	Y
17	2	1 good, 1 improper detected	1 deep squat, 1 correct	Y
18	3	3 improper reps detected	Forward lean, shallow depth	Y
19	1	Improper squat detected	Incorrect squat	Y
20	3	Improper squats detected	Incorrect squats	Y
21	5	2 good reps, 3 improper reps detected	First/last reps incorrect, middle reps good	Y
22	2	No correct reps detected	2 incorrect squats	N
23	2	1 correct rep detected	2 clean reps	N

The user interface allows users to upload videos, get real-time squat evaluations, and view detailed performance feedback. Figure 4 shows a screenshot of the interactive interface.

Pose estimation is handled by MediaPipe Pose, a full-body landmark detection tool created by Google. It uses BlazePose, a convolutional neural network (CNN) that can identify 33 body landmarks in 2D space. The system follows a bottom-up, single-person approach, starting with a fast detector and then applying a detailed landmark model. MediaPipe Pose runs efficiently in real time and is designed for mobile and edge devices, making it well-suited for interactive fitness apps. The extracted landmarks are denormalized to pixel coordinates and used to compute key joint angles, specifically at the hip, knee, and ankle, to assess squat quality. Technical details of BlazePose are discussed in the work by Zhang et al. [2].

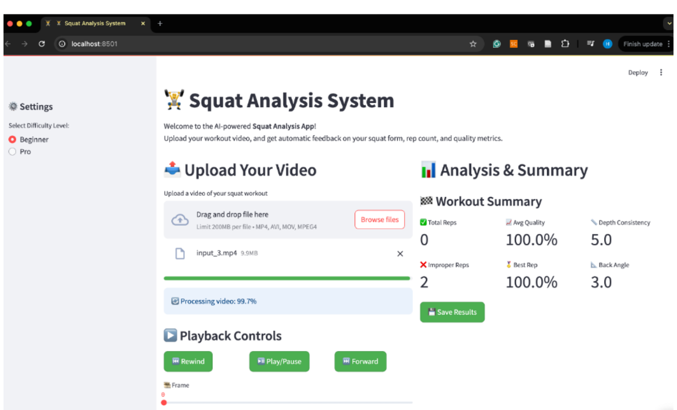

Fig. 4. Screenshot of the interactive user interface developed with Streamlit, enabling video upload, real-time squat evaluation, and detailed feedback display.

D. Experimental Results and Comparative Analysis

1) Evaluation Setup: The proposed squat evaluation system was tested on a dataset of 23 publicly available videos collected from online sources. Each video featured individuals performing squat exercises under various indoor conditions and camera setups. A total of approximately 65 squat repetitions were identified across these videos. Each repetition was manually assessed by an expert fitness trainer through naked-eye observation, referencing a standardized squat posture benchmark in a publicly available video [15]. The reference demonstrated correct squat posture elements, including neutral spine alignment, knee tracking over toes, sufficient depth, and balanced foot pressure. This benchmark ensured consistent manual evaluation across all collected samples.

2) Evaluation Results: Instead of evaluating the performance at the video level, the system was tested on each individual squat repetition to allow for more detailed analysis. Table II shows how the system's results matched up with the expert trainer's manual evaluations.

Out of 65 squat repetitions, the system correctly evaluated 59, giving it a per-repetition accuracy of around 91%. This suggests that the system is effective at identifying both proper and improper squat form, even under different video conditions and recording setups.

3) Comparative Analysis: The system's performance was also compared with the work of Hisham et al. [7], who used MediaPipe Pose landmarks combined with motion smoothing techniques to detect squat abnormalities. It is important to note that in Hisham et al.'s setup, each video corresponded to a single squat repetition, and their evaluation was conducted at the video level. In contrast, the proposed system handled videos containing multiple repetitions and was evaluated at the individual repetition level, representing a more challenging and

TABLE III

COMPARISON BETWEEN THE PROPOSED SYSTEM AND HISHAM ET AL. (2022).

Feature	**Proposed System**	**Hisham et al. (2022)**
Pose Estimation Model	MediaPipe Pose (BlazePose)	MediaPipe Pose (BlazePose)
Analysis Approach	Frame-by-frame joint angle evaluation and detailed posture fault detection	Rule-based abnormality detection with motion smoothing
Dataset	23 public videos, ∼65 squat repetitions	20 videos, 1 squat repetition each
Viewpoint Requirement	Side view only	Side view only
Real-time Capability	Yes (Streamlit CPU app)	No (offline analysis)
Feedback Detail	Rich feedback (repetitions, posture faults, depth/back consistency)	Binary classification (normal/abnormal)
Overall Accuracy	∼91%	∼85%

comprehensive assessment. A detailed comparison between the two systems is presented in table III.

While both systems achieve high levels of performance, the proposed system offers richer, repetition-level feedback rather than single-label session evaluations. Furthermore, it operates fully in real time without requiring post-processing, supporting practical deployment in fitness and rehabilitation applications where immediate corrective feedback is critical.

4) Key Observations: The proposed squat evaluation system demonstrated strong effectiveness in identifying major errors, such as incorrect form, improper squat depth, and missed repetitions due to poor movement patterns. In cases where camera positioning was suboptimal, the system correctly failed to detect clean repetitions, matching the expert trainer's manual observations and confirming its reliability under varied recording conditions. However, some limitations were observed during evaluation. First, the system exhibited a dependency on side-view camera angles, as it was optimized to assess squats based on a lateral perspective. Videos captured from other angles, such as front or diagonal views, often resulted in inaccurate joint detection and rep counting failures, highlighting the critical importance of proper camera alignment. Second, the system showed sensitivity to excessively deep squats, where the hips dropped significantly below knee level. Although such depth may be acceptable in certain training contexts, the model treated these squats as improper due to deviations from standard knee positioning and back posture. Finally, minor over-flagging was occasionally noted, where slight posture deviations such as minimal forward lean or slightly reduced depth were classified as improper, reflecting the model's strict enforcement of ideal squat form criteria.

V. EXTENDED CONTRIBUTIONS

Beyond its technical execution, the suggested squat evaluation system makes a number of advances. Without the need for costly gear or sophisticated machine learning models, it offers a quick and efficient method of assessing exercise form by fusing rule-based movement analysis with real-time posture estimation.

While previous methods mostly provided yes-or-no input, this method provides more in-depth information. It keeps track of repetitions, looks for problems with posture, and ensures that squats are consistent. In order to help users improve their technique, it may identify particular errors such as leaning forward, not squatting far enough, or misaligned knees.

The system can be used for mobile fitness apps, physical rehabilitation, and at-home workouts because it is portable and compatible with common consumer electronics. Its modular design also makes it easy to adapt for other exercises like lunges, push-ups, or deadlifts by changing the angle-checking rules.

Overall, by providing a real-time, intelligible, and useful system that links scholarly research with practical application, our study promotes the development of smart fitness equipment.

VI. CONCLUSION AND FUTURE WORK

This study used rule-based joint angle analysis and 2D pose estimation to present a portable, real-time squat evaluation system. Common posture problems such as forward tilting, shallow squat depth, and knee misalignment were detected by the system. Additionally, it offered helpful comments on the quality of the squat, such as the number of repetitions, consistency in depth, and stability of the back position. The system achieved an overall accuracy of 91% when compared to manual evaluations by a fitness expert, demonstrating its dependability under various recording circumstances.

This technique provides more thorough, per-repetition analysis without requiring GPU power or big datasets, in contrast to previous methods that primarily provide basic pass/fail feedback. This makes it ideal for usage in mobile fitness apps, physical rehabilitation, and at-home workouts.

Future research could enhance the system in a number of ways. One way to improve feedback personalization and minimize false errors is to dynamically modify the evaluation thresholds according on the user's performance. By changing the joint angle logic, the same framework might be modified to enable additional workouts like push-ups and lunges. Lastly, integrating machine learning with the existing rule-based approach may assist increase the system's performance in more challenging situations, like when the camera is not positioned correctly or when posture detection is noisy.

In conclusion, our work offers a versatile and user-friendly solution that bridges the gap between academic research and practical exercise evaluation, thereby making posture estimation more feasible for everyday fitness application.

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