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 model runs entirely in a web-based interface using Streamlit and performs frame-by-frame analysis without needing GPU acceleration. The results show that the system can provide helpful and consistent feedback on squat performance, making it suitable for personal fitness use or as a foundation for more advanced applications in sports and rehabilitation.**

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

I. Introduction

A. Background and Significance

In recent years, there has been a growing interest in applying artificial intelligence (AI) techniques to sports and fitness, especially for improving athletic performance and reducing the risk of injury [1]. Among common fitness exercises, the squat is fundamental for developing lower body strength but is also highly susceptible to form-related mistakes. Incorrect squat posture can lead to joint stress, muscle imbalance, and long-term injuries. Traditionally, athletes and fitness enthusiasts have relied on personal trainers or manual observation to correct their form, but such solutions are not always accessible, especially in home workout settings. Therefore, there is a strong need for automated systems that can monitor exercise form objectively and provide immediate feedback. Pose estimation technologies, combined with video analysis, offer a promising direction for addressing this gap, enabling the development of systems that can track body movements in real time and offer corrective guidance.

B. Challenges in Current Techniques

While advancements in pose estimation have made it possible to track human body landmarks with reasonable accuracy, several challenges remain when applying these techniques to squat form evaluation. First, most existing pose estimation systems are designed for general-purpose tasks and may not be specifically optimized for exercise analysis, leading to potential inaccuracies in joint angle detection during dynamic movements [2]. Second, 2D pose estimation models based on single-camera setups often struggle with depth perception, making it difficult to fully capture the complexity of squatting motions where joints move in three-dimensional space [3]. Additionally, external factors such as poor lighting, loose clothing, and inconsistent camera angles can introduce noise and degrade the accuracy of landmark predictions. Furthermore, many existing systems focus primarily on detecting keypoints without providing intelligent, real-time feedback to users, limiting their practical use for fitness monitoring and corrective training [4].

C. Problem Statement

Pose estimation technologies have advanced significantly, but most available systems fall short when it comes to real-time squat analysis that is both accessible and practical for everyday users. Many existing tools depend on expensive hardware like depth sensors or wearable devices, which limits their usability in home or low-resource environments. On the other hand, camera-based solutions often focus only on detecting body landmarks without interpreting the data in a way that helps users correct 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. Traditional methods for exercise analysis relied heavily on depth sensors or wearable devices, such as inertial measurement units (IMUs) [5]. However, the emergence of real-time 2D pose estimation models, such as OpenPose [6] and BlazePose [2], has made it possible to perform accurate skeletal tracking using only RGB cameras. These models detect key body landmarks and allow researchers to derive biomechanical features, such as joint angles, without the need for expensive hardware. Real-time pose estimation frameworks, particularly lightweight solutions like MediaPipe Pose [2], have opened new possibilities for developing accessible fitness monitoring systems that work on standard devices.

B. Related Work

Pose estimation has been widely applied to exercise monitoring and posture evaluation tasks. Hisham et al. [7] proposed a squat abnormality detection system using MediaPipe Pose landmarks, combined with double exponential smoothing to address noisy motion data. While their system effectively differentiated normal from abnormal squats, it primarily focused on detecting severe deviations and did not provide detailed feedback about specific joint misalignments or form quality. Gurav and Yadav [8] developed a real-time squat analysis tool that computed joint angles to classify squat correctness and provided instant feedback to users. Although their approach demonstrated the practical use of joint angle thresholds for fitness evaluation, it was limited to basic angle checks and did not capture subtle posture variations such as forward lean or knee instability. Kwon and Kim [9] introduced a workout posture correction system based on MediaPipe and OpenCV, targeting squats and push-ups. Their system emphasized accessibility and real-time performance but offered relatively simple binary feedback (correct/incorrect), without deeper analysis of squat stages or detailed tracking of movement consistency over repetitions. Winiarski et al. [10] explored human activity recognition by extracting pose features and applying supervised machine learning classifiers. Their approach complemented traditional rule-based systems by offering data-driven classification, but it required annotated datasets and offline model training, limiting its direct applicability for lightweight, real-time fitness applications. 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 pre-trained 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 adapt the framework for squat evaluation, a subset of critical landmarks was selected. Specifically, the system focuses on the shoulder, hip, knee, ankle, and foot landmarks from both the left and right sides. These points were chosen to calculate essential joint angles, such as the hip-knee-ankle angle for assessing squat depth and the shoulder-hip-ankle alignment for monitoring back posture. Concentrating on these joints enables accurate squat assessment while reducing computational overhead.

While MediaPipe reliably detects key joints, interpreting these landmarks for squat analysis presents several challenges. The raw outputs must be further processed to compute joint angles, track movement consistency, and identify common posture faults such as excessive forward lean or poor knee alignment. Moreover, variations in camera positioning, lighting conditions, and user body types can affect the stability of landmark detection. To address these challenges, a rule-based interpretation framework was developed to transform the pose landmarks into actionable squat performance metrics.

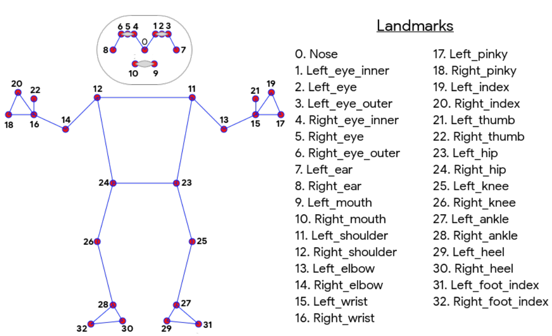

Fig. 1. The 33 anatomical landmarks detected by MediaPipe Pose.

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.

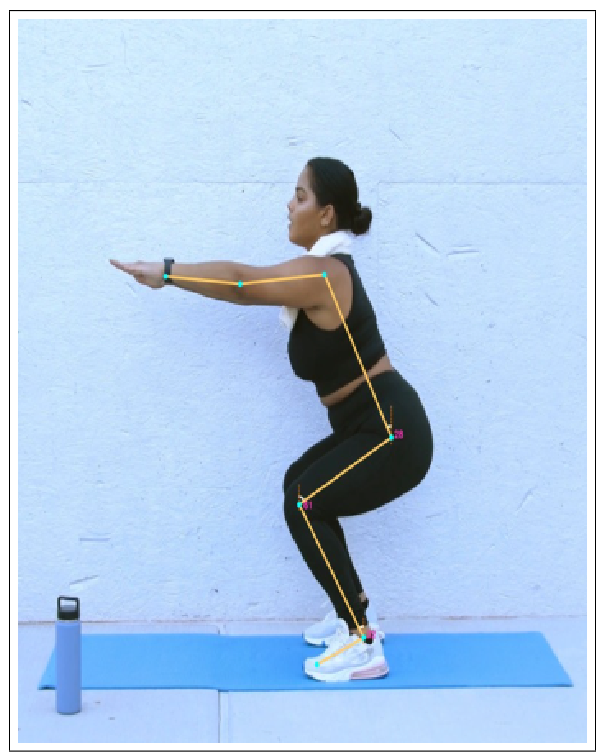

Fig. 2. Visualization of the critical joint angles measured during squat analysis, extracted from sample video frames.

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.

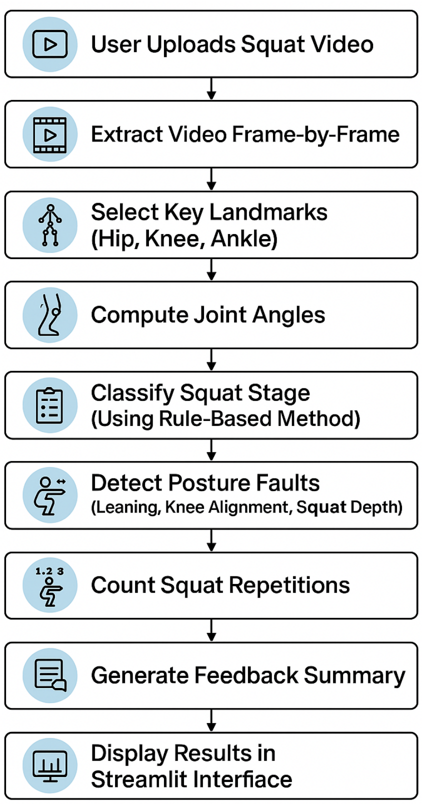

Fig. 3. Flowchart illustrating the squat analysis pipeline from video upload to feedback generation.

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.

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°

B. Performance Metrics

The squat evaluation system assesses performance through several computed metrics derived from joint angle analysis:

- Total Repetitions: Number of squat repetitions successfully detected based on progression through squat stages, evaluated using hip-knee-vertical angle changes.
- Improper Repetitions: Number of repetitions classified as improper due to failure to meet predefined angle thresholds or due to posture faults such as forward lean or improper knee tracking.
- Depth Consistency: Stability of achieving the target hip depth across multiple squats, evaluated using hip-knee-vertical angles. The acceptable range varies by user difficulty level.
- Back Angle Consistency: Monitoring of torso stability throughout the squat movement to ensure minimal forward lean. A reference offset of 35° is used for both beginner and pro modes.
- Ankle Stability: Assessment of ankle dorsiflexion by checking the minimum ankle angle achieved during squats. Different thresholds are set depending on the difficulty level.
- Knee Movement Validation: Evaluation of knee joint transitions during squats to verify proper knee bending and extension, using predefined angle ranges.

The specific threshold values used for depth consistency, ankle stability, and knee movement across difficulty levels are summarized in Table 1. Performance was tracked frame-by-frame throughout each video, and a final summary was

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

generated after the session, reporting metrics such as total repetitions, improper repetitions, depth consistency, and back angle stability. For evaluation purposes, system outputs were compared against manual naked-eye assessments performed by an expert trainer.

C. Experiment Setup

To evaluate the effectiveness of the proposed squat analysis system, experiments were conducted in a controlled software environment using Python 3.9. The system was developed with several key libraries, including MediaPipe for pose estimation, OpenCV for frame-level video processing, and Streamlit for building the user interface. Additional tools such as NumPy and SciPy supported mathematical operations. The application was executed on a standard CPU-based system, demonstrating its suitability for lightweight, local inference without reliance on GPU acceleration.

The user interface enables users to upload videos, receive real-time squat evaluations, and view detailed feedback metrics. A screenshot of the interactive interface is shown in Figure 4.

Pose estimation is performed using MediaPipe Pose, a state-of-the-art framework developed by Google for full-body landmark detection. The model is based on the BlazePose architecture, which uses a convolutional neural network (CNN) to regress 33 keypoints representing the 2D spatial configuration of human body joints. The pipeline employs a bottom-up, single-person estimation approach, beginning with a lightweight detector followed by a high-fidelity landmark model. MediaPipe Pose operates efficiently in real time and is optimized for mobile and edge devices, making it ideal for interactive applications. 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].

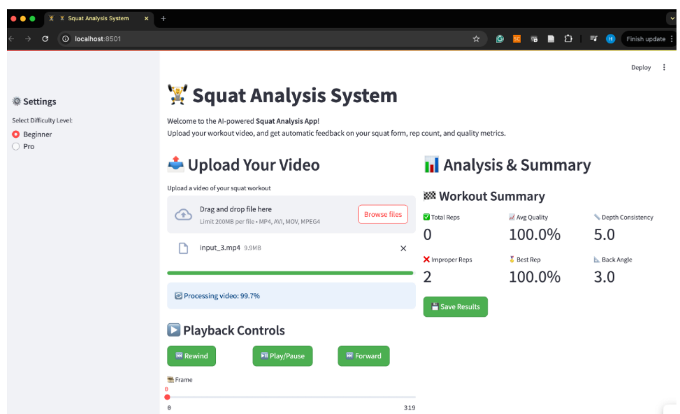

Fig. 4. Screenshot of the interactive user interface developed with Streamlit, enabling video upload, real-time squat evaluation, and detailed feedback display.

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: Rather than evaluating performance at the video level, the system was assessed on a per-repetition basis to provide a finer-grained analysis. Table 2 summarizes the evaluation by comparing the system's outputs against the expert trainer's manual assessments.

The system achieved correct evaluation on 59 out of 65 squat repetitions, resulting in a per-repetition accuracy of approximately 91%. This highlights the system's strong ability to detect correct and incorrect squat performances across varying video qualities and conditions.

3) Comparative Analysis: The system's performance was compared against a related study by Hisham et al. [7], who employed MediaPipe Pose landmarks and rule-based motion smoothing for squat abnormality detection. 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 comprehensive assessment. A detailed comparison between the two systems is presented in Table 3.

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

The proposed squat evaluation system offers several contributions beyond its core implementation. By combining real-time pose estimation with rule-based movement analysis, it provides an accessible and efficient approach to exercise form evaluation without the need for expensive equipment or complex machine learning models.

Unlike prior works focused mainly on binary classification, this system delivers detailed feedback on squat quality, including repetition counting, posture fault detection, and consistency tracking. It identifies specific movement faults, such as forward lean, insufficient squat depth, and knee misalignment, helping users understand and correct their technique.

Designed for lightweight deployment on standard consumer devices, the system supports broader applications in home fitness, rehabilitation, and mobile fitness platforms. Its modular framework also allows extension to other exercises, such as lunges, push-ups, and deadlifts, by adapting the joint angle evaluation logic.

Overall, the system contributes to the development of intelligent fitness technologies by offering real-time, explainable, and practical exercise assessment tools that bridge academic research and real-world applications.

VI. Conclusion and Future Work

This project presented a lightweight, real-time squat evaluation system based on 2D pose estimation and rule-based joint angle analysis. The system effectively detected key posture faults, including forward lean, insufficient squat depth, and knee misalignment, while providing actionable feedback on repetition quality, depth consistency, and back angle stability. When compared against expert manual evaluation, the system achieved an overall accuracy of 91%, demonstrating strong reliability across diverse recording conditions.

In contrast to previous systems that primarily focus on binary classification, the proposed solution delivers detailed, repetition-level feedback without the need for GPU resources or extensive training datasets, making it practical for home fitness, rehabilitation, and mobile applications.

Several directions for future work are identified. Dynamic threshold adjustment could be introduced to personalize evaluation criteria based on user performance, improving adaptability and reducing false error detections. The framework could also be extended to evaluate additional exercises, such as lunges or push-ups, by modifying the joint analysis logic. Finally, integrating hybrid learning approaches combining rule-based evaluation with machine learning may further enhance system robustness, especially under challenging conditions such as camera misalignment or landmark detection noise.

Overall, this work helps bridge the gap between academic pose estimation research and real-world fitness applications, providing a foundation for building accessible, real-time exercise evaluation tools.

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%

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