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AI-Based Gym Tracker and Real-Time Posture Correction APP

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Abstract: The growing popularity of home workouts has led to a surge in fitness applications; however, most lack real-time posture correction and personalized feedback, often resulting in poor form and risk of injury. To address these challenges, this paper presents PeakForm, an AI-based gym tracker that combines computer vision and deep learning to provide real-time workout analysis, posture correction, and personalized exercise recommendations. The system uses a pose estimation model, such as MediaPipe Pose, to detect 33 body landmarks from a live video stream and evaluate user posture during exercises like push-ups, squats, jumping jacks, and planks. A posture evaluation algorithm compares the user's joint angles with reference standards, offering immediate feedback through visual and auditory cues when deviations occur. For static workouts, the system includes a countdown timer with a 3-second pre-start and a beep notification upon completion. Peak Form's recommendation module generates personalized workout routines based on the user's height, weight, and fitness goals. Implemented using Python, OpenCV, and TensorFlow, the system achieved an average accuracy of 95% in exercise detection and form evaluation during real-time testing. The results demonstrate that PeakForm effectively enhances user performance and safety while offering a trainer-like experience without wearable devices. This project represents a step toward intelligent, accessible, and personalized virtual fitness training for all users.

I. INTRODUCTION

The modern fitness landscape has undergone a significant transformation over the last decade, particularly with the rise of technology-driven solutions. The increasing popularity of home workouts, fitness applications, and online training platforms has provided individuals with greater flexibility in managing their fitness goals. However, one major drawback of these digital fitness tools is the lack of real-time guidance and posture correction, which are crucial for achieving optimal results and preventing injuries. Most fitness applications today rely solely on motion tracking, time duration, or calorie estimation without evaluating the user's form accuracy. Incorrect posture during strength-based or bodyweight exercises can lead to muscle strain, poor performance, or long-term physical issues. To address these challenges, this research introduces *PeakForm*, an AI-powered gym tracking and posture correction system that aims to bring the precision of professional gym coaching into the home environment. The system uses computer vision and deep learning to analyse user movements in real time through a device camera, identify the type of exercise, and provide instant corrective feedback. Unlike traditional fitness applications that depend on manual tracking or wearable sensors, PeakForm operates entirely on vision-based motion recognition, making it more accessible and user-friendly. The system focuses on key bodyweight exercises such as push-ups, squats, jumping jacks, and planks, which are commonly performed incorrectly without supervision. PeakForm leverages pose estimation models to map body landmarks and measure joint angles, allowing it to assess whether the user is maintaining correct form throughout the workout. When a deviation from the standard posture is detected, the system provides immediate feedback through on-screen prompts or audible cues. In addition, a built-in timer module supports static exercises like planks, with a pre-start countdown and completion alert for better user engagement. A unique feature of PeakForm is its personalized workout recommendation module, which uses user-specific data such as height, weight, and fitness objectives to create adaptive workout routines. This ensures that each user receives guidance tailored to their individual needs, improving motivation and consistency over time.

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By combining real-time visual analysis, AI-based decision-making, and interactive user feedback, PeakForm bridges the gap between virtual fitness and human coaching. This project demonstrates how artificial intelligence can enhance workout quality, safety, and accessibility, contributing to a more effective and personalized fitness experience.

II. PROPOSED SYSTEM

The proposed system, *PeakForm*, is designed as an AI-integrated fitness assistant that provides real-time posture analysis, workout tracking, and intelligent exercise recommendations. The system combines computer vision, deep learning, and rule-based algorithms to emulate the supervision of a professional fitness trainer without requiring wearable sensors or external equipment. The core idea is to create an affordable and accessible fitness platform that ensures users perform exercises correctly while following routines customized to their goals. The system architecture of PeakForm is structured into five primary modules: pose detection, posture evaluation, workout monitoring, recommendation generation, and user interaction interface.

1.Pose Detection Module

This module acts as the foundation of the system. It captures the user's live video stream using a camera and processes it frame by frame. A pre-trained pose estimation model, such as MediaPipe Pose or OpenPose, is employed to detect 33 human body landmarks, including key joints like the shoulders, elbows, hips, knees, and ankles. The extracted coordinates form a skeletal representation of the user, which is then analysed in subsequent stages.

2. Posture Evaluation Module:

The detected landmarks are used to compute joint angles and body alignment. Each exercise has a defined range of motion and ideal posture parameters. The system compares the user's current angles against these standards to determine whether the movement is correct. When an incorrect posture is identified, the system immediately provides visual or auditory feedback, prompting the user to adjust their form. This feedback loop mimics real-time trainer correction, enhancing workout precision and safety.

3. Workout Monitoring Module:

This component differentiates between dynamic and static exercises. For dynamic exercises like push-ups and squats, it counts repetitions based on motion patterns and angle variations. For static exercises like planks, the module includes a built-in timer system. Users can select a desired duration, receive a three-second countdown before initiation, and an audible beep upon completion.

4. Workout Recommendation Module:

Using user-input parameters such as height, weight, age, and fitness goal, this module generates a personalized set of workouts. The logic is either rule-based or powered by lightweight machine learning models trained on standard fitness datasets.

5. User Interface Module:

The frontend presents an intuitive dashboard that displays real-time camera feedback, performance scores, and corrective alerts. It also allows users to select workouts, track history, and adjust difficulty levels. Through the integration of these modules, *PeakForm* delivers an adaptive, interactive, and intelligent fitness tracking experience that closely replicates human coaching while maintaining accuracy and engagement in home workout environments.

III. METHODOLOGY

This section describes the whole technological process used to create PeakForm, including data collecting, pose estimation, signal processing, exercise categorization, posture evaluation, repetition counting, suggestion logic, and deployment concerns. All algorithms are designed to be responsive in real time while still protecting users' privacy.

1. Data Collection and Preprocessing

A proprietary dataset was developed by recording volunteers (of varying ages, heights, and body types) completing the target activities (push-ups, squats, jumping jacks, and planks). Each film teaches corrected behaviour by using several camera angles, varying lighting, and purposeful form flaws. Video frames are shrunk and normalized, and landmark coordinates are scaled relative to the detected torso size to make features insensitive to camera distance. Data augmentation (horizontal flips, minor rotations, and brightness shifts) improves resilience.

2. Pose estimation pipeline

A lightweight, real-time pose estimator (e.g., MediaPipe Pose or a MobileNet-based OpenPose variant) produces 2D coordinates for N keypoints per frame. The pipeline outputs confidence scores per key point; low-confidence points are interpolated from neighbouring frames using linear interpolation. To reduce jitter, coordinates are smoothed with an exponential weighted moving average (EWMA):

$$x_t' = \alpha \cdot x_t + (1-\alpha)\cdot x_{t-1}' \quad (\alpha \approx 0.6).$$

3. Feature extraction and angle computation

From smoothed key points, joint angles are computed using vector math and the arctangent function. For three points A (parent), B (vertex), and C (child), the angle at B is:

$$\theta = \arccos((v1\cdot v2) / (||v1||\cdot||v2||))$$

where v1 = A−B and v2 = C−B. Relative ratios (e.g., hip-to-shoulder vertical alignment) are computed to assess posture alignment independent of scale.

4. Exercise classification and temporalmodelling
A hybrid approach combines rule-based heuristics with a lightweight temporal classifier. Instantaneous rules identify candidate exercises (e.g., repeated elbow flexion with chest-to-floor proximity ⇒ push-up). For noisy cases, a temporal model (1D-CNN or LSTM with short windows of 1–2 seconds) classifies the activity using sequences of angles and keypoint velocities. Models are trained with cross-entropy loss and validated with k-fold cross-validation.

5. Posture Evaluation and corrective Feedback
Each exercise has a set of ideal-angle ranges and alignment rules derived from biomechanics and expert input. Deviation is quantified as a percentage error:

$$err = |\theta\_user - \theta\_ref| / \theta\_ref \times 100\%$$

If err exceeds an exercise-specific threshold, the system issues a corrective message (text + arrow overlay) and optionally an auditory cue. A severity score aggregates multi-joint deviations to generate a single real-time “form score.”

6. Rep counting and state machine
Repetition counting uses a finite-state machine per exercise: defined states (e.g., DOWN, UP), transition when angle thresholds and temporal minima/maxima are met. Debounce timers and minimum time-per-rep filters prevent false counts from rapid noise.

7. Recommendation engine
A deterministic, weighted-rule engine recommends routines using inputs (height, weight, age, goals). Rules map user parameters to intensity, sets, and rest periods; historical performance (form score, reps completed) adjusts progression. Optionally, a lightweight supervised regressor can calibrate difficulty using collected user data.

8. Evaluation Protocol
Performance is measured on held-out video data: classification accuracy, precision/recall per exercise, mean angle error, rep counting F1, and inference latency (ms) and frames per second (FPS) on target devices. A user study evaluates perceived usefulness and error reduction in form across sessions.

9. Deployment and Privacy
To minimize latency and protect privacy, inference runs on-device where possible. When cloud processing is required (heavy analytics), frames are anonymized and uploaded only with explicit user consent. All stored user metrics are hashed and stored securely (SQLite / Firebase rules). This methodology balances real-time constraints, robustness to real-world variability, and user privacy forming a practical foundation for PeakForm’s posture-correction and personalization goals.

IV. RESULT AND DISCUSSION
The *PeakForm* system was implemented and tested to evaluate its performance in terms of accuracy, responsiveness, and user experience. The evaluation was conducted on a sample group of fifteen users performing four types of exercises: push-ups, squats, jumping jacks, and planks. Each participant was recorded under different lighting and background conditions using a standard webcam at 30 frames per second. The system was executed on a mid-range laptop (Intel i5 processor, 8 GB RAM) without GPU acceleration to assess real-world feasibility for consumer-grade devices.

A. Accuracy of Exercise Recognition
The system demonstrated a high accuracy in identifying different workouts based on joint motion patterns. Using a combination of rule-based analysis and temporal modelling, PeakForm achieved an average classification accuracy of 95.3% across all exercises. Push-ups and squats yielded the highest recognition rates due to their distinct upper and lower body movements, while jumping jacks presented slightly lower accuracy (92.7%) owing to faster limb motion and partial frame exits in some trials.

B. Posture Correction and Feedback
For posture analysis, the system evaluated the angular deviation between the user’s current pose and the reference pose. The mean angle error across all exercises was 6.4°, which is within acceptable limits for real-time fitness applications. Users received immediate feedback through on-screen prompts when deviations exceeded defined thresholds. Feedback latency was measured at an average of 720 milliseconds, confirming near real-time response. The corrective alerts effectively guided users to adjust their posture, improving form consistency over multiple sessions.

C. Rep counting and Timer accuracy.
Dynamic exercises were accurately tracked using the finite-state-based repetition counter, maintaining an average rep count precision of 96%. For static exercises such as planks, the integrated timer delivered consistent countdown and completion signals without noticeable delay. The auditory “beep” feedback upon timer completion was rated positively by users for its intuitive design.

D. User Experience Evaluation
A post-test survey indicated that 87% of participants found the posture feedback helpful, and 82% reported improved awareness of form. The interactive countdown, real-time feedback overlays, and simple interface contributed to a smoother experience. However, minor issues such as accuracy drops in dim lighting and background clutter were observed, suggesting the need for adaptive brightness handling and background masking in future iterations. Overall, the system successfully validated its ability to perform accurate exercise detection, posture correction, and recommendation generation in real-time. Compared with existing fitness applications that rely only on manual input or wearable devices, *PeakForm* provided a more natural, camera-based, and trainer-like experience, demonstrating strong potential for home-based fitness and rehabilitation environments.

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V. CONCLUSION

This paper presented *PeakForm*, an AI-based gym tracker that integrates computer vision and deep learning to provide users with real-time posture correction, exercise tracking, and personalized fitness recommendations. The system was designed to make professional-quality training guidance accessible from home without the need for wearable sensors or human supervision. By using pose estimation models such as MediaPipe Pose and OpenPose, *PeakForm* effectively analyses body movements and evaluates exercise form. The system was tested on common workouts pushups, squats, jumping jacks, and planks and achieved an average recognition accuracy of over 95%. Real-time feedback and rep counting further enhanced user engagement and helped correct improper postures instantly. The platform's modular design allows it to deliver a highly adaptive experience, with features like a recommendation engine that tailors workout routines based on height, weight, and personal goals. Its lightweight implementation using Python, OpenCV, and TensorFlow ensures fast performance even on devices without advanced hardware. The experimental results demonstrated that PeakForm can significantly improve user workout quality, safety, and motivation through instant feedback and customized guidance. The system offers a practical alternative to gym-based supervision and shows strong potential for integration into personal fitness and rehabilitation programs. In conclusion, PeakForm highlights how artificial intelligence can enhance the accessibility and precision of home workouts. It serves as an innovative step toward AI-driven personal fitness coaching, offering users a safer, smarter, and more effective way to achieve their fitness goals.

VI. FUTURE SCOPE

While PeakForm delivers accurate posture tracking and workout guidance, several improvements can further enhance its performance and usability. One of the key future directions is the integration of voice-based feedback that provides real-time verbal instructions, allowing users to maintain form without constantly viewing the screen. This hands-free interaction would make workouts more natural and trainer-like. Another significant enhancement involves wearable and sensor integration. By connecting PeakForm with smartwatches or fitness bands, parameters such as heart rate, calories burned, and oxygen levels can be analysed alongside posture data. This would enable more comprehensive fitness monitoring and adaptive workout adjustments based on user fatigue or intensity. To improve detection accuracy, future versions can incorporate 3D pose estimation or depth cameras, reducing the effect of poor lighting or partial visibility. Implementing cloud-based learning could also help continuously update the model with new user data, ensuring broader generalization and scalability. Additional improvements could include AI-based progress analytics, allowing users to visualize form accuracy and performance trends over time. A community or challenge feature may also encourage user motivation through competition and shared progress. Finally, PeakForm could adopt reinforcement learning techniques to personalize training dynamically, learning from each user's performance and preferences. In summary, the future development of PeakForm lies in expanding interactivity, personalization, and real-time intelligence. These advancements would transform the system into a complete virtual fitness ecosystem that empowers users to train effectively, safely, and consistently.

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