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Real-Time Exercise Monitor & Feedback System

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Abstract:

Preventing injuries and maximizing training effectiveness depend on maintaining correct exercise form. Using pose estimation and computer vision, this paper offers a real-time exercise monitoring and feedback system that guides users through strength-based exercises. Precise posture analysis is made possible by the system's use of OpenCV for visual processing and feedback generation and MediaPipe Pose for accurate real-time detection of body landmarks. Requiring just a regular webcam, a Streamlit-based web interface allows for user authentication, exercise selection, live monitoring, and performance tracking, as well as features like historical data visualization. With automated repetition counting and real-time posture correction notifications provided by audio cues and visual overlays, the platform uses joint angle calculations to find exercise stages and spot form deviations across a spectrum of movements, including squats, hammer curls, and push-ups. Unlike traditional techniques that depend on wearable sensors or post-session analysis, this approach provides a non-intrusive, affordable option. Experimental testing shows the system's high accuracy and low latency, confirming its reactivity and usefulness. The modular design enables scalability to accommodate future enhancements, including additional exercises and enhanced administrative control. A viable replacement for conventional coaching approaches, this solution greatly increases accessibility and efficacy in self-guided rehabilitation and fitness environments.

Keywords — **Pose Estimation, Real-Time Feedback, Exercise Monitoring, Computer Vision, and Human Activity Recognition.**

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I. INTRODUCTION

Often relying on personal trainers, organized workout programs, or self-guided sessions, traditional fitness training models cannot provide quick corrective feedback, which is essential for maximizing exercise effectiveness and lowering injury risk. Self-directed programs highlight this lack since users may unintentionally adopt bad posture in the real-time absence of guidance, therefore lowering training efficacy and possibly causing musculoskeletal problems from repeated incorrect motions. The increasing need for easily available fitness solutions aggravates these difficulties even more since traditional approaches often call for costly wearable sensors, specialized equipment, or delayed post-session analysis, therefore restricting their scalability and practicality. This paper offers a camera-based, real-time exercise monitoring and feedback system using pose estimation and computer vision to examine body posture during strength training exercises to solve these problems. Offering a reasonably priced substitute for conventional methods, depending on wearable technology or offline assessments, the system uses a standard webcam to deliver instantaneous, non-intrusive feedback.

With OpenCV supporting video processing, posture visualization, and real-time feedback generation, the proposed framework combines MediaPipe Pose for accurate detection of body landmarks, enabling exact tracking of joints, including shoulders, elbows, and knees. A Streamlit-based web interface improves user interaction by supporting exercise selection, live monitoring, performance tracking, and historical data analysis, therefore catering to a wide range of full-body fitness programs, including push-ups, hammer curls, and squats. Empowering users to keep correct form, the system includes automated repetition counting, real-time joint angle analysis, and posture correction notifications sent via audio and visual cues. This work adds to the development of smart fitness monitoring technologies by offering the design, implementation, and assessment of the system, including a comparison study of its accuracy, latency, and usability against current techniques.

II. LITERATURE SURVEY

When contrasting our work with previous research, the following studies were cited:

[1] ***Computer Vision for Automatic Assessment of Physical Therapy Rehabilitation Activities***

A Modular Neural Network (MNN) for assessing rehabilitation exercises with visual data is presented in this paper. It analyzes movement accuracy using machine learning and computer vision, allowing for remote patient monitoring. Although the system works well for rehabilitation, it has drawbacks such as high computational costs, limited general fitness adaptability, and scalability issues.

On the other hand, my project focuses on analyzing general fitness exercises like hammer curls and push-ups in real-time. It guarantees effective processing on consumer-grade hardware by utilizing Mediapipe-based pose estimation. Its modular design facilitates a wider variety of exercises and provides immediate feedback to improve accessibility and user performance.

[2] ***Machine Learning Algorithms for Arm and Shoulder Exercises Using Sensors***

This study evaluates algorithms employing machine learning for arm and shoulder exercises using wrist-worn sensors, looking at movement accuracy and computational efficiency. The system's limitations include its dependence on wearables, limited exercise range, and absence of real-time visual feedback, despite its effectiveness for continuous monitoring.

By using computer vision for body movement analysis instead of specialized hardware, my project gets around these restrictions. It improves accessibility and training efficacy by supporting a wider variety of exercises, such as push-ups and hammer curls, and by giving users instantaneous visual feedback to help them correct their form.

[3] ***Recognizing Video-Recorded Actions Performed in a Traditional Chinese Exercise***

In a CNN-LSTM model for video-recorded actions in traditional Chinese exercises, the LSTM captures temporal dependencies. At the same time, the CNN extracts spatial features to increase the accuracy of action recognition. However, because it only considers traditional Chinese exercises, requires a significant amount of processing power, and may struggle to generalize to other exercise styles, the model's adaptability is limited. By using Mediapipe-based pose estimation for real-time feedback on common hardware, my project, on the other hand, supports a greater variety of fitness exercises, including hammer curls and push-ups. Instant posture correction is made possible by this method, which increases the system's usefulness and accessibility for training in general fitness.

[4] ***AI Trainer: Autoencoder-Based Approach for Squat Analysis and Correction***

This study's AI Trainer system analyzes squats using an autoencoder-based method with an emphasis on joint angle detection and posture correction. Although useful for enhancing squat form, its drawbacks include a limited emphasis on a single exercise, poor generalization to other movements, and high hardware requirements that limit scalability and accessibility.

By facilitating a wide variety of exercises, such as push-ups and hammer curls, which are both upper and lower body movements, my project overcomes these constraints. It ensures accessibility and versatility by providing real-time feedback on common hardware through the use of Mediapipe-based pose estimation. It is a more adaptable and scalable fitness training solution because of its modular design, which makes it simple to incorporate new exercises.

III. DESIGN

A. System Overview

Webcam-based Real-time Exercise Monitoring and Feedback System offers strong user management and data tracking while guiding users in executing strength-based exercises like hammer curls, push-ups, and squats with correct form. It uses a modular design to provide instant visual and audio feedback, monitor progress, and assist with administrative control. The system presents results via an easy web interface, processes body movements to count repetitions and identify form deviations, and captures live video. Apart from export possibilities for further study, users may authenticate, choose workouts, see real-time feedback, and access past performance data. A specific dashboard to track user activity, handle accounts, and check logs helps administrators to guarantee scalability and security. Recent improvements include centralized data storage, enhanced export features, and increased administrative powers, which help the system to be flexible for institutional use as well as personal fitness.

B. Architecture

Three main parts define the system's modular architecture, meant to guarantee scalability, maintainability, and effective real-time operation:

1. *Pose Estimation Engine:* Using MediaPipe Pose and OpenCV to process webcam input, the Pose Estimation Engine component performs real-time detection of 33 body landmarks and computes joint angles to determine movement phases. While also starting feedback systems and producing visual overlays for posture correction and progress visualization, it supports exact posture analysis for exercises like push-ups, squats, and hammer curls.
2. *Frontend Dashboard:* Built with Streamlit, the Frontend Dashboard is a simple interface with exercise selection, session start, user authentication, performance visualization, and historical tracking. With more features for data export in CSV format, it dynamically shows session summaries, repetition statistics, and progress indicators in real-time, therefore improving user interaction and data access.
3. *Backend Logic Handler:* Supported by a Flask-based server, this module combines pose evaluation, repetition counting, exercise-specific logic customized for different movements, and feedback generation. Using a SQLite database for persistent user and exercise data, it handles data processing and storage, updates the frontend dashboard with session results, and guarantees smooth interaction and administrative control via a specific management interface.

C. Technologies Used

Robust exercise tracking, feedback delivery, user interaction, and data management are made possible by the Real-time Exercise Monitoring and Feedback System using a whole range of technologies. Key tools listed below and their particular functions are essential for the system's functioning:

- *MediaPipe Pose*: By means of webcam input, this technology allows real-time detection of 33 body landmarks, offering exact skeletal mapping for correct joint angle computations and movement analysis. Forming the basis for posture evaluation, it helps to track exercises including push-ups, hammer curls, and squats.

- *OpenCV*: Used for video frame processing, image analysis, and feedback visualization, it calculates joint angles, draws posture lines, overlays warning messages (e.g., form correction alerts), and shows performance metrics like repetition counters and gauge meters on the real-time video feed.
- *Streamlit*: The web-based user interface of this framework provides features including user authentication, exercise selection, real-time feedback visualization, historical performance tracking, and CSV data export. The interactive dashboard guarantees a quick and easy experience for both users and administrators.
- *Pygame*: Used to produce audio feedback like beeps, it notifies users of shape anomalies, therefore improving real-time interaction by matching visual cues with instant aural alerts.
- *Flask*: This technology acts as the backend server, managing HTTP requests from the frontend, coordinates session start, runs exercise logic, and provides results, ensuring smooth integration across system components.
- *SQLite*: This lightweight database solution stores user credentials, exercise history, login logs, and administrative data, supporting persistent data management with efficient querying for progress tracking, user administration, and audit logging.

Ensures exact and orientation-independent movement analysis by means of mathematical calculations, especially for joint angle computations, using NumPy.

D. Algorithms

The system combines a set of interdependent modules working together to provide exact and actionable feedback, guaranteeing correct exercise evaluation.

1. *Joint Angle Calculation*: This module calculates joint angles to allow dynamic segmentation of exercise movements using geometric methods applied to pose landmarks identified by the system. It finds different movement stages like flexion, ascent, and descent by examining angles at key joints elbows, knees thereby offering a basis for real-time posture analysis across exercises, including push-ups, hammer curls, and squats.
2. *Repetition Counting*: This part counts repetitions automatically using threshold-crossing logic, therefore guaranteeing consistency and removing human error in tracking. A push-up, for example, is logged using a debounce mechanism to avoid over-counting when the elbow angle changes from an extended state (>150°) to a flexed state (70°–150°) and back.
3. *Alerts for Posture Correction*: Rendered close to the impacted joints, e.g., "Straighten back" for squats, audio alerts, and yellow warning overlays let users change their form in real time and lower the chance of injury.
4. *Visual Feedback Overlay*: By means of real-time visual aids directly on the video frame—including progress bars, gauge meters, colored posture lines, and angle annotations—this module increases user involvement. These features offer simple performance feedback, therefore enhancing understanding and drive during workout sessions.

IV. IMPLEMENTATION

This paper offers a computer vision-based system meant to find, evaluate, and monitor body movements during strength training exercises using MediaPipe Pose and OpenCV as fundamental technologies. Engineered to provide real-time corrective feedback while guaranteeing high usability, accuracy, and responsiveness, the system supports a wide variety of exercises, including push-ups, hammer curls, and squats. Using a standard webcam, the platform offers non-intrusive posture analysis and instant feedback via a Streamlit-based interface, which supports exercise selection, live monitoring, and performance tracking. While keeping low-latency performance and joint angle accuracy, the modular design allows for scalability and the addition of more exercise kinds and sophisticated features, so improving the safety and efficacy of self-guided fitness programs.

A. System Workflow

As shown in the accompanying workflow diagram (Figure-1), the system guarantees smooth data flow and real-time feedback by means of four sequentially organized phases.

- Handling User Input: User input management starts the workflow with web-based user authentication; live video frames are obtained using a regular webcam. From the available choices, authorized users choose an exercise; the system processes these frames to identify pose markers, therefore setting the stage for the next analysis. Failed login attempts set off security alerts sent to both users and administrators, therefore strengthening system integrity.
- Pose Estimation with MediaPipe: Emphasizing on important joints including ankles, knees, hips, shoulders, elbows, and wrists, this phase uses MediaPipe Pose to identify 33 body landmarks. By mapping landmark coordinates to pixel values and calculating joint angles to define exercise stages—e.g., flexion, ascent—precise real-time movement tracking across exercises like push-ups, hammer curls, and squats is made possible.
- Exercise Detection and Feedback: With deviations causing instant audio cues and yellow visual warning overlays on the video frame to encourage correct form, predefined angular thresholds are used to validate exercise movements. Users get instantaneous fixes to improve safety and performance; administrators can monitor user activities to guarantee compliance and support.

Tracking and Reporting: Monitoring and Reporting, Joint movement sequences dynamically update stage indicators and repetition counters in real time. User and historical exercise data kept in a database drives the interface to refresh to show present repetition counts, posture feedback, and exercise progress. Users and administrators alike have access to statistics; the procedure enables session termination or continuation, therefore enabling thorough monitoring.

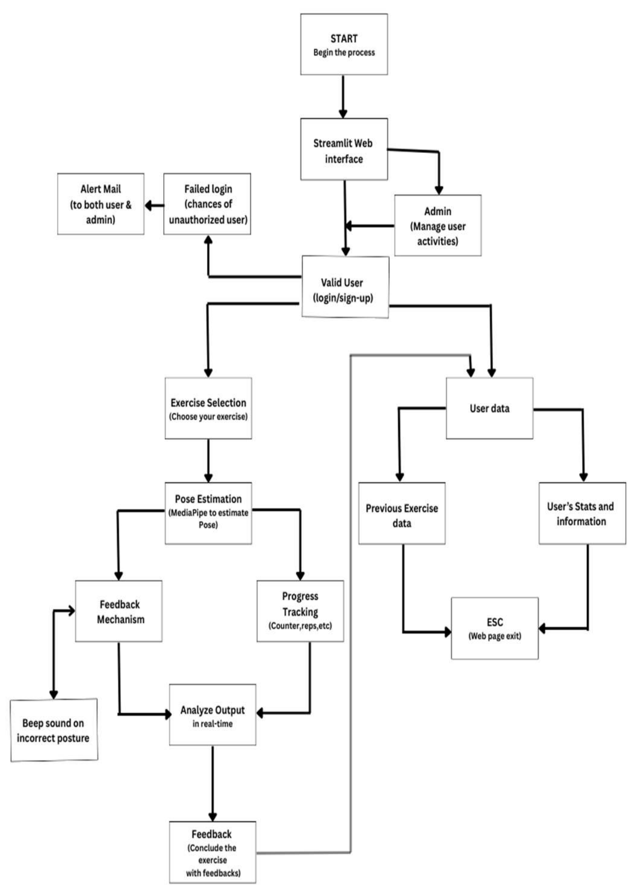

Fig.1: System's Workflow

B. Angle Calculations

The base of the posture analysis logic is joint angle estimation. The arctangent of directional vectors is used to determine the internal angle at point B for three important points, A, B, and C (shoulder, elbow, and wrist, for example).

Let:

A = upper joint (e.g., shoulder),

B = pivot joint (e.g., elbow),

C = lower joint (e.g., wrist)

The angle at B (θ) is computed using:

$\theta = |\ \mathrm{arctan2}(Cy - By, Cx - Bx) - \mathrm{arctan2}(Ay - By, Ax - Bx)\ | * 180/\pi$

For form correction and rep validation across exercises, this arctan2-based calculation, implemented with NumPy, ensures precise angle measurement independent of body orientation or limb direction.

C. Exercise-Specific Logic

Dedicated classes for each supported exercise—hammer curls, push-ups, and squats—implement the exercise-specific logic of the Real-time Exercise Monitoring and Feedback System, therefore guaranteeing a modular and extensible design. These classes examine movements using real-time landmark detection and video processing, therefore integrating smoothly with the pose estimation pipeline of the system. Executed inside the main processing loop and visualized via the interface, the logic emphasizes tracking repetitions, spotting form abnormalities, and providing instant feedback. In line with the system's scalability goals, this modularity facilitates the simple addition of extra exercises and is backed by the backend data management infrastructure.

1. *Hammers Curls*: The hammer curls class monitors bilateral arm movements using shoulder, elbow, and wrist landmarks, computing joint angles to find exercise phases. With distinct counters for left and right arms, a repetition is counted when the elbow angle moves from an extended state (angle < 47°) to a flexed state (angle > 155°) and back. Alerting users to problems like wrist height exceeding a threshold or elbow flaring (shoulder-elbow-hip angle deviation > 15°) helps to correct form by causing an audio beep and a yellow warning overlay (e.g., "Wrist too high"). Displayed on the video feed, the class outputs real-time counters, angles, warnings, progress indicators, and stage updates (e.g., "Up", "Down").
2. *Push-ups*: Using shoulder, elbow, and wrist landmarks, the push-ups class tracks torso and arm alignment to monitor exercise performance. With a 1-second debounce to avoid double-counting, elbow angle transitions determine repetitions: "Starting position" (>150°), "Descent" (70°–150°), and "Ascent" (<70°). Accompanied by audio cues and visual alerts, form correction notifications are sent for elbow flaring (>15° deviation), neck craning (head-shoulder angle > 10°), or hips sagging (hip-shoulder alignment > 5°). Visualized on the interface, the class updates a rep counter, current angle, and stage in real-time, therefore guaranteeing correct technique throughout the exercise.
3. *Squat*: The squat class tracks exercise depth and form by examining hip, knee, and ankle landmarks. Verifying sufficient range of motion, a repetition is logged when the knee angle changes from an upright position (>160°) to a squat position (70°–130°) and back. Using audio beeps and visual alerts—e.g., "Too low!"—form correction is applied by identifying excessive back curvature (hip-shoulder angle > 10°), knees extending past toes (knee-ankle alignment > 5°), or insufficient depth (knee angle > 130°). Displayed on the video feed, the class offers real-time rep counters, angles, and stage indicators, helping users to attain proper execution.

V. RESULTS & EVALUATION

A. Performance Metrics

The accuracy, latency, and real-time responsiveness of the system were assessed through three distinct exercises. The results are shown in the Table.

Exercises	Accuracy (%)	Feedback Delay (ms)
Push-ups	93.2	50
Hammer curls	91.5	45
Squats	94.0	48

Table-1: Performance Metrics Across Exercises

B. Comparative Study

A comparative analysis is presented in Table II, highlighting how the proposed system compares with existing solutions, including wearable sensor-based systems, autoencoder-based methods, and CNN-LSTM deep learning models.

Features	This System	Wearable sensors	AI-based Auto Encoder	CNN-LSTM model
Approach	Mediapipe & OpenCV	Machine learning on wearable sensor data (KNN, SVM)	Autoencoder-based squat posture correction.	Deep learning-based action recognition
Real-Time Processing & Feedback	Instant audio and posture correction with visual/ pygame.	No real-time feedback (only post-processing)	Limited feedback (only after squats are completed).	No real-time posture correction (only recognition)
Hardware Requirement	Webcam Only	External Sensors	High-Performance GPU	GPU-intensive for CNN-LSTM training.
Exercise Variety	Multiple (push-ups, squats, hammer curls)	Limited	Single	Few (Baduanjin movements)
Accessibility	High	Low	Moderate	Moderate
Feedback Type	Real-time Visual+ Alerts	Data Logging	Post-Processing	Post-Processing

Table-2: Comparative Analysis of Exercise Monitoring Systems

C. Sample Output

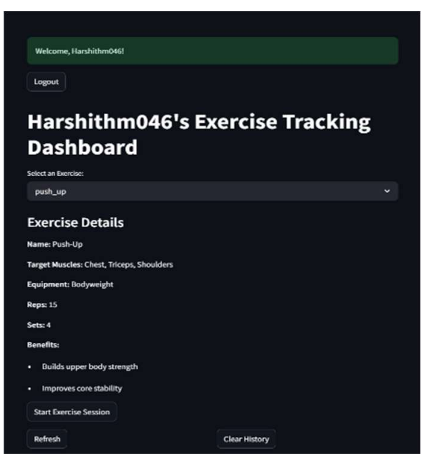

Fig- 2: Streamlit user interface (Exercise selection)

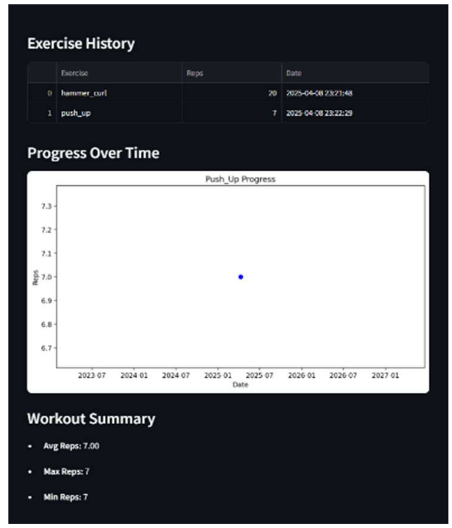

Fig- 3: Streamlit user interface (user workout history)

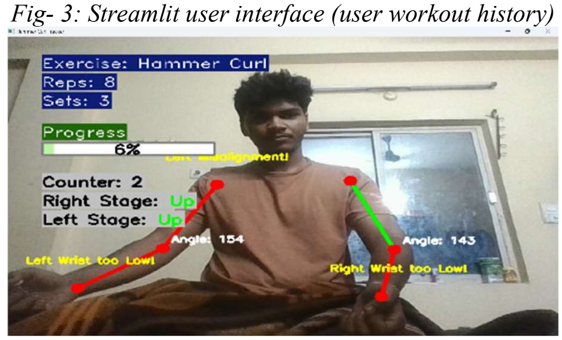

Fig- 4: Indicates a wrong Posture (Hammer curl)

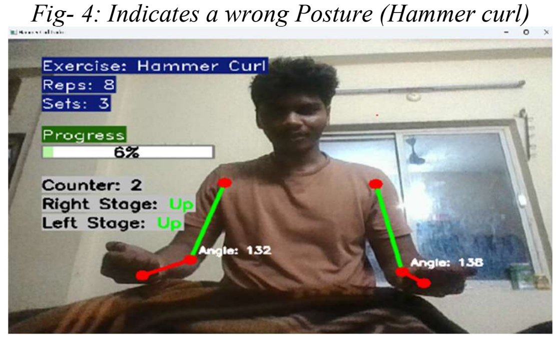

Fig- 5: Indicates a correct Posture (hammer curl)

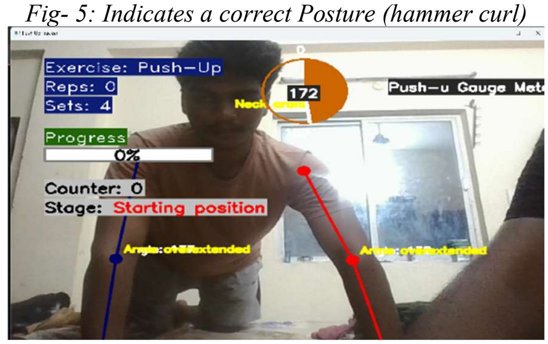

Fig-6: Indicates a wrong Posture (Pushup)

Fig-7: Indicates a correct Posture (Pushup)

VI. CONCLUSION

This paper proposes a real-time exercise monitoring and feedback system based on pose estimation and computer vision technologies as a creative tool to improve fitness and rehabilitation practices. While MediaPipe Pose is used to correctly extract important body landmarks, therefore enabling exact movement analysis, the system uses OpenCV to process video input, visualize posture in real-time, and provide instant feedback. Built on Streamlit, a frontend offers users an easy and accessible interface that allows exercise selection, live monitoring, and thorough performance tracking all possible with a regular webcam. This method offers a non-intrusive, affordable option that increases participation across many user groups, which is quite different from traditional methods depending on wearable sensors or post-processing. Currently, the system supports three fundamental exercises—push-ups, hammer curls, and squats—integrating real-time repetition counting, stage identification, and posture correction using a mix of audio cues and visual alerts shown on the screen. These qualities enable users to dynamically change their shape, therefore enhancing safety and effectiveness. Performance study has verified the system's real-time responsiveness, with high accuracy rates over 91% and feedback latency under 50 milliseconds, therefore highlighting its dependability and efficiency for practical use.

A foundation of the system's success is its modular design, which allows easy addition of more exercises and opens the way for future improvements. Looking forward, possible changes are the inclusion of voice feedback to support current audio alerts, therefore improving accessibility for visually impaired people. Developing a mobile app version could increase the system's reach and let users interact with the platform on tablets or smartphones using the flexibility of the present web-based interface. Cloud storage options also help to securely back up data and synchronize many devices, therefore meeting scalability requirements as user bases expand. To increase robustness, especially in settings where body parts might be blocked, advanced occlusion handling methods could be implemented to ensure correct pose estimation under difficult circumstances. To increase user involvement and motivation, gamification features like competitive leaderboards or achievement badges could also be included. This system greatly improves accessibility, affordability, and participation in the realm of self-guided fitness and rehabilitation, therefore qualifying it as a scalable and smart replacement for conventional workout monitoring tools relying on wearable technology or in-person trainers. These developments taken together hold the potential to increase even more the influence and use of the system in various fitness environments.

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