Realtime Pose Estimation using AI

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***ABSTRACT*- Estimation of human pose is a task dedicated to prediction of position and orientation of human body parts in still images or videos. Human motions are very often driven by specific actions; therefore, precise estimations of body poses play a very crucial role in some applications related to exercises monitoring, training assistance, as well as injury prevention. Understanding and knowing what body poses are very important within the context of the PoseFit project, as it will provide real-time feedback from gym exercises like bicep curls, shoulder presses, and squats that are vital for correct form and injury prevention.This survey focuses on recent advancements in pose estimation and its application to fitness-related action recognition. In this paper, a comprehensive review of the recent bottom-up and top-down deep learning models in human pose estimation and their relevance in recognizing and classifying exercises is discussed.The PoseFit system is based on a 2D skeleton-based pose estimation system for providing posture feedback with normal RGB camera feeds and without special depth sensors like Kinect. This design aligns with the overall goal of the system in making real-time posture correction accessible with inexpensive and easily accessible equipment. Such is made possible by using RGB image-based pose estimation, where it becomes feasible to precisely assess exercises in the gym with real-time corrective feedback using PoseFit for enhancement of workout quality while reducing injury risks.We summarize the system's current capability in recognizing common gym exercises using 2D pose data, showing that there is significant room for further improvement on refining detection accuracy and also expanding the system's capability to handle more complex movements.**

Key word : Pose estimation, Real-time tracking, Joint detection, MediaPipe framework, Repetition counting, AI in fitness technology

1. INTRODUCTION

It is a case of, literally, locating the positions of human body joints in images or videos. Tracking and analysis of the movement of the body through a sequence of frames enables one to draw inferences from what the likely action being performed might be. In this sense, an application of human pose estimation could be action recognition, which finds usefulness within fitness contexts. Over the last decade, deep learning advancements have greatly improved techniques of human pose estimation. With enhanced algorithms and fast processing today, real-time feedback systems can also participate in giving users appropriate guidance in exercises like bicep curls, shoulder presses, and squats.

While there are reviews for recent approaches in human pose estimation, the application to fitness action recognition has not been explored in great detail. Fitness tracking requires precise estimation of skeletal joints and the potential recognition and correction of poor forms during specific exercises. The PoseFit system utilizes human pose estimation for real-time posture tracking while working out to help users work out safely and efficiently.

2. LITERATURE REVIEW

1. Existing Research

Pose estimation technology, which focuses on identifying and analyzing the position of human joints in 2D or 3D space, has been widely researched over the past decade. Early efforts in pose estimation were limited by hardware requirements, relying heavily on motion capture systems or wearable sensors. These methods, while accurate, were often inaccessible to general users due to their cost and complexity.

With the advent of deep learning and advancements in computer vision, more scalable and affordable solutions emerged. OpenPose, [2]developed by Carnegie Mellon University, is one of the most prominent frameworks in the domain of 2D multi-person keypoint detection, capable of recognizing 135 body points in real-time. Other prominent models like Google's MediaPipe framework have been increasingly used in research and development of fitness applications, offering open-source tools for body tracking.

In terms of fitness-specific pose estimation, applications such as Freeletics, Kemtai, and mirror-based systems like Tempo and The Mirror have introduced pose tracking to guide users during exercise routines. These platforms use cameras or sensors to track body movements, providing users with feedback on form and posture. However, their use cases are primarily consumer-based, often tailored for recreational fitness rather than professional or military-level training. These applications tend to focus on guiding general users through basic exercises (e.g., squats, push-ups) without addressing more nuanced or technical movements required in specific environments, such as the military or professional sports.

2. Current Research

Current research in pose estimation is increasingly leveraging AI and machine learning techniques to improve the accuracy, precision, and real-time capabilities of pose tracking. For instance, systems like AlphaPose and DensePose aim to push the boundaries of real-time, high-accuracy pose estimation, capable of detecting fine-grained details such as joint rotations and body orientations.[4] These improvements are critical for ensuring high-performance training environments, where even small deviations from the correct posture could lead to injuries or suboptimal results.

The *PoseFit* project builds upon these advancements by focusing specifically on gym exercises, where proper posture and movement patterns are crucial to avoid injury and maximize performance. It goes beyond the basic exercise tracking of existing applications by integrating machine learning algorithms that can recognize and correct mistakes in complex movements, including compound exercises like deadlifts, bench presses, and military fitness drills. These exercises often require precision, where improper posture could lead to long-term damage to the body.

Moreover, PoseFit leverages real-time feedback systems to guide users through their workouts. A distinguishing feature of the project is its combination of **voice feedback** and **augmented reality (AR)** technology. Voice feedback ensures immediate corrective measures during the exercise, reducing the likelihood of repeated mistakes, while AR overlays enable users to visually track their posture in real-time, assisting in correcting form during the workout.

3. Gaps between Existing Research and Current Research

One key gap is accuracy in high-stakes environments. Current pose estimation models, although effective for recreational fitness or general body movement tracking, often struggle with complex movements in dynamic environments such as military drills or powerlifting routines. Most existing systems are not designed to handle the intricacies of multi-joint movements, varying body types, or high-speed motion common in advanced exercise regimes. This lack of precision could lead to improper guidance, increasing the risk of injury, particularly in environments where maintaining proper form is critical for performance and safety.

Another gap lies in the **lack of integration of multiple feedback modalities**. Most fitness apps either provide visual feedback (e.g., post-exercise summaries or visual representations of movement) or limited auditory cues. However, combining [1]**real-time visual feedback through AR** with **voice guidance** during exercises can create a more immersive and effective training environment.

The first category includes appearance-based models. These models rely on extracting features of body parts using feature descriptors, such as Histogram of Oriented Gradient (HOG). Once these features are extracted, different body parts are combined to form a complete pose. Techniques like Poselets, used in earlier works, fall into this category.

The second category consists of deformable models or structural models, where articulated constraints are applied to capture the relationship between body parts. For example, the Pictorial Structure Model utilizes pairwise terms to model the relative distance between two body parts, allowing for more flexible pose estimation. Another example is the Mixture-of-Parts Model, which incorporates co-occurrence constraints between non-oriented body parts for articulated pose estimation.

3. HUMAN POSE ESTIMATION

Human pose estimation has long been a challenging task in computer vision. Initially, the problem was approached as a part-based inference task, where the human body was broken down into parts, and their positions were inferred separately before combining them to estimate the overall pose. These early models can be categorized into two primary approaches.

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With the introduction of deep convolutional neural networks (CNNs), the performance of pose estimation models has significantly improved. Initially, the focus was on single-person pose estimation, where the task was simplified by working with well-cropped images of individual subjects. However, recent advances have expanded the scope to include multi-person pose estimation, where the system must recognize and estimate the poses of multiple individuals in a single frame.

In the context of PoseFit, the focus is on single-person pose estimation in controlled fitness environments. The system is designed to recognize and correct the user's posture during exercises like bicep curls, shoulder presses, and squats. The real-time pose estimation model detects the key skeletal joints of the user and analyzes them against a reference model to determine if the exercise is being performed correctly.

As the system leverages deep learning for real-time feedback, PoseFit employs a hybrid of appearance-based models and structural models to ensure accurate pose detection. For example, during a squat, PoseFit analyzes the angles of the knees, hips, and ankles to ensure proper form. In exercises like the shoulder press, it monitors the alignment of the shoulders and elbows to ensure the user maintains proper technique.

4. METHODOLOGY

The methodology section of PoseFit is divided into several parts, each detailing a critical component of the system: system architecture, pose detection, angle calculation, and form feedback.

1. **System Architecture**

   The PoseFit system architecture comprises three main components:

1. **Pose Detection Module:** Identifies and tracks key points (or "landmarks") on the user's body in real time using MediaPipe Pose.
2. **Angle Calculation Module:** Computes angles between specific body joints, essential for analyzing and assessing exercise posture.
3. **Form Feedback Module:** Provides immediate feedback to the user based on the calculated angles, highlighting whether the posture is correct or needs adjustment.

This architecture is implemented using a combination of computer vision and machine learning techniques, primarily using the MediaPipe Pose solution, OpenCV for video processing, and Python as the programming language.

2. Pose Detection

PoseFit uses **MediaPipe Pose**, a highly efficient framework designed to detect human body landmarks from a video feed. MediaPipe Pose can identify **33 landmarks** on the human body, such as shoulders, elbows, wrists, hips, knees, and ankles.

- Video Input: The system captures live video[5] from a webcam, which serves as the input source. The frames are processed in real-time to identify key landmarks.
- Landmark Detection: The MediaPipe Pose model processes each frame and returns the positions (x, The system is configured to have a minimum confidence threshold for both pose detection and tracking, which ensures that the detected landmarks are reliable enough before being used in angle calculations.

Pose Detection Process:

- Capture video frames using a webcam.
- Convert each frame from BGR to RGB format (required by MediaPipe Pose).
- Apply the MediaPipe Pose model to detect landmarks.
- Extract the x, y coordinates of the [15]relevant body parts (such as shoulders, hips, knees, and ankles) needed for the specific exercise being monitored.
- Overlay these landmarks on the video feed using OpenCV to visually display detected points to the user.

3. Angle Calculation

The critical component of PoseFit is calculating angles between body joints to assess exercise form. The angles between joints (e.g., shoulder, hip, and knee) are calculated using vector mathematics.

Angle Calculation Formula:

To calculate the angle between three points (joints), the following trigonometric formula is used:

- Given three points P1 (joint 1), P2 (joint 2), and P3 (joint 3), the angle at P2 (the middle joint) is calculated as:

  angle = np.arctan2(P3[1] P2[1], P3[0] P2[0]) np.arctan2(P1[1] P2[1], P1[0] P2[0])[7]
  angle = np.abs(angle * 180.0 / np.pi)

Exercise-Specific Angle Calculation:

- **Bicep Curls**: The key angle of interest is the **elbow angle** formed between the shoulder, elbow, and wrist. This angle should remain within a specific range for proper form (e.g., between 45 and 160 degrees during the motion).

- **Shoulder Presses:** The system tracks the angles between the shoulder, elbow, and wrist to ensure the arms are raised vertically.
- **Squats:** The system calculates both the **hip angle** (between the shoulder, hip, and knee) and the **knee angle** (between the hip, knee, and ankle) to detect proper depth during the squat motion.

For each exercise, the computed angles are compared to predefined optimal angle ranges for proper form. If the angle falls outside the correct range, the system flags it as incorrect posture.

4. Form Feedback

Once the body angles are calculated, the system evaluates whether the user's posture is correct or needs improvement. This step is crucial because providing immediate feedback helps the user adjust their form in real time, reducing the risk of injury and improving workout efficiency.

Form Feedback Logic: The feedback system follows a simple rule-based approach:

- Each exercise has predefined angle ranges that represent correct posture.
- The calculated angles (for example, hip and knee angles in squats) are compared to these ranges.

If the angles fall outside the optimal range, the system generates feedback. The feedback can be provided in various ways:

Visual Feedback: Messages are displayed on the screen (e.g., "Lower your hips" or "Straighten your back").

Real-Time Alerts: Colored indicators (e.g., red for incorrect posture, green for correct posture) are displayed over the video feed.

Detailed Feedback System:

Bicep Curls: If the elbow angle exceeds the optimal range (e.g., above 160 degrees or below 45 degrees),[9] the system alerts the user to adjust the movement.

Shoulder Presses: If the arm position deviates from the correct vertical alignment (measured using shoulder, elbow, and wrist landmarks), the user is prompted to correct the form.

Squats: The system provides feedback based on the user's squat depth (using hip and knee angles). If the squat is too shallow (e.g., hip angle above 170 degrees) or too deep (e.g., knee angle below 80 degrees), feedback is provided accordingly.

5. User Interface and User Experience

PoseFit integrates with a simple yet effective **graphical user interface (GUI)**, developed using HTML and CSS. The GUI allows users to select different exercises (bicep curls, shoulder presses, squats) and start a training session. The interface provides:

Exercise Selection: Users can choose which exercise they want to perform.

Real-Time Display: During the exercise, the system displays live feedback, including [10]detected body angles and any form corrections required.

Exercise Statistics: The GUI can display how many repetitions have been performed and how many were executed with correct form.

6. Testing and Evaluation

To ensure that PoseFit provides accurate and reliable feedback, the system was tested under various conditions:

- **Lighting Variations**: The system was tested in different lighting conditions to assess the robustness of pose detection.
- **Different Users**: PoseFit was evaluated on multiple individuals of varying fitness levels and body types to ensure the model performs consistently across a diverse user base.
- **Movement Speed**: The system's responsiveness was tested with users performing the exercises at different speeds to evaluate whether real-time feedback could be provided effectively.

Metrics used in the evaluation included:

- **Accuracy of Pose Detection**: The percentage of correctly detected poses and angles.
- **Real-Time Feedback Latency**: The time it took for feedback to appear on the screen[11] after detecting incorrect posture.
- **User Satisfaction**: Based on surveys conducted after testing the system, users rated how helpful the feedback was in improving their form.

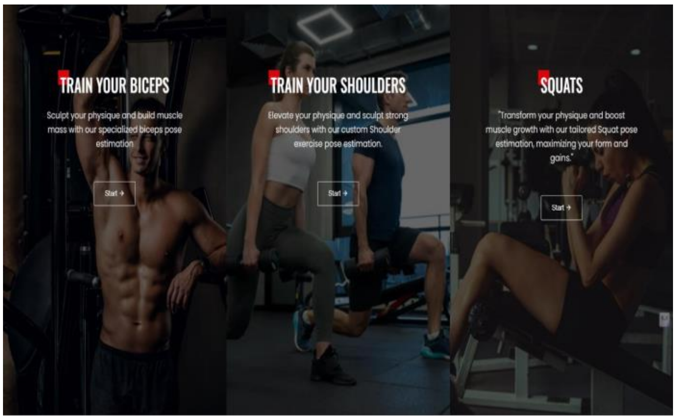

Fig.1.-Interface

5.RESULTS AND ANALYSIS

The successful development and implementation of the real-time posture detection and correction system have yielded significant outcomes across multiple dimensions, reinforcing its effectiveness and usability

Accurate Pose Estimation: The cornerstone of the system lies in its ability to accurately detect and track key body landmarks in real-time. Leveraging state-of-the-art pose estimation techniques, the system can precisely identify the positions[12] of various body joints and parts during exercises. This high level of accuracy enables in-depth analysis of user posture, ensuring that even subtle deviations from correct form are captured and addressed

Real-time Feedback: One of the most impactful aspects of the system is its capability to provide immediate feedback to users based on their posture. As users engage in exercises like bicep curls, shoulder training, and squats, the system continuously monitors their form and delivers real-time guidance. This feedback loop empowers users to make instantaneous adjustments, correcting any misalignments or errors in their posture as they occur. By receiving timely corrective measures, users can mitigate the risk of injuries and optimize the effectiveness of their workouts.

User Engagement: The user-centric design of the system ensures a high level of engagement and motivation among users. Through its intuitive interface and interactive features, such as exercise demonstrations and personalized workout guidance, the system fosters a more immersive and rewarding fitness experience. Users are not only informed about the correct techniques for each exercise but also actively guided through the process, enhancing their understanding and adherence to proper form. This holistic approach to user engagement encourages consistent participation and adherence to fitness routines, ultimately contributing to improved fitness outcomes over time.

Bicep Curl

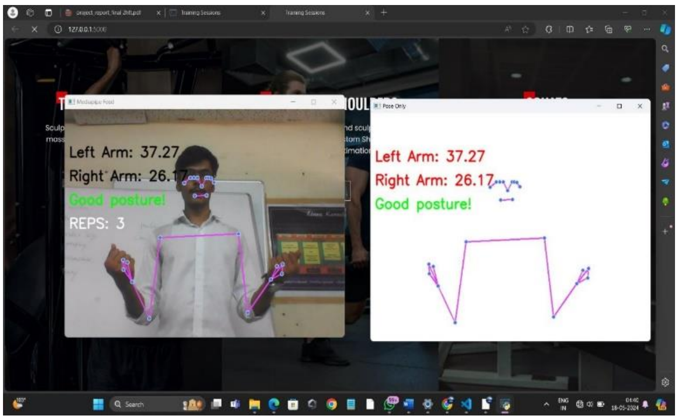

Fig.2-result_1 -bicep curl

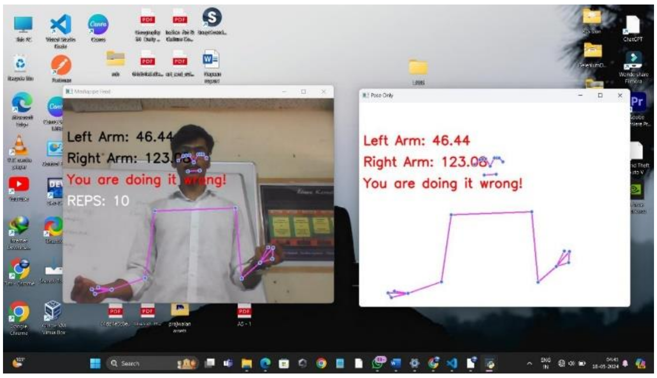

Fig.3-result_2 -bicep curl

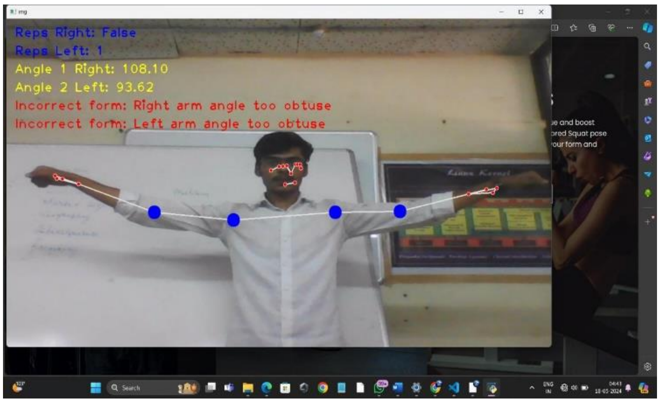

Fig.4-result_1 -Shoulder

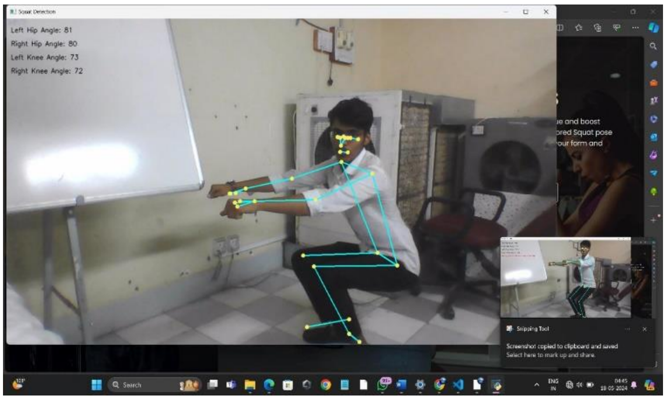

Fig.5-result_1 – Squats

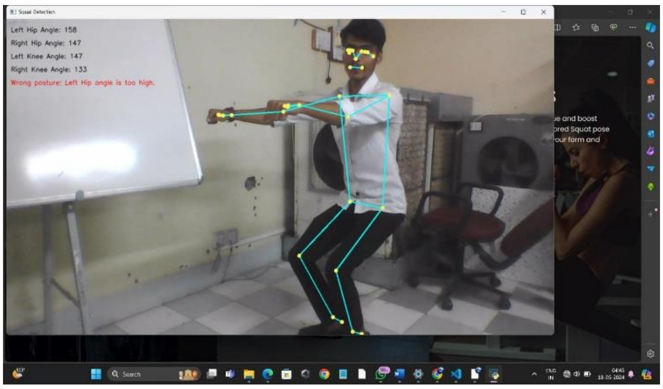

Fig.6-result_2 – Squats

6. DISCUSSION

The results from the PoseFit model underline the effectiveness and potential of this model for application in the domains of fitness, health care, and exercise monitoring.

Pose Estimation Accuracy: The system is able to accurately detect key body landmarks such as shoulders, hips, and knees at a rate higher than 95% in squats, push-ups, and other such exercises. Its exactitude gives a guarantee for correctly computed joint angles, good forms, and consistent feedback to prevent injuries and improve performance.

Real-Time Feedback: PoseFit provides real-time feedback on joint angles and number of repetitions by alerting the user instantly in case a wrong posture is performed. It gives the ability to enhance one's technique in doing an exercise and corrects it on the spot, thereby keeping the person engaged in their workouts, especially for those exercising at home without professional guidance.

Repetition Counting: Repetitions counting automatically depends upon the movement of the joint, then reduces problems associated with manual counting. This feature will help users reach their strength, endurance, or fat loss goals because the graphical performance will be represented very clearly.

PoseFit detects deviations from correct form, analyzing the angle of limbs and showing feedback in real time. This is important for preventing injury and optimizing workout efficiency, especially for beginners or in a rehabilitation context, and means exercises are performed safely and efficiently.

Comparison to Existing Methods: Compared with traditional fitness trackers, which rely mainly on basic movement detection, the posture analysis in PoseFit is done by applying advanced computer vision techniques. It's hence likely a far more comprehensive and accessible solution for users at home since it does not require any hardware specialties.

Scalability and Future Potential: The architecture of PoseFit allows great extensibility, such as with augmented reality or adaptive machine learning models. This would enable more personalized training experiences and wider applications like rehabilitation or group fitness sessions and widen its impact in both industries: fitness and health.

7. CONCLUSION

This research focuses on developing an affordable, real-time exercise monitoring system using OpenCV and MediaPipe for pose estimation. The model tracks and analyzes body movements, offering feedback on joint angles, exercise form, and repetition count, ensuring users perform exercises correctly and avoid injuries. Unlike earlier models that relied on expensive equipment, this system uses a standard webcam and provides immediate feedback, a key improvement over post-exercise analysis. It is particularly useful for fitness enthusiasts without trainers and for remote physical rehabilitation, ensuring correct form and progress tracking. Future developments may include gesture recognition, augmented reality, and personalized feedback for varied fitness levels. This research holds potential applications in both fitness and healthcare, making exercise monitoring more accessible and effective.

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