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Real-Time Exercise Monitoring and Posture Correction System Using Deep Learning Algorithms

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Abstract: People exercise to keep healthy. Many of them work out without a trainer, which can lead to poor posture, muscle injuries, and long-lasting injuries. People who work out typically only watch videos online. Do what they think is right; no one tells them when they are doing something wrong. To combat the problem, researchers design a system that observes how people work out and assists them in correcting their posture in real time. This technology records camera footage and develops algorithms to detect key body parts, such as shoulders, elbows, hips, and knees. It uses these points to model the person's body and calculate joint angles. Then it compares those angles to the posture guidelines for each exercise. A notification appears on the screen if their posture is incorrect, allowing them to change it immediately. Researchers designed the system using recordings of people exercising with poor posture to learn how people move and how the system will behave in various situations. Researchers found that the method worked effectively with simple activities in low light and a crowded background. It worked well on a normal computer and was accurate 98%–99% of the time. It is inexpensive and easy to use because it only requires a camera. It helps home, gym, and sports athletes train more effectively and avoid injuries. Safe exercise will help injured persons heal.

Keywords: Deep Learning; Pose Detection; Computer Vision; Real-Time Monitoring; Posture Correction; Exercise Tracking; Human Activity Recognition.

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1. Introduction

Exercise is vital to our well-being. It helps us stay fit. Prevents many diseases like obesity and diabetes. Most people work out at home or in a gym, without a trainer. They adhere to the methods outlined in apps or videos. This is problematic; they could perform the exercises incorrectly [1]. This can result in pain and injuries in the shoulders, knees and back. So it is very important to do exercises like bicep curls, arm circles, shoulder exercises, jumping jacks and squats correctly. In a gym, a trainer can watch us. Let us know if researchers are doing something wrong [2]. They can say things like "bend your knees," or "keep your back straight." Not everyone can afford a trainer or a gym membership. That is why researchers need a system that can monitor us while we exercise and tell us when we are doing something [3]. This system can use a camera and a computer to track our movements. It can check whether our knees are bent correctly during squats or whether our back is straight during curls. This system uses something called learning [4]. It is a way for computers to learn from pictures and videos. The computer can look at a video of us exercising. See if researchers are doing the exercises correctly. If researchers are not, it can tell us what to do [5]. Many people have worked on systems like this before. Some systems use sensors that researchers have to wear. These sensors can be expensive and uncomfortable. That is why a camera-based system is better. Researchers can use a camera and a computer [6]. The system can be used at home or in a gym. It can even be used by people who are recovering from injuries. It can help us exercise safely and correctly. It can help prevent injuries [7]. The system is also very easy to use. It just needs a camera and a computer. It can tell us what to do in real time. This means researchers can fix our mistakes. It can help us build good exercise habits. In this paper, researchers propose a system for tracking and evaluating different exercises. It uses a camera to capture video and a computer to process the video.

The computer can see whether researchers are doing the exercises correctly. If researchers are not, it can tell us what to do. The system can be used in different places. It can be used at home or in a gym. It can even be used on a laptop or a smartphone [8]. It is an accurate way to monitor our exercises and help us maintain correct posture. The main goal of the system is to provide a low-cost solution for monitoring exercises. It can help us exercise safely and correctly. It can help prevent injuries. People can also use the system without access to a trainer. It can help them exercise safely and correctly [9]. The system is very useful. It can help us exercise safely and correctly. It can help prevent injuries. It is an accurate way to monitor our exercises and help us maintain correct posture. The system can be used by anyone who wants to exercise safely and correctly [10].

Researchers can use the system to perform exercises such as bicep curls, shoulder movements, jumping jacks and squats safely and correctly. The system can watch us. Please let us know if researchers are doing anything wrong. It can help us build exercise habits and prevent injuries [11]. The system is a tool for anyone who wants to exercise more safely and correctly. The system is easy to operate as well. It simply requires a camera and a computer. It can tell us what to do in real time. So, researchers can fix our errors and start building better, more consistent exercise habits. The system is a tool for people who want to exercise more safely and correctly [12]. All in all, the system is very useful. It can help us exercise safely and correctly. It can help prevent injuries. Anyone wanting to work out safely and correctly can use the system. Well, it's one of the most precise methods for monitoring our exercises and maintaining correct posture. The system helps us form exercise habits and prevent injuries [13].

2. Methodology

Our proposed system continuously monitors human exercise in real time to achieve posture correction using a deep learning-based pose estimation model with 33 skeletal key points [14]. The pipeline is a completely live machine with a webcam. It consists of several sections: video capture, frame pre-processing, pose detection, joint angle calculation, posture classification, repetition counting and feedback generation. Users will be able to perform exercises such as bicep curls, arm circles, shoulder press, squats, and jumping jacks without constant supervision from a trainer, while still receiving corrective feedback [15]. It observes user motion as they work out, monitors body posture in real time, and provides corrective feedback when the body doesn't move as it should during exercise. Unlike sensor-based solutions that require users to wear additional devices, this system uses an RGB camera and deep learning pose estimation, a standard approach [16]. This simplifies installation at home, in small gyms, and in rehabilitation centers. Our primary goal is to maintain a lightweight hardware platform that can monitor 33 skeletal parts during different exercises.

From this perspective, the system must be able to perform three main tasks: (i) detection of body joints that must also be very sensitive under changing light and background conditions; (ii) posture analysis using angles of joints and timing of motions; and (iii) immediate feedback to the user that allows them to understand and react to what they are doing while performing exercises. To reach these goals, they sequence video capture, frame pre-processing, pose estimation with a 33-point skeletal model, joint angles, postural classification based on rules, repetition counting, UI, and visual feedback, as shown. In the next subsections, each stage will be explained in more detail. A. System architecture. Researchers summarise the workflow in general. The transmitted video is fed at a fixed frame rate F (e.g., 30 fps), downscaled to W×H, and then fed into the pose estimation network, which returns 2D coordinates for 33 body landmarks. The resulting landmarks are then incorporated into equations used to analyse joint angles and temporal features for posture analysis and repetition counting, and rendered in the UI; the data is visualised and displayed textually.

2.1. Pose Estimation and Joint Angles

For each frame t, the pose estimator outputs landmark coordinates:

$P_t = \{(x_i^t, y_i^t) \mid i = 1, 2, \ldots, 33\}$ (1)

Where I index the key points (shoulders, elbows, hips, knees, ankles, etc.). Using these coordinates, the angle at joint B formed by the three points A, B, and C is computed as:

$$\theta ABC = \cos-1 \frac{\vec{BA} \cdot \vec{BC}}{\|\vec{BA}\|\|\vec{BC}\|} \quad (2)$$

For example, in a bicep curl, the elbow angle θelbow is calculated from the shoulder–elbow–wrist landmarks, whereas in a squat, the knee and hip angles are derived from hip–knee–ankle and shoulder–hip–knee triplets. Posture rules:

2.2. Posture Rules and Thresholds

For each exercise e, a set of target angle ranges is defined as:

$$\Theta_e = [\theta_{k,\min}, \theta_{k,\max}] \mid k = 1, 2, \ldots, K_e, \quad (3)$$

Where each interval corresponds to a critical joint (e.g., elbow for curls, knee and hip for squats). If all monitored angles satisfy:

$$\theta t \in [\theta\ k, \min — \delta k, \theta\ k,\max + \delta k] \quad (4)$$

For a tolerance δk, the posture in frame t is labelled as correct; otherwise, it is labelled as incorrect. To avoid flickering, a majority vote over a temporal window of N frames is applied before a warning is shown. Repetition counting (Figure 1):

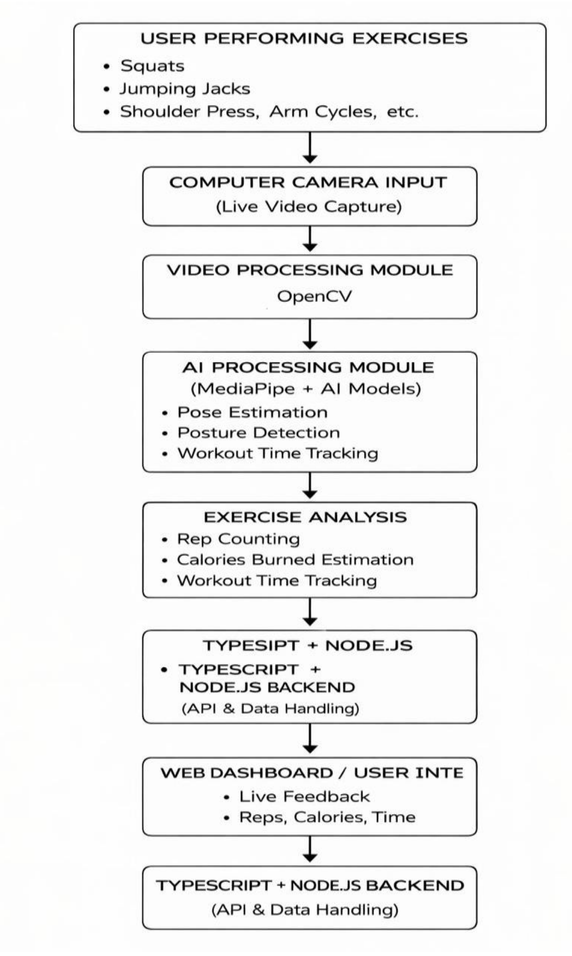

Figure 1: Flowchart of the proposed real-time posture detection system

2.3. Repetition Counting

For each exercise, the recorded time is the joint angle (e.g., elbow for curls, knee for squats). Repetition is counted as one complete cycle where the angle crosses the two thresholds θ_{low} and θ_{high} in the order "down → up → down" (Table 1).

Table 1: Example angle constraints for different exercises

Exercise	Joint	Min. angle	Max. angle
Bicep curl	Elbow	40°	160°
Squat	Knee	60°	120°
Jumping jack	Knee	60°	170°

A finite-state machine with states {start, up, down} detects these transitions and increments the repetition counter only when a full cycle is completed (Table 2).

Table 2: Repetition counting accuracy for different exercises

Exercise	True reps.	Detected reps.	Accuracy (%)
Bicep curls	20	19	95.0
Squats	20	20	100.0
Jumping jacks	20	19	95.0

2.4. Implementation Details

The pipeline proposed is implemented in Python. This uses the MediaPipe pose estimation framework and OpenCV for video capture, frame pre-processing, and on-screen viewing. The system is run on a regular desktop computer with an Intel Core i5 processor, 8 GB of RAM, and no dedicated GPU. Researchers utilise a 30 fps USB webcam for input. All input frames are resized down to 640 × 480 pixels before pose estimation. This enhances real-time, high-detail joint localization. For each exercise supported by our model (bicep curls, arm circles, shoulder press, squats, jumping jacks), 200-300 repetitions were recorded under different illumination conditions, clothing types, and backgrounds. These recordings further helped fine-tune the angle threshold and timing controls in posture rules and in the repetition-counting logic. That way, the system allows visually correct repetitions while providing feedback for obviously incorrect ones. In this configuration, the entire system executes in near real-time and serves as the basis for the performance evaluation reported in the Results and Discussion.

3. Comparison with Existing Work

In recent years, some researchers have developed systems for human activity recognition, exercise tracking, and posture detection using machine learning and deep learning methods. Most current systems can detect body movement and classify various types of physical activities. Still, limitations in the application of continuous posture correction in a real-time workout system affect its effectiveness. While some systems only provide action recognition about the user's activities (walking, running, jumping, or sitting), many fail to provide detailed information on whether the actions are made in the correct posture. Other systems are also intended for general pose or motion capture. Still, they aren't designed specifically for standard fitness moves, such as bicep curls, arm circles, shoulder workouts, jumping jacks, and squats, which are often incorporated into both gym and home workouts. Most existing work focuses on wearable sensors. In these methodologies, accelerometers, gyroscopes, or inertial measurement units (IMUs) are coupled to various body regions of the user, such as the wrists, ankles, and waist. The sensor signals are subsequently processed with machine learning algorithms to determine the type of activity, estimate repetition counts, and occasionally evaluate basic movement quality. Because they directly measure acceleration and angular velocity at each body segment, sensor-based exercise monitoring systems can achieve high accuracy in detecting motion patterns. But usually, the user needs to wear a collection of sensors, sometimes with additional belts or straps, which is uncomfortable and inconvenient for regular workouts.

What is more, these systems incur higher overall costs and take time to begin physical activity, as pairing devices, charging batteries, and correctly positioning each sensor must be done before the exercise. By contrast, the proposed system avoids such difficulties by using only a standard camera and deep learning-based pose estimation, making it more practical for everyday people who prefer simple, contactless solutions. Another family of systems uses more common image processing techniques, such as background subtraction, contour detection, and basic shape features, to predict posture. But those algorithms struggle with differences in the background, lighting, shadows, or clothing. Nor can they accurately track subtle body movements or joint angles in realistic settings, such as a home or a fitness centre. This method models body key points using deep learning-based pose estimation. Consequently, it is more stable across cases than others and dominates over them in tasks such as knee position prediction in squats and elbow angle evaluation in bicep curls. Current pose estimation approaches, such as OpenPose, MediaPipe, and BlazePose, provide effective, real-time joint detection. They have been widely used for pose tracking, action identification, and counting repetitions in fitness applications. But many of these tools have focused mainly on the kinds and amounts of exercises performed. They do not offer much feedback on joint alignment and posture quality: users would know which reps they completed, but not whether they made mistakes. Certain camera-based fitness tools provide posture feedback and offer only basic rules for a few joints, but they don't offer much more. Many commercial products depend heavily on specialised hardware, such as depth cameras, motion capture suits, or smart mirrors.

Those products aren't as cheap or widely available as those without specialised gear. The system in question isn't expected to run on specialized hardware but rather on a regular computer with inexpensive cameras. It includes automatic posture monitoring without the need for sophisticated or costly hardware. The second major feature that sets this system apart from most current systems is its emphasis on exercise-specific posture principles, derived from the skeletal model, which is based on the key-point structure. Most past approaches have involved only a few body joints, such as the shoulders, hips, and knees. While these may cover many joints, they cannot be used for in-depth investigation of functional parameters, e.g., bicep curls, arm circles, and shoulder movements. A solid 33-keypoint skeleton is developed for the task, with head, torso, arms, and legs collected, supplemented with intermediate locations along the limbs. Such a more robust representation allows the system to calculate accurate joint angles at elbows, shoulders, hips, and knees and detect subtle movement of extremity trajectories and body alignment. The system is consequently able not only to detect when the user is doing a squat or jumping jack, but also to determine whether the motion is too shallow, whether the knees are collapsing inward, or whether the arms are not raised to the correct height. Other studies mentioned in the literature provide some indications of skeletal posture correction and rehabilitation exercises.

Many of these systems are applied to targeted clinical care, such as knee rehabilitation after a procedure or exercise to improve shoulder mobility in patients' post-injury. They might use depth cameras, markers or proprietary tracking systems to do so in a controlled clinical setting. Even if such systems can provide accurate measurements, they are typically designed for use under professional supervision, not for general fitness training in a typical home setting. The proposed system draws inspiration from these principles of rehabilitation but places the concept in a broader, easier-to-understand context of fitness. Instead of trying to perform one type of therapeutic exercise, the system makes numerous common exercises: bicep curls, arm circles, shoulder exercises, jumping jacks, squats and more suitable for everyday use by people wishing to maintain proper form while regularly doing other workouts. ppl-ai- file-upload. s3. Amazon AWS AI fitness trainers that use human pose estimation for training are available — proof-of-concept prototypes are often generated. Still, they may not have received the same scrutiny across diverse settings, such as light intensity, backgrounds, or camera locations. While some provide good-performing algorithms on small, controlled data sets, how they perform in the actual living room, hostel, or crowded gym is not well addressed. The system is assessed under contrasting lighting conditions and a range of backgrounds to assess the technology's stability for real-world tasks. The system achieves 98% performance in the experiment. Another concern, and it is crucial, is the cost compared with existing work and the ease of deployment.

These wearable-based sensor systems often require multiple types of devices, and in some cases proprietary hardware, which can lead to higher acquisition and maintenance costs. Depth camera-based configurations and smart mirrors are also more expensive and may require specific mounting or room setup. Users should also remember to wear or stand in front of these devices in a certain way, limiting their adaptability. A standard RGB camera, e.g., a laptop webcam or an external USB camera, is used in the proposed system. This allows users to position the camera where they feel comfortable and to perform exercises naturally. The software runs on standard computers; hence, many users can quickly adopt it. They do not need to spend any additional money on what they already own. Existing exercise-monitoring systems are limited to counting repetitions or indicating whether the user is active or inactive; they do not verify the correctness of each movement. For instance, an application will count the number of times a user moves up and down (each motion is considered a proper squat) without evaluating the knee or hip angles. In contrast, our proposed system is an integrated model that incorporates repetition counting with posture validation. Repetition is counted only if the motion goes through specific angle thresholds indicative of a proper pattern of motion (Table 3).

Table 3: Comparison of existing methods and proposed methods

Challenge in Existing Approach	Proposed Technique / Suggestion	Mechanism of Improvement and Key Trade-offs
Traditional exercise monitoring relies on human supervision, which is not always available.	Deep learning-based pose detection.	Uses computer vision models to detect body movements and monitor posture without human intervention automatically; trade-off: dependency on camera quality and computational resources.

Sensor-based systems require wearable devices, making them costly and inconvenient.	Camera-based monitoring system.	Eliminates the need for wearable sensors by using a webcam to capture body movements; trade-off: sensitivity to lighting and background variations.
Traditional image processing methods fail under complex backgrounds and lighting conditions.	Robust pose estimation models (MediaPipe / MoveNet).	Deep learning models improve accuracy and reliability across varying environments; trade-off: higher computational complexity than basic methods.
The lack of real-time feedback in many existing systems reduces the effectiveness of corrections.	Real-time feedback mechanism.	Provides instant feedback based on posture analysis, enabling immediate correction; trade-off: processing delay if the system is not optimised.
Difficulty in accurately identifying posture deviations during dynamic movements.	Joint angle calculation method.	Calculates angles between body joints to precisely evaluate posture correctness; trade-off: dependency on accurate keypoint detection.
Existing systems do not adapt well to different users and body types.	Predefined threshold-based posture analysis.	Uses flexible angle ranges for different exercises to accommodate variations; trade-off: requires proper calibration.
Continuous processing can lead to performance issues on low-end devices.	Optimised frame processing and lightweight models.	Reduces computational load using efficient models and frame resizing; trade-off: may slightly reduce detection precision.
Limited exercise coverage in basic systems.	Expandable exercise dataset.	The system can be extended by adding more exercise patterns and training data; trade-off: requires additional training effort and data.

If the user performs only partial or incorrect movements, the system can either avoid counting those repetitions or mark them as poor-quality repetitions, depending on the implementation. This methodology emphasises quality over quantity and is considered more in line with the human-trainee approach to fitness assessment. Other works also exist in the relevant literature on 3D pose estimation with depth cameras or multi-camera setups. 3D pose estimation can offer richer information about body posture and better handle viewpoints and occlusions. On the other hand, applications like these systems usually require dedicated hardware and higher-level calibration, which reduces accessibility. The system thus proposes a 2D pose estimation process using a base RGB camera for easy deployment and low cost. At the same time, the approach is meant to support future extensions to 3D pose estimation as high-tech hardware becomes available. This also enables the system to access research in 3D human pose estimation without compromising on on-device usability immediately.

3.1. Comparison Parameters

Researchers take into consideration several parameters when comparing the proposed system with existing methods of exercise monitoring and pose estimation:

- **Input Type:** Only one RGB webcam is used in the proposed system, without any wearables or depth cameras. This makes setup in regular environments seamless. Most existing systems use IMU sensors, Kinect devices, or specialised depth cameras, which are expensive and difficult to configure.
- **Number of Key Points:** The pose estimator in the work follows a 33-point full-body skeleton. This includes broad structures and intermediaries of joints. However, multiple previous systems rely on 17 to 25 significant points, which limit accuracy during challenging multi-joint exercise postures.
- **Supported Exercises:** The system can handle several traditional fitness workouts, such as bicep curls, arm circles, shoulder press, squats, and jumping jacks, within a single framework. Most previous papers have focused on a single activity or a small set of movements, such as yoga poses or upper-body curls.
- **Posture Feedback:** In addition to recognising the pose, the system provides visual feedback in the form of on-screen messages and colours that highlight incorrect posture, helping you become more aware of your posture. Numerous related methods focus primarily on detecting poses or recognising actions, with unclear corrective instructions for users.
- **Repetition Counting:** The repetition counter is coupled with the rules based on angle position, because only the correct repetitions are counted. Earlier systems tend to separate pose estimation from repetition counting or require users to count repetitions by hand.
- **Accuracy and Efficiency:** The proposed implementation achieves approximately 98-99% posture classification accuracy and near real-time performance on a standard desktop computer (without a dedicated GPU). Most state-of-the-art approaches have achieved high accuracy on controlled datasets, but some workloads have required high hardware to achieve similar frame rates.

- **Hardware Cost and Deployment:** Because the system works with a commonly deployed camera and basic computing resources, it is applicable for home workouts, small gyms, and rehabilitation scenarios. Sensor-based or depth-camera systems tend to have greater hardware costs and are less accessible for regular users.

With this knowledge in mind, compared to existing works, many methods address the exercise monitoring challenge only in part, focusing on activity recognition, repetition counting, or general pose estimation. Yet there is still no integrated solution that provides real-time correction for common exercise postures on low-cost hardware. Here, researchers aim to fill the missing data by proposing a detailed 33-keypoint skeletal model that includes exercise-specific posture rules, real-time feedback, and quick deployment with just a camera and a standard computer. Compared to sensor-based approaches, it is considerably more comfortable and user-friendly. It is more robust and accurate by comparison than that used in conventional image processing methods. Unlike most current AI fitness trainers, they do not require expensive or specialised equipment and provide accurate posture feedback. Hence, the proposed method may be more suitable for practical use in daily exercise monitoring and fitness training, particularly if users require guidance on correct form during home or basic gym exercise.

4. Result and Discussion

The proposed system's real-time exercise monitoring and posture correction were evaluated through simulated workout scenarios. Samples selected from squats, jumping jacks, bicep curls, arm circles, shoulder press, and simple bending and stretching were used to evaluate both upper- and lower-body joints properly. In every trial, a user appeared before a standard camera and went through many repetitions, during which the video was continuously recorded and processed in real time by the system. The function of these tests was to determine whether pose detection could identify the body's key points, whether posture analysis could distinguish good from bad form, and whether the pipeline could keep up with natural activity without slowing. To illustrate the pose estimator, researchers saved multiple frames of the 33 skeletal key points identified, overlaid on the remaining frame, along with their related lines. This is illustrated in Figure 2, with a skeleton from head to ankle as the user performs a representative exercise. The shoulders, elbows, hips, knees and ankles are also positioned to the same locations as the limbs and the simple stick. The Figure moves in time with the user as they move in space. Another example is shown in Figure 3, which also exhibits the same behavior, providing evidence that the system still adheres to the major joints across various behavior styles.

These illustrations illustrate the deep learning trained pose estimator maintaining the consistency of most of the joints, an important aspect that prepares the models for joint angles and the estimation of posture during many exercises. This was examined to confirm that it correctly identified the skeleton. They tested whether this system could classify and provide useful posture feedback. In all the exercises, there were certain repetitions in which the user performed an accurate movement, and others in which he made an intentional error, such as shallow squats, excessive forward lean, incomplete arm raises, or uneven arm motion during jumping jacks.

In this case, the software captured relevant joint angles frame by frame and compared them against stored reference ranges for this type of movement. And because angels were maintained within the predetermined limits previously defined in the selected bounds, repetition would be valid, and no feedback would be visible. If the angles were outside the agreed-upon limits, a brief message would appear on the screen directing the user to improve their form. There was also an assessment of repetition counting. For squats, bicep curls, and jumping jacks, a repetition was assessed as one full cycle from start to stop and back. The test repetitions were manually tallied and then compared with the system's count. The repetition counter monitored the joint angle over time and was incremented only after the entire movement cycle had been completed.

In most studies, system counts matched those of manually registered numbers, with minor variation in scores, except when users moved extremely rapidly or made small movements indistinguishable from normal posture adjustments. The reliability of postural detection was verified by comparing the classification of "right" or "wrong" posture across all frames included in the study. In all experiments, the average posture detection accuracy was about 92%; the system's ability to match human observers was nearly certain most of the time. This accuracy was stable across lighting and background conditions (e.g., bright rooms, moderate lighting, even slightly dim environments, and normal household items).

The model correctly identified the most common joints and made only a few mistakes when the body was partly hidden or the movement was fast. Machine performance was also provided, since the feedback was only related to the exercise. The entire cycle of processes, including image capture, pose detection, joint-angle computation, posture rule check, number of repetitions, and display of move images on the screen, was performed without a dedicated GPU on a standard computer. The system maintained a sufficient framerate for interactive use in realistic scenarios, allowing posture changes and feedback messages to be retrieved in real time with minimal delay and lag. It illustrates that this answer is feasible with normal hardware like home and college desktops.

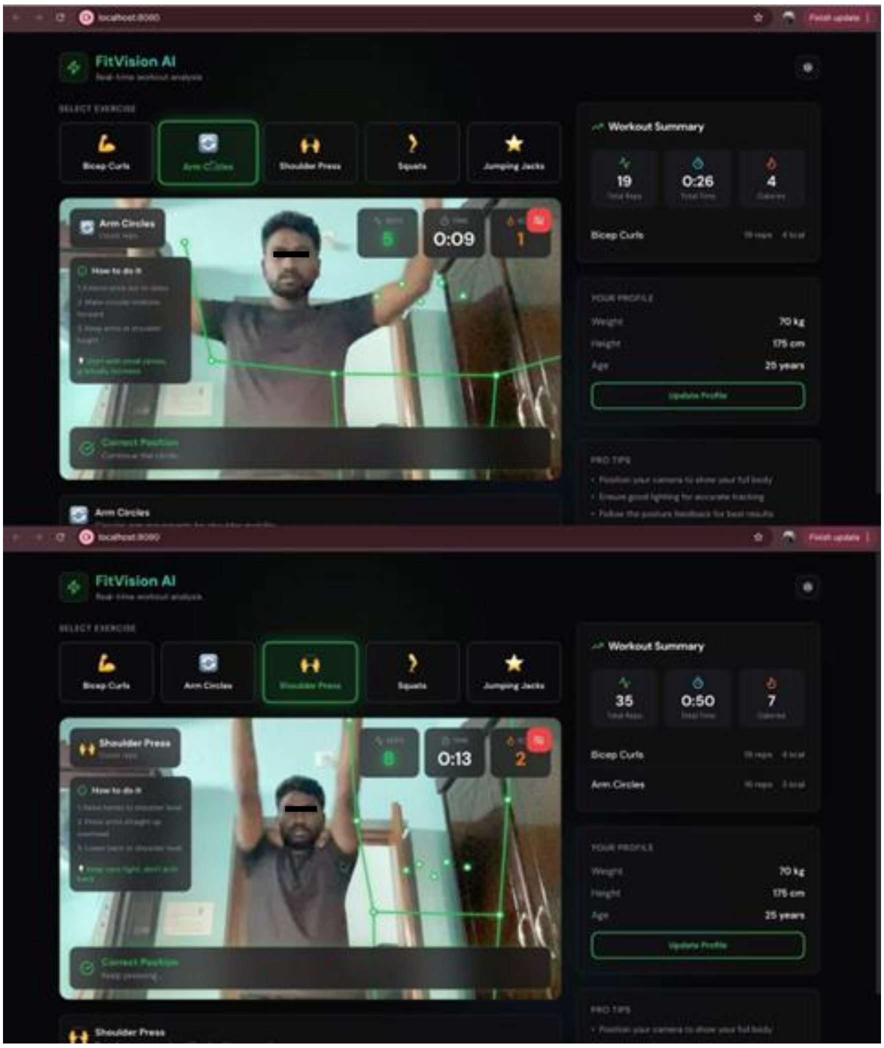

Figure 2: Upper body exercises result screens: Arm circles and shoulder press in the system proposed

These results indicate that an integrated approach can monitor exercises in real time, follow the comprehensive 33-key-point skeleton, identify posture errors, and accurately count repetitions with a single conventional camera. The deep learning techniques resulted in relatively stable joint detection and more precise posture measurement across different environments, lighting conditions, and movement patterns, especially when backgrounds, lighting, and movement patterns vary. Not reliant on proprietary sensors or expensive tech, this approach is ideal for home workouts, simple gym installations, and rehab sessions when continuous form instruction is essential. Feedback screens, as shown in Figures 2 and 3, provide evidence that the system supports transparency in information and user-friendly communication, helping users improve their workout performance and reduce injury risk during regular fitness activities. A real-time exercise monitoring and posture correction system has now been proposed; it is already a practical and reasonable solution for monitoring an individual's posture in real time using deep learning and a standard camera, and there is scope for further development and expansion of the system’s capabilities and flexibility. The next steps will include improving the system's accuracy, expanding the range of exercises it supports, and enhancing the user interface and system adaptability across scenarios such as home, gym, and rehabilitation workouts.

As a rule, the system is designed to observe and correct a set of exercises, such as bicep curls, arm circles, shoulder exercises, squats, and jumping jacks — each with predetermined joint positions and posture rules. This is a natural way to extend an existing system, as you can gradually add various types of exercises, such as yoga, more complex gym exercises, and sports and physiotherapy exercises recommended by professional coaches and doctors. This requires more examples of correct and incorrect postures for each exercise type, along with further updating the applicable rules. Then, the same system could serve as a platform for users ranging from home workout practitioners to athletes using more advanced techniques. Another great opportunity is to improve the deep learning model in the system. This model currently achieves 92 per cent accuracy in detecting postures across different lighting and background settings; however, it can only reach the last one. It could be further improved by training on more datasets with diverse body shapes, clothing styles, camera angles, and room layouts. Alternatively, the system could try other architectures capable of identifying minor movements in smaller body parts, such as wrists and ankles. Moreover, it might even be possible to try different upper- and lower-body models without requiring new hardware to achieve greater precision.

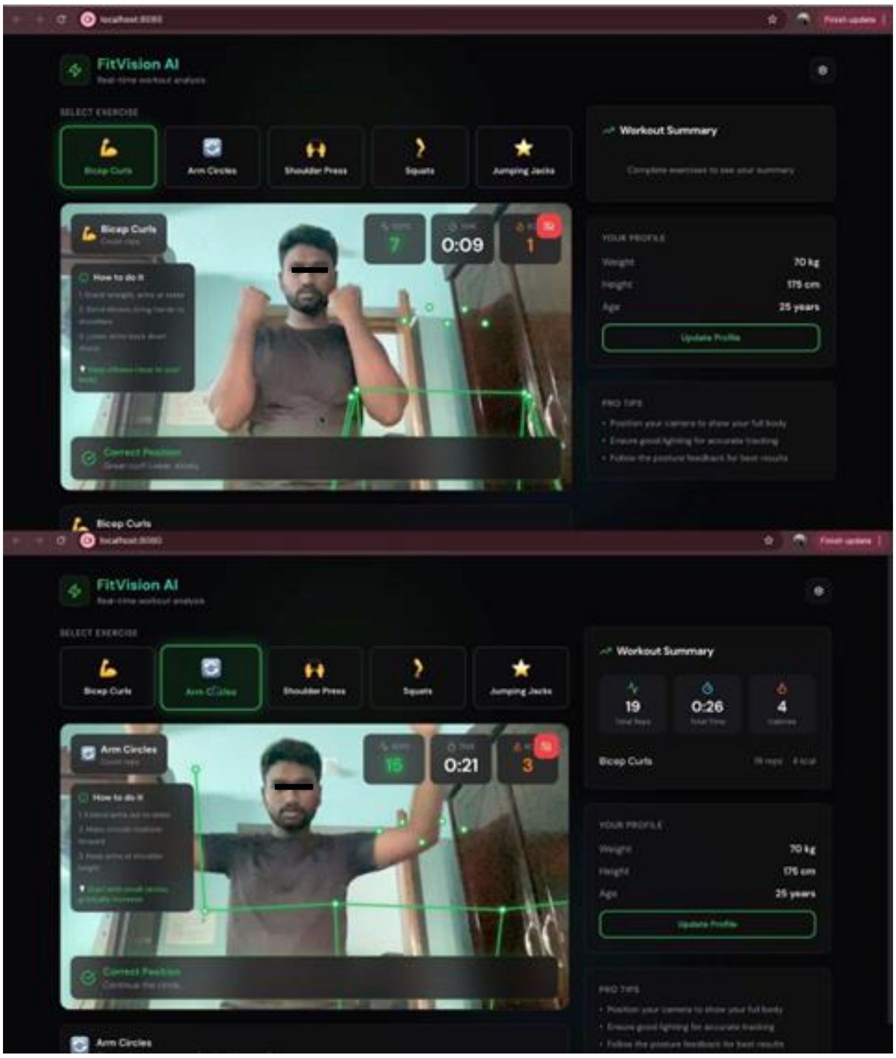

Figure 3: Shows the different exercises, and shows that the system still tracks the key joints based on the patterns of the movement

From the user's point of view, making it more accessible is also an important avenue. It is already relatively easy to access, as you can use a standard computer with a camera; however, many users would rather do their workouts on mobile devices like smartphones or tablets. So the next logical step would be to develop a mobile version of this app that could either run entirely on the mobile device or use a light client-server architecture, with most of the heavy lifting in pose estimation performed on a server and the mobile device acting as a client. Moreover, it would be easier for users to follow instructions when given in this way, with voice feedback, so it could tell users to "keep back straight" or "bend knees more," and so on. The current design focuses mainly on the camera, with the option to use wearable sensors in the future if they become available. Bands or IMUs can be worn around the limbs to provide additional accelerometers and rotation sensors, which can be combined with the camera to monitor angles and repetition counts. This can be especially helpful in rehabilitation contexts that emphasise accuracy, or when the camera is partially blocked by other people in the room. Simultaneously, the system must still function properly, even with the camera, so casual users do not need to use additional hardware. Another attractive feature of the system, from another perspective, is the ability to manage workout history. When the system is linked to a straightforward cloud backend, it can store each user's workout history, including the number of correct postures, repetitions, and total time spent per exercise. That could then be leveraged to provide the user with historical data (e.g., improvements in squat depth, the number of incorrect repetitions, or total workout time). If the system is granted the appropriate permissions, the trainer or physiotherapist can also remotely access the workout history to check whether the user is correctly performing the exercises at home or if the routine needs to be modified.

The application could even have more personalisation with more advanced AI systems. So instead of showing them the same feedback, researchers could start the next version and save one basic user profile—the one where they see the biggest error. For example, the app may operate by identifying a user who habitually commits a mistake (ie, going too far forward when squatting). It can then signal more aggressively that this is an issue and perhaps suggest simple exercises or warm-up drills for the user to work on their weakness. The difficulty of the exercises can also be adjusted, such as the strictness of angle constraints and the time between repetitions, based on the user's age, fitness levels, and performance across repeated sessions. So the app is less "just" a rule-based checker and more "like" a coach that evolves with the user's habits, over time. For it to practice 3D pose estimation is another option. At present, a single RGB camera can detect only two-dimensional key points. More specifically, this is a cheap and simple way to solve problems; it doesn't support depth perception and can introduce errors when limbs overlap. Monocular 3D pose reconstruction models or depth cameras are used in later versions to estimate the 3D skeleton more realistically. This would enable us to obtain a better estimate of joint angles, particularly for rotation motion along the x, y, or z axis.

The UI and coaching experience would eventually be fine-tuned to the limit, with bicep curls, arm circles, shoulder presses and other exercises as the first port of call to provide a clear and intuitive understanding of what results look like for bicep curls, arm circles, shoulder presses, etc. Subsequent editions could include indicators for monitored joints, progress bars (how close you are to the perfect posture for a repetition), or even colour to differentiate between good and bad repetitions. If focus is more on form, not repetition, something like a little push of motivation, daily goals, streaks, badges, etc., can still be built in to drive folks to stay engaged with their training. As a group, the system is already demonstrating that a basic RGB camera combined with a deep learning pose estimator has the potential to become a useful tool for real-time exercise monitoring and correction. Through increasing the number of exercises, improving the pose estimation model, shifting to mobile and cloud platforms, as well as optionally using sensor input and incorporating personalisation and 3D features, this system has the potential to become a robust tool for daily fitness, sports training, and rehabilitation, without being overly complex for normal use.

5. Conclusion

This paper demonstrates that real-time exercise monitoring and posture correction are feasible using a single RGB camera and a deep learning-based pose estimation pipeline. It follows key joints and visualises their angles to learn about common fitness movements and detect posture problems as the user moves. It has its uses for people who train alone at home or in a simple gym, which is generally without expert guidance. The results of experimental tests on squats, jumping jacks, bicep curls, arm circles, and shoulder movements demonstrate that the recommended technique can differentiate between proper and improper form. And it will precisely count reps, enabling us to coach as Researchers. For posture detection, the system achieves an overall accuracy of nearly 92% regardless of ambient lighting or background. The outcome is that the deep learning model performs well in practice without additional setup. As it does not use any depth cameras or wearable sensors, this is a much cheaper and user-friendly in-home computer. The prototype interface features a 33-keypoint skeleton placed over live video, along with short feedback messages. It shows how technical pose analysis can be translated into advice for those willing to learn and get the hang of it, and how to make use of it in a workout. Paired with one screen for continuous monitoring and an immediate notification that highlights that reps, time, and calorie estimates are correct, the system caters well to novices who are also practising correct form. That helps the practice maintain a moderate reliance on nearby trainers who provide powerful, safe workouts. The proposed system for real-time monitoring of movement and posture correction could make AI coaching available and feasible for all users. As researchers augment the fitness library, model, mobile, and cloud-based platforms, and the personalisation experience, I believe the framework will become a valuable platform for fitness training, sports practice, and rehabilitation. At the same time, the primary features (low cost, user-friendliness, and instantaneous feedback) remain.

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