A Project Report
on

FITNESS POSE CORRECTION

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Odd Semester- 2024-25

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ABSTRACT

The **Fitness Pose Correction** project presents an innovative approach to improving exercise form using machine learning and pose estimation techniques. The project focuses on two specific exercises: **Squat** and **Bicep Curl**, each represented by separate models. Using **MediaPipe** for pose estimation, the system detects key body landmarks (LMS) to track movement and posture during the exercises. Two versions of models are developed for both exercises: a **3-layer** and a **5-layer** model, each trained using **Keras**. The **ReLU** activation function is employed for model output, ensuring efficient performance in predicting the accuracy of form.

The system analyzes pre-recorded exercise videos, applying the models to evaluate the correctness of the user's form. **OpenCV** is utilized to generate a window that overlays the predictions onto the video, providing real-time feedback on the pose accuracy. This approach enables a dynamic and interactive evaluation, helping users to identify and correct improper posture during their workout routines. By leveraging machine learning, pose estimation, and real-time visual feedback, this project offers a promising solution for fitness pose correction, enhancing exercise performance and reducing injury risks.

INTRODUCTION

At the core of this project are two machine learning models—one for **Squats** and another for **Bicep Curls**—each designed to evaluate the user's form. For each exercise, two versions of the models have been developed, consisting of a **3-layer** and a **5-layer** neural network. These models were trained using **Keras**, a widely-used deep learning framework, and employ the **ReLU** (Rectified Linear Unit) activation function to efficiently produce output, determining the accuracy of the user's pose. The models analyze key movement patterns and provide real-time feedback, guiding users towards the correct form.

To track the user’s body posture, the project utilizes **MediaPipe**, a powerful pose estimation tool developed by Google. MediaPipe detects **landmarks** (LMS) on the user's body by identifying key points, such as joints, during exercise movements. These landmarks are used to extract data on how the user's body moves and whether their posture aligns with the expected form for each exercise. This landmark data serves as input to the machine learning models, which then assess the user’s posture and provide an evaluation based on the model's training.

Another integral component of the project is **OpenCV**, a computer vision library that enables the system to display real-time feedback through a graphical window. Users can record their exercise sessions, and the recorded videos are processed by the model. OpenCV generates a visual overlay on the video, showing the predicted pose accuracy and providing corrective insights, allowing users to make adjustments as they train. This interactive element enhances user engagement and makes the system highly accessible, even for beginners in fitness training.

Overall, this project showcases the potential of combining machine learning with pose estimation technology to improve the effectiveness and safety of physical training. By offering an automated solution for fitness pose correction, it provides users with the tools they need to improve their exercise performance and reduce the risk of injury, all while benefiting from advanced real-time feedback.

PROBLEM STATEMENT

In the modern fitness landscape, home workouts have gained significant popularity due to their convenience and accessibility. However, without the guidance of a professional trainer, individuals often perform exercises with improper form, leading to suboptimal results and an increased risk of injury. Exercises like squats and bicep curls are fundamental to strength training but are frequently executed incorrectly, especially by beginners. Inaccurate posture or movement patterns during these exercises can strain muscles, joints, and ligaments, potentially causing long-term harm. Furthermore, the lack of real-time feedback during home workouts compounds this issue, as individuals are unable to identify and correct their mistakes promptly.

Existing fitness applications predominantly focus on tracking workout metrics, such as time, repetitions, or calories burned, but very few provide precise, real-time guidance on exercise form. While personal trainers or physical therapists can offer such insights, access to them is often limited by cost, time, or geographic constraints. As a result, the need for an accessible, affordable, and reliable system that delivers real-time feedback on exercise form remains unmet for many fitness enthusiasts.

This project, **Fitness Pose Correction**, aims to bridge this gap by using machine learning and computer vision to analyze the user's posture during exercises and provide instant corrective feedback. By focusing on exercises like squats and bicep curls, the system addresses a critical issue in the fitness industry, ensuring users can work out safely and effectively from the comfort of their homes.

PROPOSED SOLUTION

To address the problem of improper form during home workouts, the “Fitness Pose Correction” project proposes a machine learning-based system that provides real-time feedback to users performing exercises like squats and bicep curls. This solution leverages MediaPipe, an advanced framework for pose detection, and integrates machine learning models to analyze the user’s body posture and movement patterns. By utilizing computer vision techniques, the system detects key body landmarks (LMS) such as joints and limbs, which are then compared to the ideal posture for the exercise.

The proposed system focuses on two specific exercises: squats and bicep curls, both of which require precise form to prevent injury and maximize workout efficiency. For this purpose, two separate machine learning models are developed: a **Squat model** and a **Bicep model**. The **Squat model** is a 3-layer neural network trained using **Keras** , a popular deep learning library, while the Bicep model is a more complex 5-layer network to address the mechanics of the bicep curl. Both models are trained on video datasets in MP4 format, where the system learns to recognize correct and incorrect poses by analyzing the landmarks extracted from the videos.

OpenCV, a widely-used computer vision library, is integrated into the system to provide real-time visual feedback. As the user performs the exercise, OpenCV processes the video input and overlays corrective instructions onto the video feed. For example, if the user’s knees are not properly aligned during a squat, the system will detect this deviation and display guidance on how to adjust the posture. Similarly, if the elbows are not positioned correctly during a bicep curl, the system will provide instant feedback to ensure the user engages the correct muscles.

The real-time feedback mechanism is critical to the system’s effectiveness. By providing users with instant corrective suggestions, the system helps them adjust their posture as they perform the exercises, mimicking the role of a personal trainer. This ensures that users can maintain proper form throughout their workout, reducing the risk of injury and improving the overall effectiveness of the exercise.

In summary, the proposed solution combines the power of pose detection, machine learning, and real-time video analysis to create an intelligent fitness assistant that helps users perform exercises with proper form. This system addresses the key issues faced in home workouts by providing personalized, real-time feedback, making it an affordable and accessible alternative to personal trainers while improving the safety and effectiveness of home fitness routines.

TECHNOLOGICAL COMPONENTS

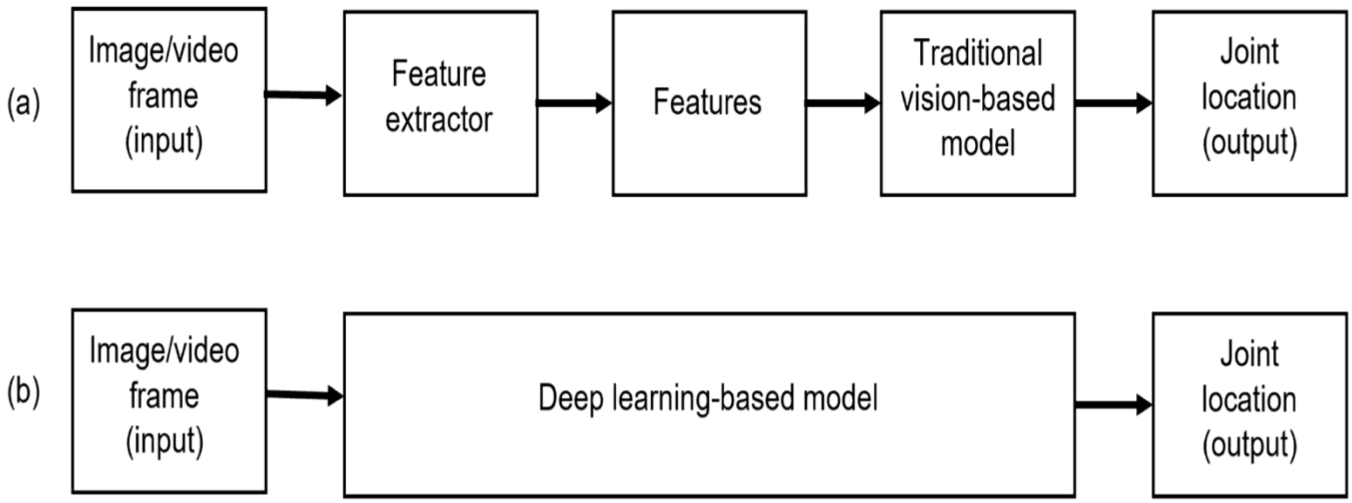
Hardware Components

1. **Servers:**
   - High-performance CPUs and GPUs for model training and inference.
2. **Storage Solutions:**
   - Fast SSDs for quick data access and storage of model weights.
3. **Networking:**
   - Reliable high-speed internet for accessing external data sources.

Software Components

1. **Programming Language:**
   - **Python:** Primary language for implementing the Pose Correction model.
2. **Machine Learning Libraries:**
   - **Mediapipe: Used for pose generation and feature extraction**.
   - **Keras**: Used for model training.
   - **Opencv**: Used for model assessment on the dataset.
   - **Sci-kit learn**: Used for fine-tuning and model training.
3. **Retrieval Frameworks:**
   - **Elasticsearch:** For scalable and efficient document retrieval.
   - **Faiss:** For fast similarity search in dense vector spaces.
4. **Data Handling:**
   - **NumPy, Pandas :** For data manipulation and preprocessing.
   - **Matplotlib:** To plot the graphs for the LR regression models.
5. **Web Frameworks:**
   - **Vue.js and Django :** To create APIs and UI for the entire project.

ARCHITECTURAL DIAGRAM



METHODOLOGIES

1. **Data Collection:**
    - Collect a diverse dataset consisting of videos showcasing individuals performing exercises such as squats and bicep curls. The dataset should include examples of both correct and incorrect forms to allow for effective training and evaluation. Data can be sourced from publicly available fitness videos, curated video datasets, or through web scraping fitness platforms. For personalized data, a recording setup could be used to collect real-time workout data from different users under controlled conditions.
    - Each video should be annotated with key body landmarks (joints, limbs) using MediaPipe to detect and track pose landmarks, which will serve as the input for the machine learning models.
2. **Data Preprocessing:**
    - Preprocess the collected video data by extracting pose landmarks (LMS) from each frame. This includes normalizing the pose data to remove noise and variations caused by camera angles, lighting, or other environmental factors.
    - Use MediaPipe to extract 3D coordinates of key joints such as knees, hips, and elbows, creating a dataset that accurately reflects the user's posture during exercises.
    - Organize the extracted pose landmarks into time-series data to capture the dynamic nature of the exercises.
    - Label the dataset based on correct and incorrect posture to train models in classifying proper form and providing corrective feedback.
3. **Model Training (Pose Classification):**
    - Squat Model: Train a 3-layer neural network using Keras for squats. This model will analyze the input pose landmarks and classify whether the squat posture is correct or needs adjustment. The model should be trained to focus on the alignment of the hips, knees, and ankles.
    - Bicep Curl Model: For the bicep curl, use a 5-layer neural network to handle the more complex mechanics of the upper body during the movement. This model will evaluate the elbow and shoulder alignment, ensuring that the exercise targets the intended muscles.
    - Use supervised learning techniques to train these models, using labeled datasets (correct vs. incorrect form) as ground truth. Apply techniques like cross-validation to ensure robust performance.
4. **Real-Time Feedback Integration:**
    - Use OpenCV for real-time video processing, overlaying corrective feedback onto the user's video feed. The models will analyze the user’s current form based on the pose landmarks and provide instant feedback. For instance, if the knees are misaligned during a squat, the system will display instructions to adjust the knee position.
    - The feedback can be delivered visually (annotations over the video) and verbally (via text-to-speech systems for spoken instructions), enhancing the user’s engagement.

5. **Posture Detection Pipeline:**
    - Build a pipeline that integrates the pose detection and model inference systems. This pipeline will take input from the user's camera, use MediaPipe to extract pose landmarks, and then pass these landmarks through the trained models for classification and feedback generation.
    - The pipeline should support real-time processing with minimal latency, allowing users to receive immediate corrections while performing exercises.
6. **Evaluation:**
    - Evaluate the accuracy and reliability of the models using quantitative metrics such as accuracy, precision, and recall, focusing on how well the models can distinguish between correct and incorrect forms.
    - Additionally, conduct user studies to assess the qualitative effectiveness of the system. Users can perform exercises with and without the system's feedback, and their experiences, comfort, and performance improvement can be measured.
    - Cross-check model predictions with actual biomechanical data, if available, to ensure the models are producing biomechanically sound corrections.
7. **Iterative Refinement:**
    - Based on the evaluation results, fine-tune the models by increasing the dataset size, adding more layers to the neural networks, or experimenting with advanced techniques like reinforcement learning. In reinforcement learning, the system could improve its feedback based on real-time user corrections and input.
    - Continuously improve the pipeline to reduce latency in real-time processing and ensure feedback is delivered instantly without lag.
8. **Deployment:**
    - Deploy the system as a mobile or web application using frameworks like Flutter (for cross-platform apps) or FastAPI (for backend API handling).
    - Ensure the deployment environment supports real-time video processing and pose detection. Optimize the system for mobile platforms to offer users the convenience of working out from their smartphones with real-time feedback.

By following these methodologies, the Fitness Pose Correction project can provide users with an intelligent and responsive system that ensures proper form during workouts, reducing the risk of injury and maximizing the effectiveness of their exercise routines.

CODE SNIPPETS

```python
# Determine important landmarks for plank
IMPORTANT_LMS = [
    "NOSE",
    "LEFT_SHOULDER",
    "RIGHT_SHOULDER",
    "RIGHT_ELBOW",
    "LEFT_ELBOW",
    "RIGHT_WRIST",
    "LEFT_WRIST",
    "LEFT_HIP",
    "RIGHT_HIP",
]

# Generate all columns of the data frame

HEADERS = ["label"] # Label column

for lm in IMPORTANT_LMS:
    HEADERS += [f"{lm.lower()}_x", f"{lm.lower()}_y", f"{lm.lower()}_z", f"{lm.lower()}_v"]
```

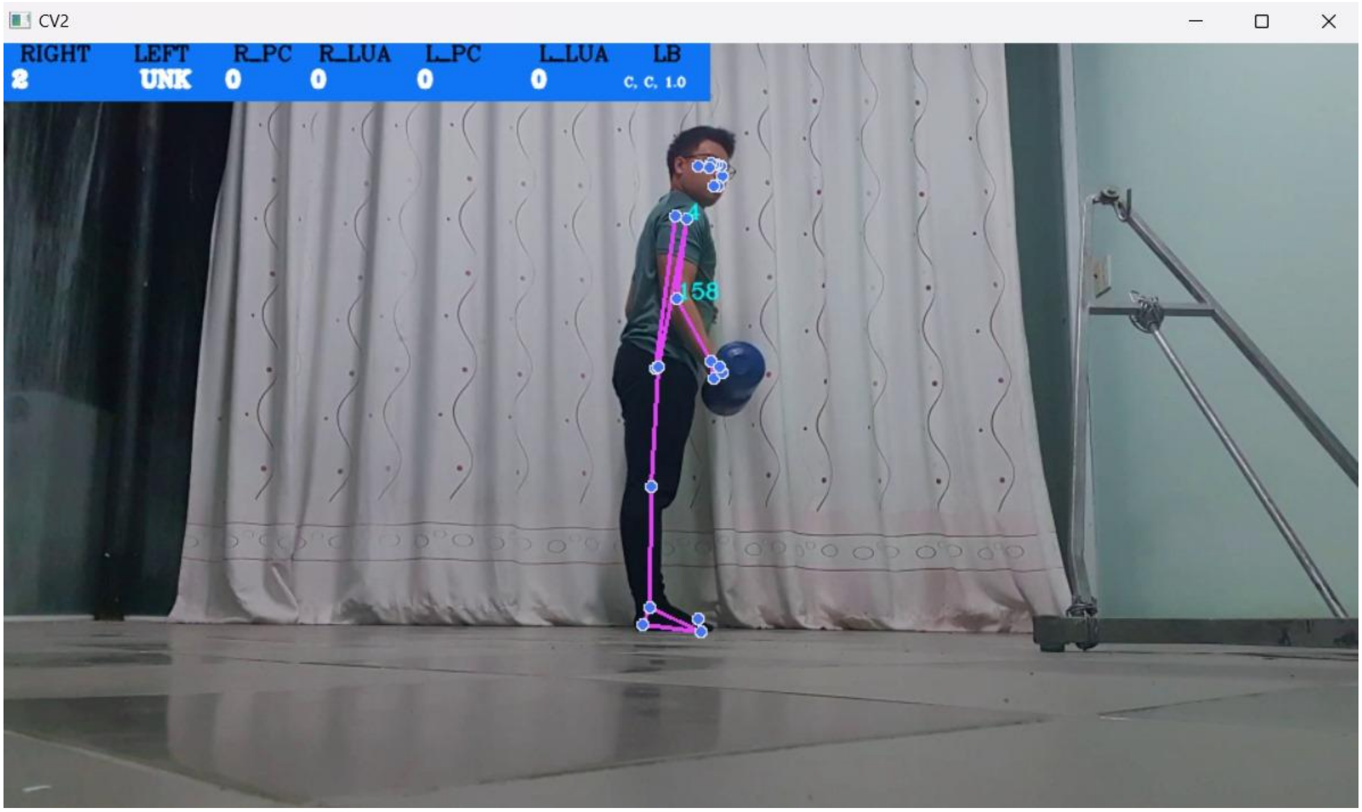
```python
model_3l = get_best_model(tuner_3l)
model_3l.fit(x_train, y_train, epochs=100, batch_size=10, validation_data=(x_test, y_test), callbacks=[stop_early])
```

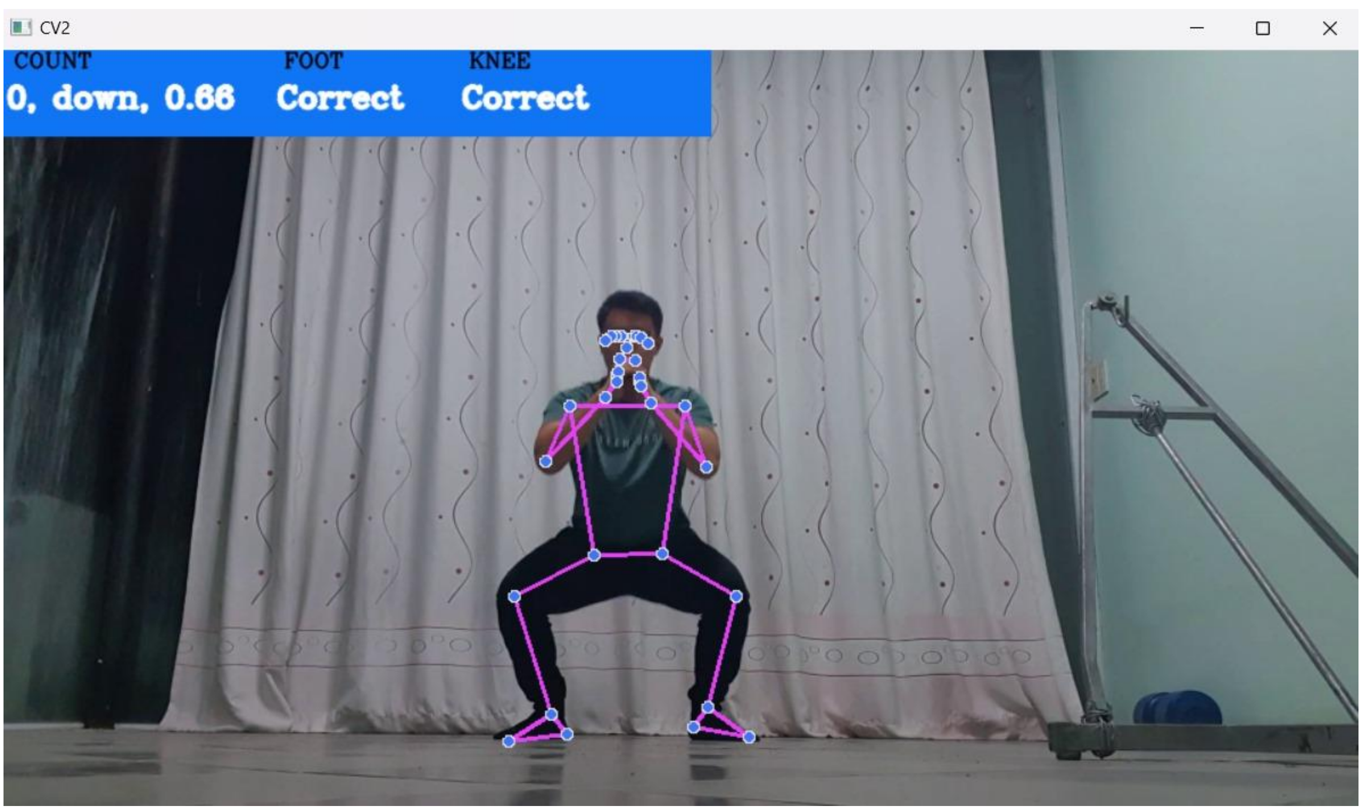
✓ 21.5s

```
Describe models architecture
Layer-1: 36 units, func:  <function relu at 0x000002B00C0160C0>
Layer-2: 96 units, func:  <function relu at 0x000002B00C0160C0>
Layer-3: 2 units, func:  <function softmax at 0x000002B02C884040>

Other params:
learning_rate: 0.001
Epoch 1/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.9396 - loss: 0.1541 - val_accuracy: 0.9954 - val_loss: 0.0167
Epoch 2/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9940 - loss: 0.0240 - val_accuracy: 0.9954 - val_loss: 0.0149
Epoch 3/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9961 - loss: 0.0141 - val_accuracy: 0.9971 - val_loss: 0.0093
Epoch 4/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9963 - loss: 0.0122 - val_accuracy: 0.9964 - val_loss: 0.0125
Epoch 5/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9971 - loss: 0.0100 - val_accuracy: 0.9980 - val_loss: 0.0085
Epoch 6/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9977 - loss: 0.0080 - val_accuracy: 0.9974 - val_loss: 0.0139
Epoch 7/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.9972 - loss: 0.0092 - val_accuracy: 0.9967 - val_loss: 0.0123
Epoch 8/100
1230/1230 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9973 - loss: 0.0090 - val_accuracy: 0.9980 - val_loss: 0.0094
```

OUTPUT


CV2
RIGHT LEFT R_PC R_LUA L_PC L_LUA LB
2 UNK 0 0 0 0 C, C, 1.0
158


CV2
COUNT FOOT KNEE
0, down, 0.66 Correct Correct

CONCLUSION

- **Addressing a Critical Need:**
  Fulfilling the Need for Corrective Feedback in Home Workouts:
  As the popularity of home fitness continues to grow, so does the challenge of maintaining proper form without professional guidance. Many fitness enthusiasts lack real-time feedback, which is crucial for maximizing the benefits of exercises while minimizing the risk of injury. The **Fitness Pose Correction** project directly addresses this issue by creating a system that provides instant corrective feedback during exercises, focusing on squats and bicep curls. The system ensures that users receive continuous, accurate guidance on their form, thereby promoting safer and more effective workout routines.

- **Combining Machine Learning and Pose Detection for Accurate Analysis:**
  The use of **MediaPipe** for pose detection, combined with **machine learning models** developed using **Keras**, allows for precise analysis of body posture. MediaPipe's ability to track 3D body landmarks in real-time is leveraged to detect key points such as knees, hips, and elbows. These landmarks serve as input for the machine learning models that have been trained to classify posture correctness. In the **Squat model**, a 3-layer neural network evaluates the alignment of joints during squats, while the **Bicep model** uses a 5-layer neural network to assess elbow and shoulder positioning during bicep curls. These models have been trained on labeled datasets with both correct and incorrect poses, allowing the system to detect deviations and recommend adjustments in real-time.

- **Real-Time Feedback as a Critical Component of the Solution:**
  One of the most significant advantages of the system is its ability to deliver **real-time feedback**. By integrating **OpenCV** into the pipeline, users receive visual cues directly on their video feed as they perform the exercises. For example, if a user's knees are not aligned correctly during a squat, the system highlights the deviation and provides instructions for correction. Similarly, during a bicep curl, the system can detect improper elbow positioning and suggest adjustments to ensure the correct muscles are being targeted. This immediate feedback is crucial for maintaining proper form throughout the workout and mimics the guidance of a personal trainer.

- **Enhancing Safety and Maximizing Workout Effectiveness:**
  By ensuring proper form, the system reduces the likelihood of injuries that can occur from incorrect posture. Common exercise-related injuries, such as knee strain during squats or shoulder discomfort during bicep curls, often arise from poor technique. With real-time feedback and posture correction, users can perform exercises safely, without the need for professional supervision. Additionally, by maintaining proper form, users are able to engage the correct muscles more effectively, improving the efficiency of their workouts. This results in better workout outcomes, including strength gains and muscle tone, while also preventing unnecessary strain on the body.

- **Scalability and Future Expansion:**
  The system's modular design offers significant potential for expansion. Currently focused on squats and bicep curls, the system can be extended to cover a wider range of exercises, making it a comprehensive fitness assistant. Future iterations of the project could include other complex movements, such as lunges, push-ups, or even full-body workouts. Additionally, with the integration of user profiles, the system could offer personalized corrective feedback based on individual biomechanics, further enhancing its effectiveness.

- **Impact on the Home Fitness Landscape:**
  In summary, the **Fitness Pose Correction** project bridges a critical gap in the home fitness market by providing an affordable, accessible, and intelligent solution for real-time posture correction. By integrating **pose detection**, **machine learning**, and **real-time video processing**, the system offers a virtual fitness coach experience, empowering users to perform exercises safely and effectively. It brings professional-quality workout guidance into users' homes, reducing reliance on expensive personal trainers while enhancing the quality of home workouts. This innovation has the potential to transform how individuals approach fitness training at home, making personalized, injury-free exercise accessible to everyone.

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