AI-BASED REP COUNTING AND MONITORING

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Abstract-- **Conventional gym training frequently fails to offer a dependable system to guarantee that users maintain proper workout amplitude and does not provide them with a way to assess their performance in relation to conventional angles. The lack of an automated measurement mechanism leads to inconsistent forms and less than ideal exercise results. Identifying this gap, our project seeks to transform the fitness experience through the seamless integration of cutting-edge technologies like MediaPipe and OpenCV with AI-based personal training methods. We strive to empower gym-goers with a tool that not only measures and compares exercise amplitudes but also guides them in real-time, promoting consistency and correctness in their workout routines. Users now have the ability to receive instant feedback on their exercise form, fostering a dynamic learning environment and facilitating continuous improvement. This feedback loop not only enhances the overall workout experience but also contributes to the prevention of potential injuries resulting from improper form.**

Moreover, our project aims to provide a comprehensive and personalized fitness solution by incorporating features such as a vast exercise library, customizable workout plans, progress tracking, nutritional guidance, and integration with wearable devices and smart home systems. By leveraging gamification elements and social integration, we seek to boost user engagement and motivation, fostering a supportive community for achieving fitness goals. Additionally, our project prioritizes accessibility by offering multilingual support and remote coaching capabilities, ensuring that individuals from diverse backgrounds and locations can benefit from our AI-powered personal training experience.

Keywords— **Gym training, Correct amplitude, Standard angles, Real-time analysis, Personalized fitness, Progress tracking, Social community, Accessibility, Remote coaching.**

I. INTRODUCTION

In the rapidly evolving landscape of fitness and exercise monitoring, the infusion of Artificial Intelligence (AI) has ushered in unprecedented possibilities for enhancing user experience and achieving heightened precision in assessments. This project is strategically crafted to address a crucial need in the fitness domain—real-time exercise identification and accurate repetition counting, all facilitated through the use of webcam footage. As the demand for personalized and efficient fitness solutions continues to grow, the project leverages computer vision techniques, with OpenCV serving as the gateway to accessing webcam data. Real-time pose estimation, enabled by a pre-trained Convolutional Neural Network (CNN), forms the bedrock of the project's capability to discern and analyze exercise movements in real-time.

At its core, this endeavor revolves around the meticulous development of custom deep-learning models, meticulously implemented using TensorFlow and Keras. These models are intricately designed with the explicit goal of recognizing a diverse array of exercises, forming a robust framework for exercise classification. A carefully orchestrated guided data collection pipeline is integrated into the project, playing a pivotal role in generating essential training data, a linchpin for the success of the ensuing deep learning models.

Beyond exercise recognition, the project seamlessly incorporates joint angle extraction from pose estimate coordinates, introducing heuristic techniques for precise repetition counting and exercise monitoring. Visualization tools enhance user comprehension and engagement by providing insightful metrics, including joint angles, repetition counts, and probability distributions.

Furthermore, the project incorporates an innovative feature that analyzes the user's form and movement patterns, delivering real-time suggestions and guidance to improve exercise technique and prevent potential injuries. This personalized feedback loop is facilitated through a messaging system that seamlessly communicates with the user, fostering a more engaging and effective fitness experience.

This messaging system, crucial for initiating user interaction and delivering tailored feedback, leverages real-time data analysis from keypoint detection and neural network outputs to provide immediate, context-sensitive suggestions that help correct user posture and movement during workouts.

The system enhances the interactivity of training sessions, making them more dynamic and responsive to the user's immediate needs. Through this technology, the project not only supports users in achieving more precise and safer workouts but also encourages consistent engagement by integrating motivational messages and corrective feedback directly into the workout experience. This approach ensures a comprehensive, user-focused fitness solution that enhances both the effectiveness and enjoyment of personal exercise routines.

The Following are our work's primary goals.:

Effectiveness in terms of money: Engaging a personal trainer can be costly, particularly if you require frequent sessions to meet your fitness objectives. A more affordable option is to hire an AI personal trainer, who can give you individualized exercise schedules and dietary guidance for a fraction of the price.

Convenience: You don't need a personal trainer or a gym membership to work out with an AI personal trainer at any time or place. Those with hectic schedules or those who would rather work out at home would especially benefit from this.

24/7 support: No matter the time of day or night, an AI personal trainer is always there to offer you advice and assistance.

Motivation: Real-time feedback and analysis can significantly boost user motivation and engagement with their fitness regimen. By seeing their progress and receiving encouragement during workouts, individuals are more likely to stay committed to their exercise goals and maintain a consistent workout routine.

Accessibility: This project makes exercise guidance and analysis accessible to a wide range of users, regardless of their location or access to fitness facilities. With just a webcam or smartphone camera, individuals can engage in real-time exercise monitoring and receive professional-quality feedback in the comfort of their own homes.

Personalized Feedback and Suggestions: A standout feature of this project is its sophisticated capacity to deliver personalized feedback and actionable suggestions directly to users as they engage in their exercise routines. Leveraging the power of real-time data analysis from keypoint detection and advanced neural network models, the system meticulously evaluates each movement, enabling it to provide specific, customized advice. This feedback focuses on correcting and refining users' exercise form and techniques.

Remote Coaching: For fitness professionals and coaches, this project offers a valuable tool for remote coaching and training. Trainers can remotely monitor their clients' workouts, provide real-time guidance, and track their progress over time, enabling more effective and convenient coaching services.

Seamless Communication: The project features an advanced messaging system that acts as a conduit for uninterrupted communication between the user and the AI-powered personal trainer. This sophisticated system is designed to deliver personalized feedback, actionable suggestions, and motivational messages directly to users, enhancing the interactive aspects of the fitness experience. By integrating this messaging system, the project ensures that users are not only guided through their exercises with precision but are also continually encouraged and supported throughout their fitness journey.

II. RELATED WORK

The project leverages the capabilities of webcam footage and advanced computer vision techniques to facilitate real-time identification of exercises and accurate counting of repetitions. By employing custom deep-learning models built with TensorFlow and Keras, a robust framework is established to recognize a wide array of exercises effectively. These models are trained using a guided data collection pipeline, ensuring comprehensive coverage of various exercise movements and postures. Additionally, the incorporation of joint angle extraction and heuristic algorithms further enhances the precision of repetition tracking, enabling users to monitor their workout progress with high accuracy.

A key aspect of the project lies in its visualization tools, which provide users with valuable insights into their exercise performance. These tools display detailed metrics such as joint angles and estimated calorie expenditure, offering a comprehensive overview of each workout session. By presenting this information in an intuitive and user-friendly manner, the project enhances the overall fitness monitoring experience and empowers users to make informed decisions about their training regimen.

Moreover, the project is designed to improve user engagement by offering real-time feedback on exercise posture correctness. By analyzing the user's movements in real time, the system can identify and highlight any deviations from proper form, allowing users to make immediate adjustments and optimize their workout technique. This real-time feedback mechanism not only helps users prevent injuries but also fosters a sense of accountability and motivation, driving them to strive for continuous improvement in their fitness journey.

1. Attention-based LSTM network with dilated CNN characteristics for human action recognition

Khan Muhammad, Mustaqeem, Amin Ullah, Ali Shariq Imran (2021) [1] Using cutting-edge AI-based technologies, the goal of this research is to improve human activity recognition in videos. By combining a bi-directional long short-term memory (BiLSTM) network with a dilated convolutional neural network (DCNN), the suggested method overcomes the drawbacks of earlier techniques that relied on pre-trained weights. By selectively focusing on important aspects inside video frames, an attention mechanism is integrated to improve the discriminating of temporal and visual cues. In the dynamic realm of computer vision and pattern recognition, the primary aim is to enhance the system's accuracy in detecting a wide array of human actions, thereby rendering it invaluable for applications spanning security and behavior assessment domains. By leveraging cutting-edge AI technologies, the research endeavors to push the boundaries of action recognition capabilities, enabling more precise and robust identification of human activities in video footage.

The fusion of DCNN and BiLSTM architectures allows for a comprehensive analysis of both spatial and temporal features, facilitating a deeper understanding of human actions within video sequences. By mitigating the reliance on pre-trained weights and implementing attention mechanisms, the proposed method aims to enhance the model's adaptability to diverse action scenarios, leading to improved recognition performance across various real-world applications. Ultimately, the overarching goal is to contribute to the advancement of human action recognition systems, equipping them with the capability to accurately and reliably identify a wide spectrum of actions in video data. The results of this study might have a big influence on domains including human-computer interaction, surveillance, and video analytics, where accurate action identification is essential for behavior analysis and sound decision-making.

2. Python with Mediapipe for Real-Time 3D Pose Classification and Pose Detection

Taha Anwar and Rizwan Naeem (2021) [2] This project delves into the realm of computer vision with a focus on Pose Detection, a key point estimation problem, aiming to localize 33 body landmarks in real-time. Applications span from full-body Gesture Control and Sign Language Recognition to Fitness monitoring and Augmented Reality overlays and introduces the implementation of Mediapipe's Pose Detection, a state-of-the-art solution that combines a two-step detector and lightweight object tracker for efficient landmark localization in real-time video feeds on diverse devices. Despite its speed and high fidelity, it is optimized for single-person pose detection and offers three models with varying trade-offs between speed and performance.

3. PERSONAL ARTIFICIAL INTELLIGENCE TRAINER

Neeraj Rajput, Saurabh Singh Rajput, Shravan Singh, and Aashna Rachh (2021) [3] The AI Trainer project leverages OpenCV and Python to harness the CPU's posture estimation capabilities, enabling the extraction of key points and subsequent calculation of corresponding angles. Its primary focus lies in identifying a diverse range of movements based on these angles, with a specific application geared towards counting biceps curls. Designed with simplicity in mind, the code empowers users to effortlessly determine angles between any three points with just a single line of code. This streamlined approach ensures accessibility and ease of use, catering to individuals with varying levels of programming proficiency.

The overarching goal of the AI Trainer is to develop an efficient and user-friendly tool for analyzing and monitoring exercises through pose estimation and angle calculations. By providing accurate feedback on exercise form and technique, the AI Trainer aims to enhance users' workout experiences and facilitate progress towards their fitness goals. Through its intuitive interface and seamless integration of OpenCV and Python, the AI Trainer offers a versatile solution for fitness enthusiasts and professionals alike. Whether utilized for personal training or integrated into gym equipment for real-time feedback, this project has the potential to revolutionize the way individuals approach exercise analysis and monitoring. Ultimately, the AI Trainer seeks to empower users to optimize their workout routines and achieve optimal performance safely and effectively.

4. Artificial Intelligence-powered Personal Fitness Trainer and Tracker made possible with MEDIAPIPE and OpenCV

Ira Nath, Aditya Shaw, Aniruddha Bhadra, Diya Dey Bhowmickdefault stance (2023) [4] Advances in technology have transformed the fitness industry, introducing AI personal trainers as a cost-effective and convenient alternative to traditional gym memberships and personal trainers. These AI-powered virtual trainers make fitness more accessible by providing individualized training regimens, dietary guidance, and progress monitoring. The rise of digital fitness programs and digital coaching services has contributed to the popularity of AI personal trainers. Accessible from anywhere at any time, they cater to individuals with busy schedules or a preference for home workouts. By analyzing user data, including fitness levels and goals, AI personal trainers create customized workout plans, continually adapting them for optimal results.

5. Human Action Recognition in Videos using Convolution Long Short-Term Memory Network with Spatio-Temporal Networks

According to recent research, the use of two-stream convolutional networks—a combination of recurrent neural networks (RNN) and convolutional neural networks (CNN)—has become essential for accurately identifying human behaviors in videos [7]. In particular, our technique presents a novel two-stream network architecture consisting of two CNNs and Convolution Long-Short Term Memory (CLSTM) units. The goal of this integration is to provide reliable video activity detection by utilizing both temporal and spatial information. First, two CNNs pretrained on ImageNet models are used to extract spatio-temporal features, which capture temporal and spatial trends. Learning of long-term interdependence is facilitated by merging and feeding extracted characteristics into CLSTM. The influence of feature mapping at various CNN layers is evaluated, and different fusion functions are investigated. Intensive testing determines the ideal layer number and fusion function. Data augmentation increases the diversity of training data, which reduces overfitting. Using pre-trained ImageNet models, the model delivers notable performance increases on benchmark datasets, with accuracy of 70.4% on HMDB-51 and 95.4% on UCF-101. These findings show the effectiveness of action recognition, which has applications in the fields of human-computer interaction, sports analysis, and surveillance.

III. LITERATURE REVIEW

Author	Year	Algorithm	Inference
Khan Muhammad Mustaqeem, Amin Ullah, Ali Shariq Imran	2021	Bi-LSTM	For security and behaviour assessment applications, bi-directional long short-term memory (BiLSTM) and an attention mechanism can increase the accuracy of identifying a variety of human actions..
Taha Anwar, Rizwan Naeem	2021	Mediapipe, OpenCV	Pose detection implemented by Mediapipe: using pose detection in photos and videos.

Neeraj Rajput, Saurabh Singh Rajput, Shravan Singh, Aashna Rachh	2021	No use of Bi-LSTM Model	Using OpenCV and Python, will create an AI Trainer for this project.

IV. PROPOSED WORK

In this section, we present our proposed model for AI-Based personal trainer using the LSTM model.

A. Import the Dependencies:

Import the various libraries, including [5] OpenCV, NumPy, Mediapipe, and TensorFlow, to implement a comprehensive solution for human action recognition in videos. It combines attention processes, bi-directional long short-term memory (BiLSTM), and dilated convolutional neural networks (DCNN) as machine learning techniques.

B. Keypoint using MP Pose:

It initializes a pose estimation model, captures video feed from the webcam, and processes each frame to detect and draw key landmarks on the detected human pose [6]. The landmarks are extracted and stored for further analysis. The code includes functionality for visualizing the pose landmarks on the video feed.

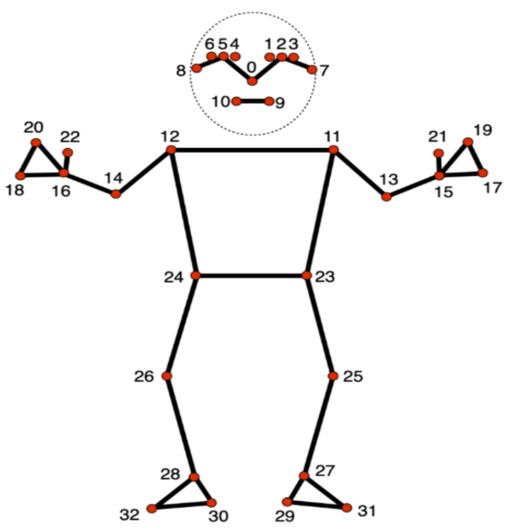


Fig 4.1 Mediapipe Landmark

C. Setup Folders for Collection:

Set up the directory structure for collecting and organizing data for a human action recognition model. It defines a path for exported data, creates the necessary directories if they do not exist, and specifies the target actions (curl, press, squat). The variables 'no_sequences' and 'sequence_length' determine the number of video sequences and the frames per sequence, respectively. The loop generates folder paths for each action, sequence, and frame, facilitating the storage of video data for subsequent model training. The starting folder index is set to 101 to avoid overwriting previously collected data.

D *Collect Keypoint Values for Training and Testing*

Capture and collect training data for human action recognition. It uses the webcam to record video sequences for each specified action (curl, press, squat) and saves the corresponding pose landmarks as NumPy arrays. The Mediapipe Pose model is employed for real-time pose estimation. The code displays visual cues such as 'STARTING COLLECTION' and ongoing collection information on each frame. It exports keypoints (pose landmarks) to the specified directory structure, organized by action, sequence, and frame.

E. LSTM:

In the endeavor to develop a robust model for human action recognition, a comprehensive set of callbacks and TensorBoard logging is employed to monitor the training process and optimize model performance. Leveraging TensorFlow and Keras, the model architecture incorporates multiple LSTM layers, dense layers, and a softmax activation for classification, as specified in the project requirements [7]. This architecture is meticulously configured to effectively capture temporal dependencies and extract discriminative features from input sequences. Upon defining the model architecture, a range of callbacks is integrated to enhance the training process. TensorBoard logging is utilized to visualize various metrics such as loss and accuracy over time, providing invaluable insights into the model's performance and convergence behavior. EarlyStopping is employed as a callback mechanism to halt training when the validation loss fails to improve, thereby preventing overfitting and ensuring optimal generalization capability. Furthermore, a Learning Rate Scheduler is incorporated to dynamically adjust the learning rate throughout the training process, enabling fine-grained control over the optimization trajectory. This adaptive learning rate strategy facilitates faster convergence and improved model performance. Additionally, the ModelCheckpoint callback is utilized to save the model weights periodically during training, safeguarding against potential loss of progress and enabling seamless resumption of training from the most recent checkpoint in the event of interruptions.

With the model architecture defined and callbacks configured, the training process commences using the designated optimizer, loss function, and evaluation metrics. Training data (X_train, y_train) and validation data (X_val, y_val) are utilized to iteratively update model parameters over a predetermined number of epochs, with batches of data processed at each iteration. The specified batch size ensures efficient utilization of computational resources while balancing between computational efficiency and model convergence.

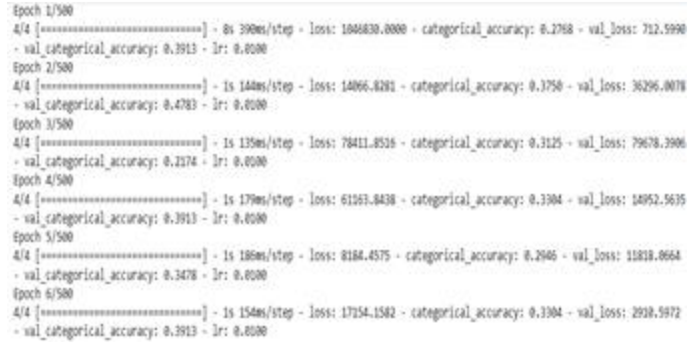
Through the collaborative efforts of these components, the LSTM model undergoes rigorous training and optimization, guided by the insights provided by the integrated callbacks and TensorBoard logging [8]. The iterative refinement process facilitated by these mechanisms ultimately yields a high-performing model capable of accurately recognizing human actions in video sequences, thus fulfilling the project's objectives and enabling a wide range of real-world applications in action recognition and analysis.

Fig 4.2 Collection of Real-time data

F. LSTM + Attention:

The algorithm harnesses TensorFlow and Keras to construct an attention-based LSTM model tailored for workout recognition. To facilitate monitoring and optimization, it configures callbacks and TensorBoard logging. The model architecture comprises a Bidirectional LSTM layer followed by a distinctive attention mechanism, aimed at focusing on relevant input data. Subsequently, a fully connected layer incorporating dropout is applied to the output for regularization purposes. Upon construction, the model is trained using input sequences along with corresponding labels, employing a predetermined optimizer and loss function. The code provides an overview of the model architecture, elucidating its components and functionalities. Additionally, it integrates various callbacks to enhance the training process and mitigate overfitting, ensuring the model's robustness and generalization capability.By leveraging the capabilities of TensorFlow and Keras, the algorithm empowers users to develop sophisticated models for workout recognition tasks[9]. The attention mechanism enables the model to selectively attend to salient features within the input sequences, enhancing its ability to discern and classify different workout activities accurately.

Overall, the utilization of advanced deep learning techniques, coupled with meticulous training strategies and callback mechanisms, culminates in a powerful framework for workout recognition and analysis[10]. The model's effectiveness and reliability make it a valuable tool for fitness monitoring applications, providing users with actionable insights and facilitating informed decision-making in their fitness journey.



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Epoch 1/500
4/4 [==============================] - 8s 390ms/step - loss: 1046830.0000 - categorical_accuracy: 0.2768 - val_loss: 712.5990
- val_categorical_accuracy: 0.3913 - lr: 0.0100
Epoch 2/500
4/4 [==============================] - 1s 144ms/step - loss: 14066.8281 - categorical_accuracy: 0.3750 - val_loss: 36296.0078
- val_categorical_accuracy: 0.4783 - lr: 0.0100
Epoch 3/500
4/4 [==============================] - 1s 135ms/step - loss: 78411.8516 - categorical_accuracy: 0.3125 - val_loss: 79678.3906
- val_categorical_accuracy: 0.2174 - lr: 0.0100
Epoch 4/500
4/4 [==============================] - 1s 179ms/step - loss: 61563.8438 - categorical_accuracy: 0.3304 - val_loss: 14952.5635
- val_categorical_accuracy: 0.3913 - lr: 0.0100
Epoch 5/500
4/4 [==============================] - 1s 186ms/step - loss: 8184.4575 - categorical_accuracy: 0.2946 - val_loss: 11818.0664
- val_categorical_accuracy: 0.3478 - lr: 0.0100
Epoch 6/500
4/4 [==============================] - 1s 154ms/step - loss: 17154.1582 - categorical_accuracy: 0.3304 - val_loss: 2910.5972
- val_categorical_accuracy: 0.3913 - lr: 0.0100
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Fig 4.3 Model Training

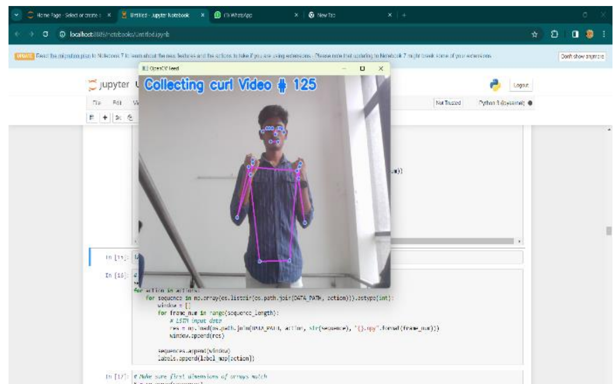

Fig 4.4 Model Training for Curl

G Calculate Joint Angles & Count Reps

The \`calculate_angle\` function computes the 3D joint angle formed by three key points in a skeletal structure. Given three points, representing the first, middle, and end joints, it calculates the angle formed by these joints based on their relative positions[11]. The function uses trigonometric functions to determine the angle in radians and then converts it to degrees. The resulting angle is returned, ensuring it is within the range of 0 to 180 degrees for better interpretability. The function provides a measure of the joint angle, which can be valuable in applications such as pose estimation or biomechanics analysis.

Define a function \`count_reps\` that tracks and updates repetition counts for three exercises (curl, press, squat) based on key joint angles[12]. It utilizes landmarks from a pose estimation model provided by the \`mp_pose\` library. The function calculates joint angles, distances, and updates global counters for each exercise. The logic includes detecting specific movement stages (e.g., 'up' and 'down') to accurately count repetitions. Visualizations of joint angles are displayed on the input image for monitoring. Global variables (\`curl_counter\`, \`press_counter\`, \`squat_counter\`, \`curl_stage\`, \`press_stage\`, \`squat_stage\`) are used to maintain state across function calls.

H Test in Real-Time:

Captures real-time webcam video, applies pose detection using MediaPipe, and predicts exercises using a pre-trained model. It maintains a sequence of keypoint information over time for predicting actions. If the prediction confidence surpasses a threshold, it updates the current action, visualizes prediction probabilities, counts exercise repetitions, and displays graphical information on the screen [13]. The code also records a video of the real-time test and utilizes OpenCV to display and save the processed frames. Users can perform exercises in front of the camera, and the system provides real-time feedback on detected actions and exercise repetitions.

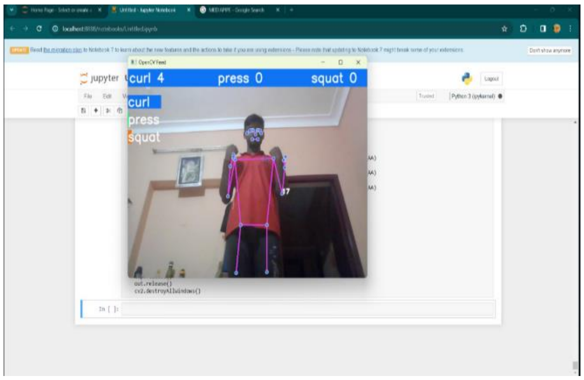

Fig 4.5 Real-time output

I Visual Feedback through Probability Distribution

One of the significant additions to our system is the implementation of a visual probability distribution graph. This feature dynamically displays the model's predictions over different exercise classes directly on the user interface. Each exercise probability is visualized as a horizontal bar graph on the output frame, where color-coded bars represent the confidence levels of the detected actions. For example, if the system is unsure about a squat's execution, it provides visual cues to the user to adjust their form, aiding in real-time correction and learning.

J Real-Time Messaging and Server Communication

To foster a more interactive training environment, we have established a server setup that handles real-time communication between the user and the AI system. This setup involves using a socket connection to send personalized messages to users based on their performance. These messages include motivational remarks, corrective suggestions, and updates on the calories burned during exercises, tailored according to the intensity and accuracy of the user's movements.

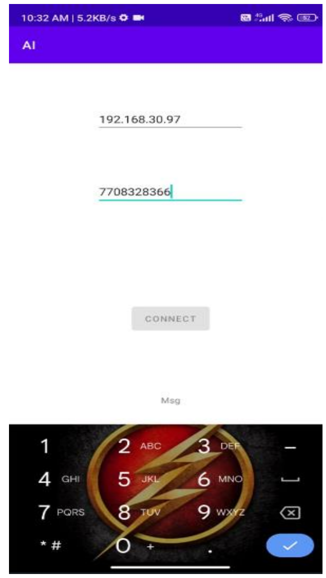

Fig 4.6 *Mobile app*

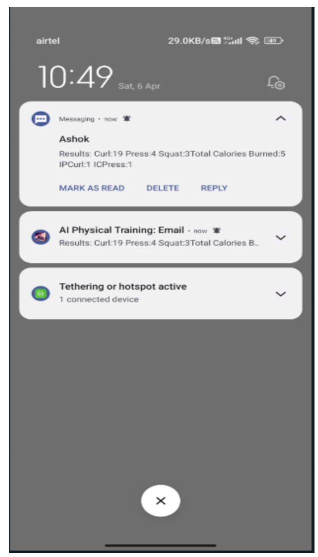

Fig 4.7 Notification

K Enhanced Exercise Monitoring and Feedback

The system now includes functionality to monitor exercise execution and provide immediate feedback on form and technique. For example, when a user performs a curl and the system detects a potential error in posture or execution, it displays a corrective message such as "Too Down, Lift Up Properly" directly on the output frame. This instant feedback mechanism is essential for ensuring that exercises are performed safely and effectively, minimizing the risk of injury and maximizing the benefits of the workout.

L. Nutritional and Caloric Output Calculation:

The system also computes the calories burned by utilizing the metabolic equivalent (MET) values for various exercises including curls, presses, and squats. This calculation takes into account the duration and intensity of the activity, offering users a quantitative measure of their workout efforts. This functionality not only boosts user motivation by displaying concrete results of their exercise routine but also aids in managing fitness goals related to weight loss or maintenance.

V. FLOW CHART

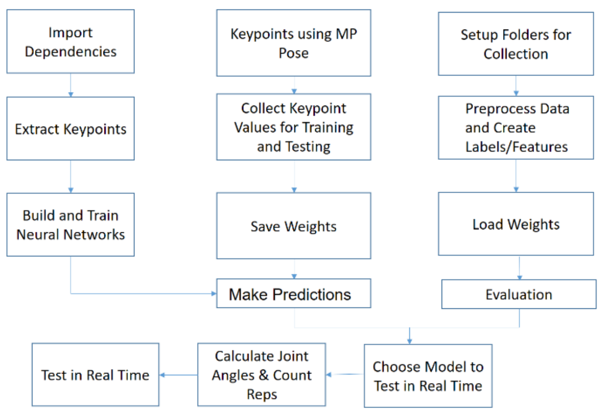

***Fig* 5.1** Flow chart

The workflow outlines a detailed method for designing and deploying a system dedicated to human pose detection and exercise recognition. This comprehensive approach starts with importing necessary dependencies, including libraries crucial for MediaPipe (MP Pose) pose detection. After initializing pose detection, keypoints are extracted from the detected human poses, forming the basis for subsequent steps in the process. The next phase involves setting up an organized structure for data collection. Folders are prepared to systematically gather and store keypoints, which will serve as input for creating datasets aimed at both training and testing. Once collected, this data undergoes preprocessing to label features effectively, preparing them for the next stage of neural network training. During this phase, the network architecture is constructed, and following the training, the model's weights are saved. These saved weights can be reloaded as needed for future use.

Once the model is trained, it is employed to make predictions on new data. The effectiveness of the model is assessed using accuracy metrics and a confusion matrix, providing insights into the model's performance and allowing for adjustments to be made if necessary. This flexibility in model selection and assessment is crucial for real-time testing and deployment.

In real-time operation, the system calculates joint angles and counts exercise repetitions, providing users with immediate feedback on their performance. This instant feedback is critical for users to adjust their movements, enhancing both safety and effectiveness of their workout.

Moreover, the system is enriched with additional functionalities that significantly elevate the user experience. It offers real-time suggestions to improve exercise form and a client-server communication setup that relays exercise results and caloric expenditure directly to the user's device. Progress tracking and potential integration with wearable devices further extend the capabilities of the system, making it a robust and dynamic tool for pose analysis and real-time exercise detection in humans.

Overall, the process aims to deliver a reliable and interactive system from inception to completion, equipped with a comprehensive suite of features designed to enhance user engagement, monitor progress, and support health and fitness goals comprehensively.

VI. OUTPUT

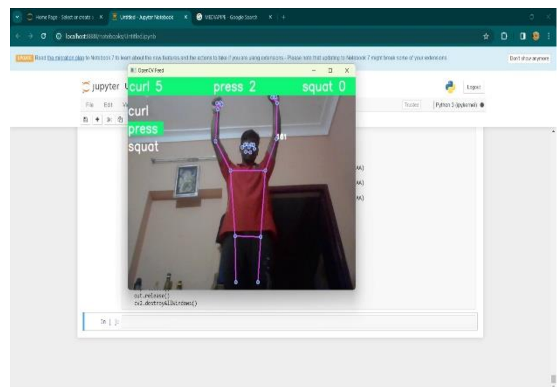

***Fig* 6.1 Output of press**

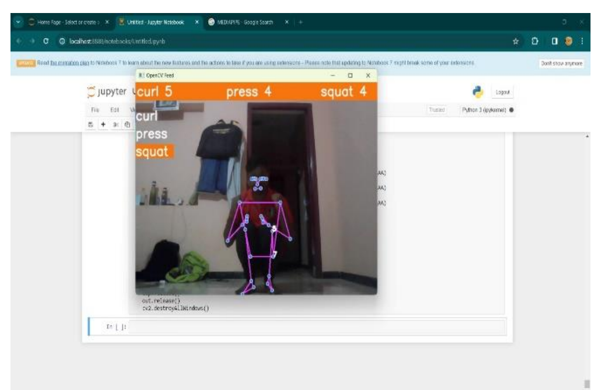

Fig 6.2 Output of Squat

VII. CONCLUSION

In conclusion, the project aims to create a robust system for real-time human exercise recognition and pose analysis using keypoint detection and neural networks. The workflow encompasses importing dependencies, extracting keypoints through MediaPipe Pose, organizing data collection, preprocessing datasets, building and training neural networks, and evaluating model performance. Additionally, the system is enhanced with a sophisticated messaging and suggestion feature that provides users with personalized feedback and corrective guidance during their workouts. This communication is facilitated through real-time data analysis, allowing the system to send targeted messages that help users improve their exercise form and technique instantly.

The initiative fosters flexibility to a variety of activities by allowing users to gather and classify their own keypoint data for training and testing. Neural network topologies may be developed and chosen thanks to the implementation, which also lets you save and load model weights. Real-time testing uses repetition counting and joint angle computations to give instant feedback on workout performance, further enriched by interactive suggestions and motivational messaging that enhance user engagement and efficacy of workouts.

Through evaluations involving confusion matrices and accuracy metrics, the project provides a quantitative measure of model effectiveness. The flexibility to choose different models for testing ensures versatility in deployment scenarios. Overall, the project combines computer vision, machine learning, and real-time analysis to create an interactive and personalized system for guiding and assessing physical exercises. The potential applications span fitness monitoring, training assistance, and health and wellness tracking, offering a comprehensive tool that not only tracks but also motivates and educates users on achieving their fitness goals.

VIII. REFERENCE

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