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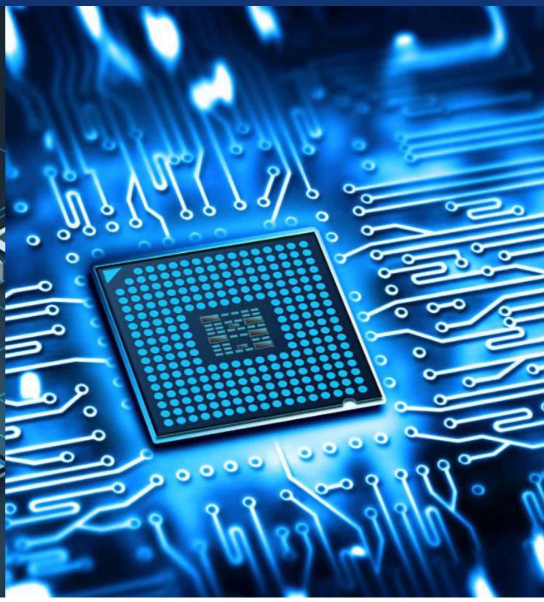


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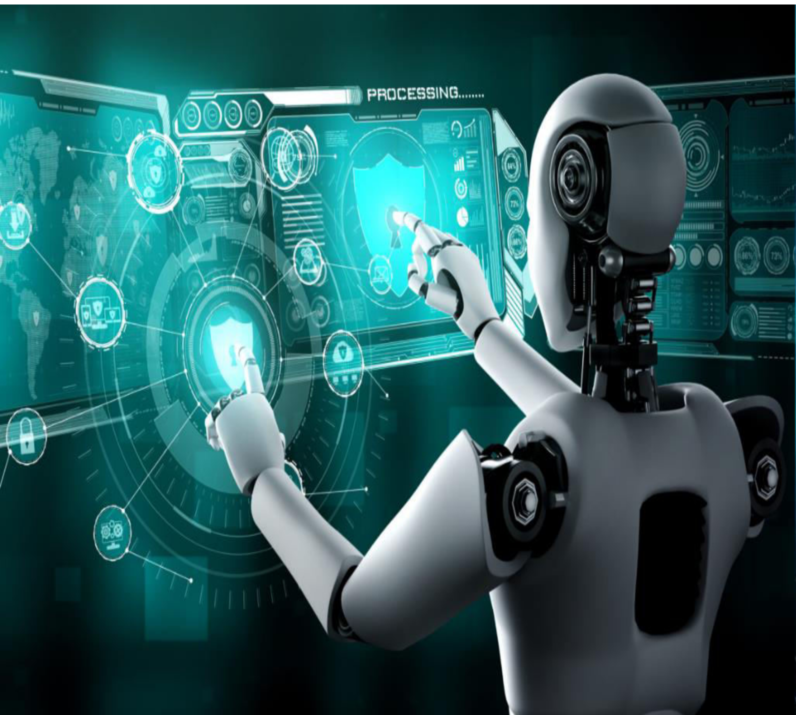

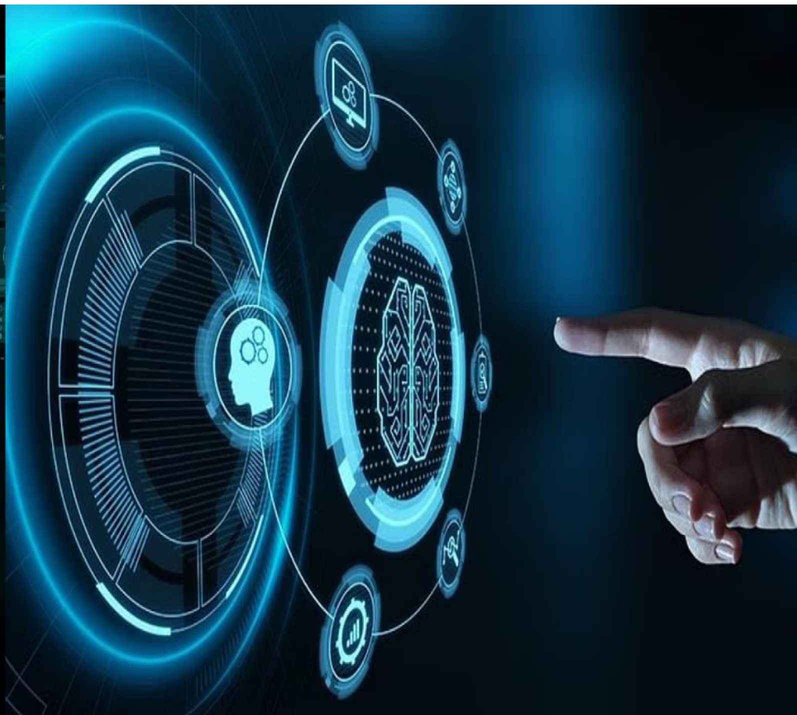

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# Smart Fitness Coaching Platform for Real-Time Exercise Analysis

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**ABSTRACT:** This study presents a real-time method for recognizing exercises using a Bidirectional Long Short-Term Memory (BiLSTM) model, specifically designed to work effectively in real-life conditions. Many existing exercise recognition systems depend heavily on synthetic datasets and only use raw joint coordinates. However, these coordinates can vary significantly depending on factors such as different users, camera positions, and environmental conditions. In addition, such systems often do not fully capture the temporal aspect of motion, which leads to reduced performance when used outside controlled environments.

To address these issues, the proposed method combines joint angle features with raw spatial coordinates (x, y, z). This hybrid approach allows the model to better handle variations in viewpoint, body proportions, and positioning, while still maintaining precise spatial details of movement.

The BiLSTM model is trained using sequences of 30 frames, enabling it to learn how movements change over time. To improve robustness, a diverse dataset was created by combining synthetic data from the InfiniteRep dataset with real-world videos from the Kaggle Workout/Exercises dataset and other online sources. The dataset includes four common exercises: squats, push-ups, shoulder presses, and bicep curls. During testing, the model achieved an accuracy of over 99% and showed strong performance when evaluated on separate real-world datasets, indicating good generalization ability. Comparisons with existing methods demonstrate clear improvements.

In addition to exercise classification, the system also includes features such as automatic repetition counting, real-time posture correction, personalized workout and diet planning, and a chatbot that supports both physical and mental well-being. All these features are integrated into a single web-based application, providing a complete and user-friendly fitness solution.

**KEYWORDS:** Real-time Exercise Classification, BiLSTM, Human Pose Estimation, Joint Coordinates (x, y, z), Joint Angle Features, Motion Sequence Analysis, Deep Learning, Exercise Recognition, Posture Correction, Repetition Counting, Workout Planner, Diet Planner, Mental Health Assistant, Web-Based Fitness System.

## I. INTRODUCTION

Physical exercise is one of the most important factors in maintaining a healthy and balanced lifestyle, as it positively influences both bodily fitness and mental well-being. Engaging in regular physical activity helps strengthen the cardiovascular system, build muscle endurance, improve flexibility, and support overall physical coordination. Along with physical improvements, exercise also contributes significantly to mental health by reducing stress levels, improving concentration, and enhancing emotional stability. Despite knowing these benefits, many individuals are unable to follow a consistent exercise routine.

A major reason for this inconsistency is the lack of proper guidance regarding correct exercise techniques. Without accurate instruction, users may perform workouts incorrectly, which can reduce effectiveness and increase the chance of injury. Another challenge is the unavailability of personalized coaching, as professional trainers are not accessible to everyone due to cost or location constraints. In addition, manually tracking workout performance, such as counting repetitions or monitoring progress, is often time-consuming and prone to human error. Traditional fitness support systems, including personal training sessions, are often expensive and not feasible for a large section of users.

In recent years, technological advancements in Artificial Intelligence have opened new possibilities for solving these challenges. Fields such as computer vision and machine learning have made it possible to analyze human movement in real time using digital systems. One of the key techniques used in this area is pose estimation, which identifies and tracks important human body joints from images or video input. This allows the system to understand how a person is moving and whether the posture is correct or not.

When pose estimation is integrated with machine learning models, it becomes possible to build intelligent systems that can automatically identify exercises, monitor movements, and count repetitions without manual effort. These systems can also analyze body posture and provide immediate corrective feedback to the user. As a result, fitness training becomes more accurate, interactive, and engaging. Moreover, such AI-based solutions make professional-level fitness guidance more accessible to users regardless of their experience level, physical location, or financial situation. This shift toward intelligent fitness systems represents a modern and efficient approach to health and exercise monitoring.

**Objective of the Work:**
The objective of this project is to develop an intelligent fitness assistance system that leverages Artificial Intelligence and computer vision techniques to support users during physical exercise. The system aims to accurately detect and classify different types of exercises in real time by analyzing human body movements using pose estimation and machine learning models. It also focuses on providing immediate feedback on posture and exercise form to help users perform workouts correctly and safely. In addition, the system includes automatic repetition counting to eliminate the need for manual tracking and to ensure accurate monitoring of exercise performance. Another important goal is to track and store workout progress over time so that users can evaluate their fitness improvements. The project further aims to make professional fitness guidance more accessible and affordable, especially for individuals who exercise at home or do not have access to personal trainers. Ultimately, the system is designed to improve exercise accuracy, reduce the risk of injuries, and promote consistent fitness habits through real-time intelligent feedback and guidance.

## II. LITERATURE REVIEW

- **Maminitaina Alphonse Rafidison et al. (2023)** presented an image classification method using a lightweight Convolutional Neural Network (CNN) combined with a Pulse-Coupled Neural Network (PCNN). The approach uses convolutional layers to extract visual features, while PCNN performs efficient pixel-level clustering. This design is optimized for fast and lightweight deployment, making it suitable for real-time applications due to its low computational cost. However, it has limitations such as weaker feature extraction and difficulty handling complex backgrounds. This study is useful for understanding basic image classification relevant to pose estimation, but it lacks temporal modeling, which is important for real-time fitness applications. It also highlights the need for improved preprocessing to handle varied backgrounds.
- **Tushar Rangari et al. (2022)** proposed a video-based exercise recognition system using LSTM and OpenPose. OpenPose extracts human keypoints, and LSTM models temporal sequences of motion, achieving an accuracy of 97.01%. The system effectively handles multi-angle inputs and captures motion patterns well. However, its performance depends heavily on video quality and struggles to scale across many exercise types. Additionally, OpenPose requires high computational resources, limiting its use on low-end devices.
- **Sushma V. et al. (2023)** developed a fitness trainer application using MediaPipe, TensorFlow, and OpenCV. The system tracks repetitions and provides posture correction through visual and audio feedback. It is user-friendly and suitable for beginners. However, it has moderate accuracy and limited capability for handling complex movements. While it provides a strong base for pose detection in fitness, it requires further improvements for advanced workouts and adaptability.

- **Dsouza, Deepak Maurya, and Anoop Patel (2022)** introduced a smart gym trainer using human pose estimation with OpenPose. The system captures body keypoints in real time and evaluates exercise posture based on predefined rules. It offers advantages such as real-time feedback, no need for wearable devices, and usability in both home and gym settings. However, it is sensitive to lighting conditions, occlusions, and low-resolution inputs, and it struggles with complex poses. Despite these limitations, it provides a practical and cost-effective solution for AI-based fitness training.
- **Colin Arrowsmith et al. (2022)** proposed a physiotherapy exercise classification system using single-camera pose detection and CNN. The method performs well in classification and requires minimal equipment. However, it focuses only on classification and lacks motion correction, which may lead to inaccurate results for unclear poses. This work demonstrates a low-cost approach that can be enhanced with corrective feedback and motion modeling.
- **Boudjemaa Boudaa et al. (2022)** explored the use of Graph Convolutional Networks (GCNs) for health recommender systems. The method models user-item interactions as a graph and applies GCN layers to improve recommendation accuracy. It effectively handles data sparsity and cold-start problems, making it useful for personalized health recommendations.
- **Fotos Frangoudes et al. (2022)** provided a review of machine learning techniques, including CNNs and RNNs, for analyzing human motion during exercise. The study highlights both strengths and limitations of current methods and emphasizes the lack of diverse and high-quality datasets. It suggests the need for better datasets to improve model robustness and real-world applicability.
- **Bang and Park (2024)** improved exercise classification using ensemble learning with CNNs. Initially, traditional models like KNN and Random Forest performed poorly due to lack of temporal understanding. They introduced LSTM for sequence modeling and combined it with CNNs for spatial feature extraction, forming a CNN+LSTM hybrid model. Further improvement was achieved using a CNN ensemble with soft voting, reaching 92.12% accuracy, outperforming earlier approaches.
- **Moran et al. (2022)** developed a real-time exercise classification system using MediaPipe and BlazePose. The system extracts 3D keypoints (33 landmarks) and uses sequences of frames as input to an LSTM model to capture motion over time. This improves the ability to distinguish between exercises with similar poses but different movements. The approach is effective due to its strong temporal modeling capability.
- **Jindřich Adolf et al. (2025)** introduced OffiStretch, a camera-based system providing real-time feedback for stretching exercises. It uses a single RGB camera and compares user poses with predefined target poses using angular and spatial features. The system improves user motivation and engagement, although it shows limited performance improvement in accuracy. Its simplicity and affordability are key advantages, but it is restricted to certain viewing angles and requires more precise feedback mechanisms

## III. EXISTING MODEL

Existing exercise monitoring and classification systems mostly depend on wearable sensors or traditional computer vision techniques. These methods include manual repetition counting, basic posture detection, and guidance from trainers for real-time feedback. Although CNN-based and frame-wise classifiers are commonly used, they analyze each frame separately without considering motion over time. This limits their ability to understand continuous movement patterns and distinguish similar exercises accurately. Additionally, many systems rely only on raw joint coordinates, making them sensitive to changes in camera angle, user position, and distance, which reduces overall reliability and performance.

## IV. PROPOSED METHODOLOGY

This work presents an AI-based fitness assistant that uses a Bidirectional Long Short-Term Memory (BiLSTM) network to perform real-time exercise classification along with automatic repetition counting. The BiLSTM model is used because it is capable of learning temporal patterns in both forward and backward directions, allowing it to understand how exercise movements change over time more effectively than traditional frame-based methods. For pose detection, the system utilizes the BlazePose framework, which efficiently identifies key body landmarks from webcam input and enables accurate tracking of human movement.

To improve the quality of feature representation, the system combines raw joint coordinates with calculated joint angles. This hybrid feature approach helps reduce the impact of variations such as camera angle, user positioning, and

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distance from the camera. As a result, the model becomes more robust and reliable in real-world conditions. By integrating both spatial and angular information, the system achieves better understanding of exercise posture and movement patterns.

The proposed system is implemented as a real-time web application that works using a standard webcam, making it easy to access and use without specialized equipment. It is designed with a user-friendly interface to ensure smooth interaction for all users. The system is capable of recognizing and tracking four main exercises: squats, push-ups, bicep curls, and shoulder presses, while simultaneously counting repetitions and providing real-time feedback during workouts.

## V. IMPLEMENTATIONS

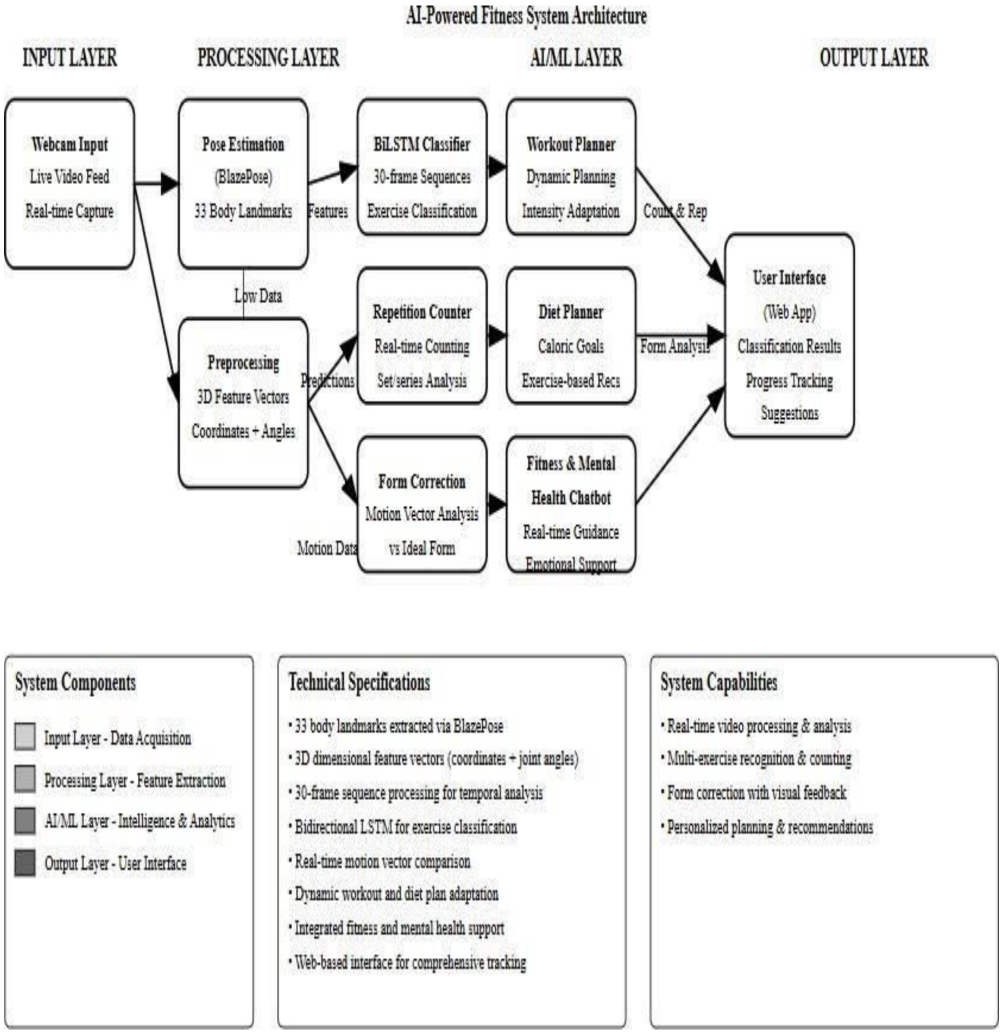


Fig. 1 Proposed Architecture

**1. Data Preprocessing**

**1) Pose Detection and Landmark Extraction**

Data pre-processing begins with capturing live video input from the webcam, which is then processed using the MediaPipe BlazePose framework. This framework detects human body posture by identifying key landmarks on the body. Each video frame is converted into a structured set of coordinates (x, y, z), representing different joints of the human skeleton.

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**2) Data Cleaning and Normalization**

After extracting the landmarks, the data is cleaned to remove noise and handle missing or unstable values. Smoothing techniques are applied to maintain consistency in the motion data. The coordinates are then normalized so that variations in camera distance, user position, and body size do not affect the model's performance. This ensures uniform input data for all users.

**3) Feature Engineering and Sequence Formation**

In this stage, additional features such as joint angles are calculated from the normalized coordinates to improve posture understanding. These angle-based features are combined with raw coordinates to form a richer dataset. Finally, the data is arranged into fixed-length sequences (e.g., 30 frames per sequence) and reshaped into the required format for the BiLSTM model, enabling it to learn movement patterns over time effectively.

**2. CNN Architecture**

The CNN architecture used in this system is designed to extract meaningful spatial features from input data such as pose images or landmark representations. The model begins with the input layer, where the captured frame or pose data is fed into the network. The first convolution layer applies multiple filters (e.g., 32 filters with a 3×3 kernel) and uses the ReLU activation function to detect basic features such as joint positions and body structure patterns. This is followed by a max pooling layer, which reduces the spatial dimensions of the feature maps while retaining important information.

In the next stage, a deeper convolution layer is applied with a higher number of filters (e.g., 64 filters), allowing the model to learn more complex patterns related to human posture and movement. Another max pooling layer is used to further downsample the features and reduce computational complexity. A third convolution layer (e.g., 128 filters) is then used to capture high-level abstract features that represent overall body posture and exercise-specific patterns.

Finally, the extracted feature maps are flattened into a one-dimensional vector and passed through a fully connected (dense) layer with ReLU activation. The final output layer uses the Softmax function to classify the input into different exercise categories such as squats, push-ups, bicep curls, and shoulder presses. This CNN architecture effectively learns spatial features, which can further be combined with temporal models like BiLSTM for improved real-time exercise classification.

**3. Model Compilation**

- **Optimizer Selection**

○ The model compilation begins by selecting an appropriate optimizer to update the network weights efficiently during training. In this system, the Adam optimizer is used because it provides adaptive learning rates and faster convergence compared to traditional optimization methods. It helps the model learn effectively from complex pose and movement data while maintaining stability during training.

- **Loss Function and Objective**

○ The next step involves defining the loss function, which measures how well the model is performing during training. Categorical cross-entropy is used since the system deals with multiple exercise classes such as squats, push-ups, bicep curls, and shoulder presses. This loss function compares the predicted probabilities with the actual labels and helps the model reduce classification errors over time.

- **Evaluation Metrics and Final Setup**

○ Finally, evaluation metrics such as accuracy are defined to monitor the model's performance during training and testing. Accuracy indicates how correctly the model classifies different exercises. After setting the optimizer, loss function, and metrics, the model is compiled and becomes ready for training, enabling it to learn both spatial and temporal patterns for effective real-time exercise recognition.

**4. Model Training**

The model is trained using pre-processed pose sequences extracted from video frames. Each sample consists of 30-frame motion sequences that include joint coordinates and joint angle features, representing different exercise movements.

The BiLSTM model is trained on these sequences to learn both spatial and temporal patterns of exercises. The Adam optimizer is used to update weights, while categorical cross-entropy loss helps minimize classification errors during training over multiple epochs.

Model performance is evaluated using accuracy on both training and validation data to ensure proper learning and generalization. As training progresses, the model improves its ability to accurately classify exercises such as squats, push-ups, bicep curls, and shoulder presses.

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**5. Model Evaluation**

- The trained model is evaluated using a separate test dataset containing unseen pose sequences to check its real-world performance. This helps in understanding how accurately the model can classify different exercises outside the training data.
- Performance is measured using metrics such as accuracy, precision, recall, and F1-score, along with a confusion matrix for error analysis. The results show high accuracy and good generalization across real-time exercise conditions.

**6. Visualization**

- Training and validation accuracy and loss graphs are used to visualize the model's learning performance over time. These plots help in understanding how well the model is improving and whether it is overfitting or generalizing properly.
- A confusion matrix is also used to show the classification results for different exercises. It helps in identifying correct predictions and errors between similar exercise classes, giving a clear view of model performance.

**7. Fine-Tuning and Optimization**

- Fine-tuning of the model is performed to improve its accuracy and generalization by adjusting hyperparameters such as learning rate, batch size, and number of epochs. Pre-trained weights or improved initialization techniques are also used to speed up convergence and enhance performance on exercise classification tasks.
- Optimization techniques such as the Adam optimizer, learning rate scheduling, and early stopping are applied to stabilize training and prevent overfitting. Dropout layers and regularization methods are also used to improve model robustness, ensuring reliable real-time performance under different user conditions.

## VI. CLASSIFICATION

The classification process involves identifying the type of exercise performed by the user based on the input pose sequences. The trained BiLSTM model analyzes temporal movement patterns and outputs probability scores for each exercise class. These probabilities are passed through a Softmax activation function to determine the most likely exercise category.The system classifies exercises into predefined classes such as squats, push-ups, bicep curls, and shoulder presses. The class with the highest probability is selected as the final prediction. This classification enables real-time exercise recognition along with repetition tracking and posture analysis for accurate fitness monitoring.

## VII. RESULT

The Virtual AI Fitness Coach performed effectively in real-time conditions, achieving high accuracy in exercise classification using the BiLSTM model. The system showed strong reliability in repetition counting, posture correction, and personalized fitness recommendations. Overall, it maintained consistent performance across different environments such as home and gym settings.

## VIII. CONCLUSIONS

The proposed Virtual AI Fitness Coach demonstrates how artificial intelligence can be effectively applied to improve personal fitness training. By combining MediaPipe BlazePose for pose estimation with a BiLSTM-based deep learning model, the system is able to recognize exercises such as squats, push-ups, bicep curls, and shoulder presses in real time. The use of both joint coordinates and joint angle features improves model robustness, allowing consistent performance under different lighting conditions, camera angles, and user body variations.

The system also extends beyond classification by including automatic repetition counting and real-time posture correction, which help users maintain proper form and reduce injury risk. Additional modules like the personalized workout planner, diet recommendation system, and AI-based chat support enhance usability by providing customized fitness and wellness guidance. Overall, the system offers a scalable and user-friendly AI-powered fitness solution and can be further improved with advanced features like 3D motion analysis and wearable device integration.

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## REFERENCES

[1] Maminiaina Alphonse Rafidison et al., “Image Classification Based on Light Convolutional Neural Network Using Pulse-Coupled Neural Network,” Computational Intelligence and Neuroscience, vol. 2023, pp. 1-17, 2023.
[2] TusharRangari, Sudhanshu Kumar, Partha Pratim Roy, Debi Prosad Dogra, and Byung-Gyu Kim, “Video Based Exercise Recognition and Correct Pose Detection,” Multimedia Tools and Applications, vol. 81, no. 21, pp. 30267-30282, 2022.
[3] Sushma V. et al., “Fitness Trainer Application Using Artificial Intelligence,” InternationalResearchJournalofEngineeringandTechnology(IRJET),vol.10,no.5, p.826, May 2023.
[4] Grandel Dsouza, Deepak Maurya, and Anoop Patel, “SmartGymTrainerUsingHuman Pose Estimation,” 2022 IEEE International Conference for Innovation in Technology (INOCON), pp. 1-4, 2022.
[5] Colin Arrowsmith, David Burns, Thomas Mak, Michael Hardisty, and Cari Whyne, “Physiotherapy Exercise Classification with Single-Camera Pose Detection and Machine Learning,” Sensors, vol. 23, no. 1, p. 363, 2022.
[6] Boudjemaa Boudaa, Imen Bestani, and Noureddine Benadjrouda, “Graph Convolutional Networks for Designing Collaborative Filtering-Based Health Recommender Systems,” 2022 2nd International Conference on New Technologies of Information and Communication (NTIC), pp. 1-6, 2022.
[7] Fotos Frangoudes, Maria Matsangidou, Eirini C. Schiza, Kleanthis Neokleous, and Constantinos S. Pattichis, “Assessing Human Motion During Exercise Using Machine Learning: A Literature Review,” IEEE Access, vol. 10, pp. 86874-86903, 2022.
[8] Bang, G. S., & Park, S. B., “Workout Classification Using a Convolutional Neural Network in Ensemble Learning,” Sensors, vol. 24, no. 10, p. 3133, 2024.
[9] Moran, A., Gebka, B., Golodshteyn, J., Beyer, A., Johnson, N., & Neuwirth, A., “MuscleVision:Real-TimeKeypointBasedPoseClassificationofPhysicalExercises,” vol. 1, no. 1, pp. 1-5, 2022
[10] Jindřich Adolf,PeterKán,TiareFeuchtner,BarboraAdolfová,Jaromír Doležal,& Lenka Lhotská. “OffiStretch: camera-based real-time feedback for daily stretching exercises.” The Visual Computer, vol. 41, no. 2 (February 2025), pp. 1555–1571.