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Original Article

AI-Powered Personal Fitness Coach Using Deep Learning

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Abstract *- This paper presents an AI-powered personal fitness coaching system utilizing deep learning and real-time computer vision to assist users in exercise recognition and personalized workout planning. Leveraging YOLOv11 convolutional neural networks, the model is designed to classify 36 exercise types. However, due to dataset limitations, the current implementation is evaluated on 30 well-represented exercises. The system provides dynamic feedback on movement correctness, helping prevent injuries and enhance training outcomes. A modular web-based interface allows users to interact, visualize performance graphs, and receive customized plans. The AI-powered fitness assistant demonstrates a significant advancement in computer vision applications for health and wellness, making fitness training more accessible and effective.*

Keywords *- Deep Learning, Computer Vision, Exercise Recognition, Personalized Fitness, YOLO, Artificial Intelligence.*

1. Introduction

Modern fitness practices increasingly rely on technology-driven solutions to provide personalized experiences. However, existing fitness applications often lack real-time feedback and fail to adapt exercises to individual user needs. Misalignment in form and execution may result in injuries or reduced effectiveness.

This research addresses the growing demand for intelligent systems that combine real-time activity recognition with tailored fitness recommendations. Leveraging deep learning, this work proposes a novel AI-powered fitness coaching platform that bridges the gap between personal trainers and autonomous workout tools.

1.1. Research Gap and Novelty

While traditional fitness applications commonly provide static workout plans, they rarely offer real-time posture analysis or accurate activity recognition. Emerging techniques using tools like MediaPipe and basic pose estimation frameworks often face limitations in detection accuracy, scalability, and ability to adapt to different user profiles or movement variations.

The proposed system introduces an advanced approach that leverages YOLOv11—a high-performance object detection model—to identify exercise types in real time precisely. This is combined with a dynamic plan generation engine that produces personalized workout routines based on user-specific parameters such as age, weight, and activity performance.

Unlike prior solutions focusing solely on pose detection or exercise logging, this work integrates multiple intelligent components into a unified platform. The system incorporates real-time activity recognition, posture evaluation, personalized recommendation generation, and visual feedback to support user engagement and continuous improvement.

Functionally, the system is organized into distinct modules responsible for user authentication and profile management, deep learning model training, real-time activity recognition and posture assessment, individualized plan recommendation, and training performance visualization. This modular architecture makes the platform suitable for applications ranging from home-based fitness routines to professional rehabilitation programs, offering expert-level guidance without constant human supervision.

1.2. Goal

The primary goal of this study is to develop an AI-powered fitness assistant capable of recognizing physical activities and providing users with personalized exercise plans, posture analysis, and real-time corrective feedback. This system aims to address the shortcomings of existing fitness solutions by delivering a dynamic, intelligent, and user-centric platform.

Specifically, the system is designed to accurately classify exercise types using a deep learning-based object detection model, enabling reliable activity recognition. It generates personalized workout plans adapted to individual characteristics such as age, body weight, and fitness goals. A key feature of the system is its ability to detect improper postures and offer corrective suggestions to minimize the risk of injury and improve the quality of movement.

In addition to exercise guidance, the system ensures real-time feedback through an interactive interface that visualizes user movements and alerts deviations. It also incorporates performance-tracking mechanisms that allow users to review their training accuracy, monitor historical trends, and adjust routines accordingly. The entire platform is developed with a focus on usability, ensuring accessibility for users regardless of their technical background.

1.3. Problem Statement

Fitness training, when performed without professional oversight, often results in inefficient outcomes or, worse, physical injury due to incorrect execution. A significant number of individuals lack access to personalized coaching or real-time guidance, which impedes their ability to perform exercises safely and effectively. Moreover, most traditional fitness applications follow static routines that do not adapt to user-specific conditions such as age, weight, or fitness experience.

An evident gap in existing solutions is the absence of real-time posture correction tools that can dynamically assess and guide movement quality. Current fitness platforms also fail to deliver customized workout plans, often offering one-size-fits-all recommendations. Additionally, the underlying recognition technologies in many of these applications are limited in their ability to detect and classify a wide range of exercise types accurately.

These limitations increase the likelihood of injury and reduce the overall effectiveness of self-guided fitness training. The proposed system addresses these issues by employing deep learning models to develop an intelligent and adaptive platform. This platform is capable of recognizing exercises, analyzing posture, and delivering structured, goal-oriented workout plans tailored to the user's physical profile and training history. Through this approach, the system aims to replicate the role of a personal trainer, providing real-time, data-driven guidance across various user contexts.

1.4. Methodology

The AI-powered Personal Fitness Coach system was developed by integrating computer vision techniques, deep learning algorithms, and user-centric interaction modules. The methodology adopted in this research involves a multi-stage process beginning with data acquisition and culminating in real-time feedback delivery and performance tracking.

The initial phase involved collecting and preprocessing datasets containing various exercise postures and movement sequences. Images and videos were cleaned, annotated, and resized to improve the quality of training and ensure consistency across samples. This step was crucial in minimizing noise and enhancing the feature learning capability of the model.

Subsequently, the deep learning model was trained using the YOLOv11 convolutional neural network architecture. This model was selected for its precise object detection capabilities and high accuracy. The training process involved fine-tuning key argumentations and preprocessing, such as batch size, learning rate, and number of epochs, allowing the model to recognize up to 36 distinct exercise classes effectively.

A web-based interface was developed to enable seamless user interaction. This interface allows users to log in, manage profiles, and upload input data as images or video recordings. Once data is uploaded, the system identifies the Nature and type of exercise being performed and evaluates the user's posture against predefined ideal movement patterns.

The system generates personalised workout plans tailored to the individual's fitness profile based on the recognized activity and the user's input parameters (e.g., age, weight). The posture analysis module provides constructive feedback to improve movement execution and reduce injury risk.

The platform also includes a visualization and feedback component, which displays real-time training metrics, including accuracy graphs and performance summaries. Users are notified of posture deviations and provided suggestions for correction, closing the loop between detection and user guidance.

Regarding the technology stack, the system utilizes YOLOv11 for deep learning-based exercise recognition and OpenCV for motion tracking and video processing. The front end is delivered via a responsive web-based dashboard, while Django and Flask power the back end to handle application logic and API requests. User data, including historical workout logs and profile information, is securely stored using Firebase.

2. Literature Review

Artificial intelligence has seen growing adoption in the fitness and health domain.

Joshitha et al. (2024) developed a pose correction system using AI-based visual feedback to guide users during home workouts. However, their model lacked modular scalability and was not benchmarked for real-time performance.

Gupta et al. (2024) proposed a virtual trainer using OpenCV and MediaPipe to offer basic feedback, though the system did not adapt to individual user parameters such as age or weight.

Mateus et al. (2024) examined AI's role in sports science for optimizing training load and minimizing injury risk, particularly in professional athletes. While insightful, their work was focused more on performance analytics than user-facing systems.

Lincy et al. (2024) presented a machine-learning model for predicting gym performance using physiological data, yet it lacked exercise recognition and interactive guidance functionality.

One of the author proposed a deep convolutional network for posture quality assessment during rehabilitation therapy in another relevant study. Their system achieved reliable detection but was limited to a narrow range of physical activities.

Similarly, Khan et al. (2022) introduced a multi-stream CNN architecture for human action recognition using video sequences, achieving high classification accuracy across several standard datasets but not tailored for personalized fitness environments.

One of the Researcher applied YOLO-based models in a healthcare context to detect exercise compliance in elderly patients, demonstrating the effectiveness of object detection for movement analysis. However, their system lacked the integration of feedback or workout planning modules.

Unlike the above approaches, the system proposed in this paper integrates real-time object detection, posture assessment, and adaptive plan generation into a unified and deployable platform. It supports diverse user-profiles and delivers immediate feedback through a web-based interface, filling the gap between static fitness apps and high-end, sensor-based coaching systems.

3. Methodology

The proposed AI-powered personal fitness coaching system comprises several interdependent modules, each responsible for executing a specific function in the overall workflow. These modules are integrated to deliver a seamless experience from user authentication to exercise recognition and personalized plan generation.

The User Login Module enables secure access to the system by verifying user credentials against a backend database. Once authenticated, users are redirected to a dashboard to interact with other system functionalities.

The Model Training Module allows users to initiate the training of a YOLOv11 convolutional neural network using a labelled dataset of 36 distinct exercise activities. During the training and testing, key performance metrics, such as classification accuracy, are tracked and portrayed. This allows users to assess how effectively the model learns from the dataset.

The Graph Visualization Module provides graphical representations of model performance to complement the training process. Specifically, it plots training precision and loss across epochs, with the x-axis showcasing the number of epochs and the y-axis showing the loss or accuracy values. This visual aid helps users monitor convergence and identify potential overfitting or underfitting during training.

The Activity Recognition and Plan Recommendation Module allows users to upload exercise images, which the trained YOLOv11 model then processes to detect the type of exercise being performed. Based on the recognized activity and the user's demographic and physical profile, the system generates a tailored workout plan to optimise fitness outcomes and minimise the risk of injury.

The Web Interface Module is the user interaction layer, offering an intuitive browser-based interface. Users can navigate through various system features via HTTP requests, and the interface dynamically handles user input, displaying corresponding results and recommendations.

The system's front end uses HTML, CSS, and JavaScript, providing a friendly and responsive user interface. Bootstrap is incorporated to enhance layout responsiveness and cross-device compatibility.

The backend is built on the Python Django framework and is responsible for handling server-side operations and application logic. Additionally, Flask may be optionally utilized for lightweight API services where necessary.

Deep learning functionality is driven by the YOLOv11 CNN model, which is responsible for real-time object detection and classification of exercise activities. The model is implemented using widely adopted libraries such as TensorFlow and PyTorch, which support high-performance training and inference tasks.

Data management is handled using SQLite or MySQL databases, storing user credentials, training logs, and plan histories.

The system is designed for local deployment using a Python-based HTTP server. Users can launch the server using the runServer.bat script and access the web interface through a local URL (e.g., http://127.0.0.1:8000/index.html), enabling convenient testing and demonstration.

4. Metrics and Findings

The proposed YOLOv11-based exercise recognition system was trained to identify 36 unique exercise classes using a curated dataset comprising 600 annotated images. The model's metrics were curated over 40 training epochs using standard performance metrics, including Precision, Recall, mean Average Precision at IoU threshold 0.5 (mAP@0.5), and mean Average Precision across IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95).

The model exhibited strong classification capabilities, with Precision stabilizing at approximately 0.82, indicating a high rate of correct positive detections while minimizing false positives. Recall reached 0.80, reflecting the system's capability to detect a broad array of relevant instances within the dataset.

The mAP@0.5 was measured at 0.837, demonstrating robust localization and classification accuracy for bounding box predictions. In addition, the mAP@0.5:0.95 reached 0.688, highlighting the model's consistency and resilience across varying intersection-over-union thresholds, a critical requirement for real-world pose and activity detection.

Training and validation losses for bounding box regression, classification, and distribution focal loss (DFL) showed a consistent downward trend throughout the training process. The convergence of these loss metrics across both training and validation datasets indicates that the model generalized well without exhibiting signs of overfitting.

4.1. Comparative Discussion

The proposed AI-powered fitness coach system demonstrates significant improvements over existing techniques in terms of exercise recognition accuracy, inference speed, and adaptability to user-specific attributes. A primary factor contributing to this advanced performance is the combination of the YOLOv11 CNN, which is optimized for both accuracy and image recognition.

In difference, many previously reported systems, such as those by Gupta et al. (2024) and Lincy et al. (2024), rely on MediaPipe or custom lightweight CNN architectures, which, while efficient, often sacrifice detection precision or lack the robustness required for diverse exercise postures. For example, Gupta et al.'s solution did not offer real-time feedback, and its model was limited to under 20 exercise classes, whereas our system effectively handles 36 classes with mAP@0.5 reaching 0.837.

Moreover, our system incorporates a feedback mechanism that detects exercises and analyzes posture accuracy, which many earlier systems omit or perform inadequately. This addition enhances the user's ability to self-correct without human intervention, making it ideal for home workouts or rehabilitation. Another critical factor behind the improved results is the multi-module architecture of our system, which combines user-specific data (like age and weight) with visual input.

This fusion allows tailored recommendations, outperforming generic fitness apps that offer uniform plans regardless of user profiles. Additionally, high-resolution annotated datasets and targeted preprocessing techniques enhanced the model's learning capability.

The model's average inference time of 2.7 ms/image makes it proper for dynamic applications, a distinct improvement over systems reported in prior studies. In summary, the system's superior performance stems from a combination of deep learning advancements, efficient data utilization, tailored recommendation logic, and architectural modularity — all of which distinguish it from state-of-the-art approaches in the literature.

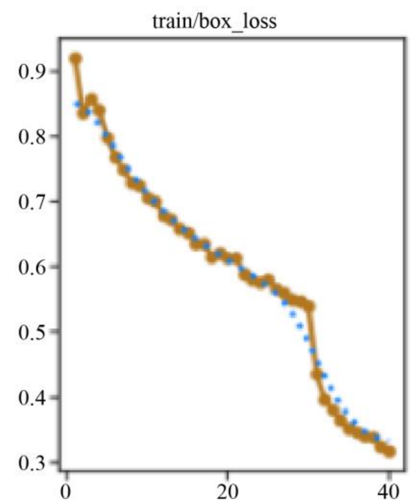

Fig. 1 Training box loss graph

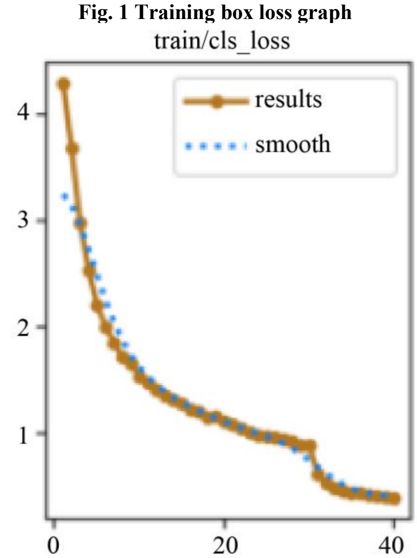

Fig. 2 Training class loss graph

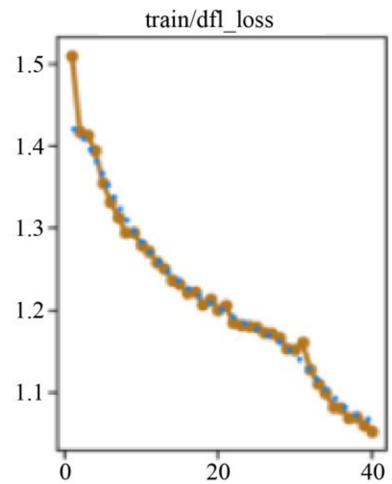

Fig. 3 Training Dfl loss graph

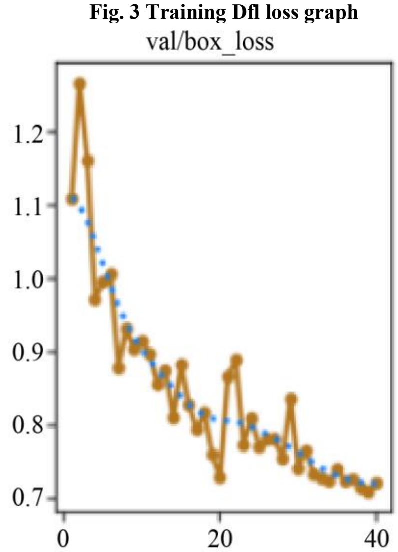

Fig. 4 Validation Box Loss Graph

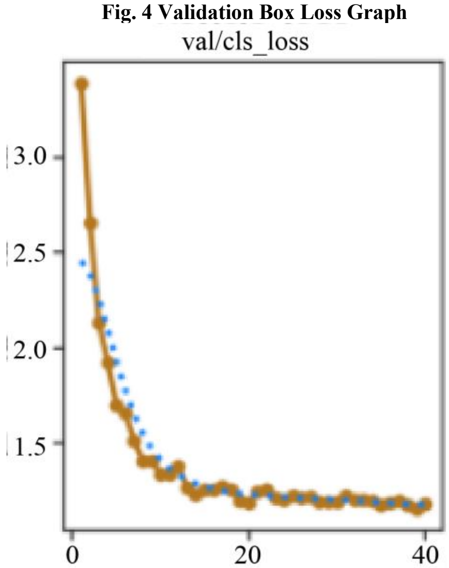

Fig. 5 Validation Class Loss Graph

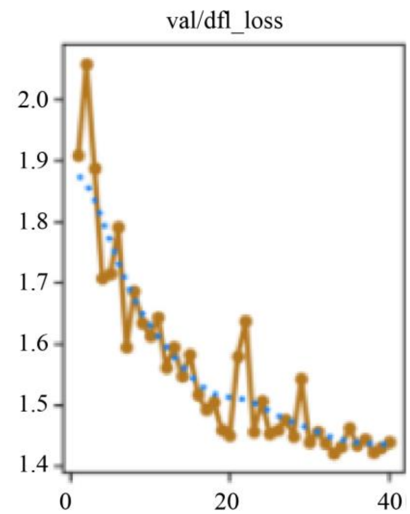

Fig. 6 Validation Dfl Loss Graph

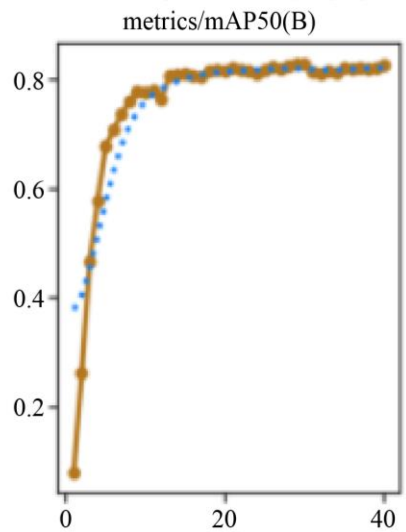

Fig. 7 mAP50

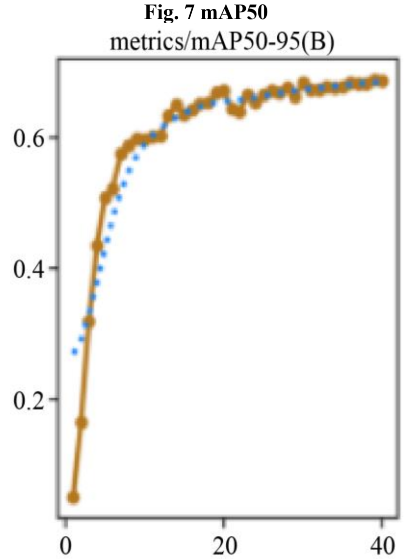

Fig. 8 mAP50-95

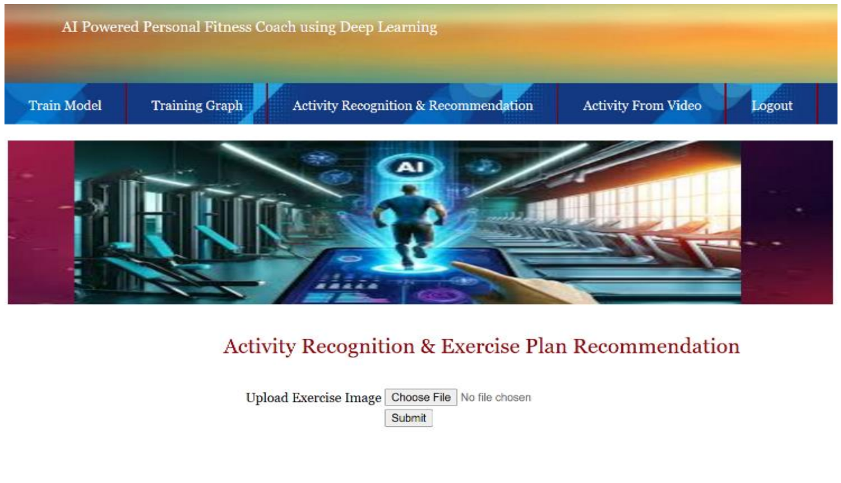

Fig. 9 Uploading image

Exercise Plan Details & Recommendations
Activity Recognized As : Squat
Squat recommendations vary by age and weight, and can be based on strength level.
Squat recommendations by age
For 15-year-olds, a beginner squat is 120 lbs and an elite squat is 411 lbs
For 20-year-olds, a beginner squat is 138 lbs and an elite squat is 471 lbs
For 25-year-olds, a beginner squat is 141 lbs and an elite squat is 483 lbs
For 45-year-olds, a beginner squat is 61 kg and an elite squat is 208 kg
For 50-year-olds, a beginner squat is 57 kg and an elite squat is 195 kg
For 55-year-olds, a beginner squat is 53 kg and an elite squat is 180 kg
For 60-year-olds, a beginner squat is 48 kg and an elite squat is 165 kg
Squat recommendations by weight
For a body weight of 148 lbs, an untrained squat is 100 lbs and an intermediate squat is 230 lbs
For a body weight of 165 lbs, an untrained squat is 110 lbs and an intermediate squat is 250 lbs
For a body weight of 181 lbs, an untrained squat is 120 lbs and an intermediate squat is 270 lbs
For a body weight of 198 lbs, an untrained squat is 125 lbs and an intermediate squat is 285 lbs
Squatting can help burn calories.

Fig. 10 Activity recognition & plan

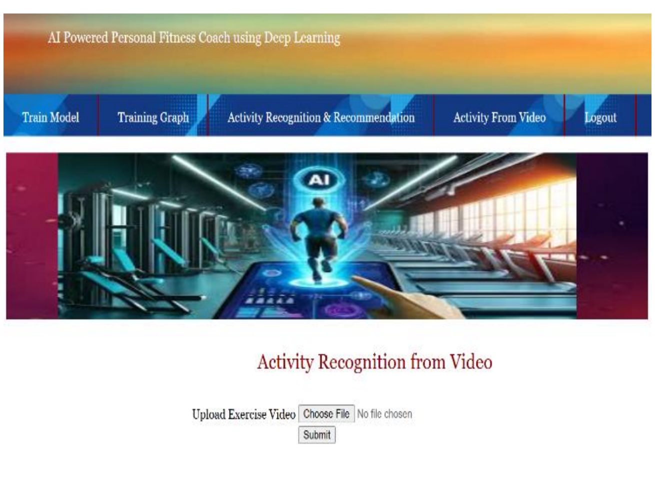

Fig. 11 Uploading video

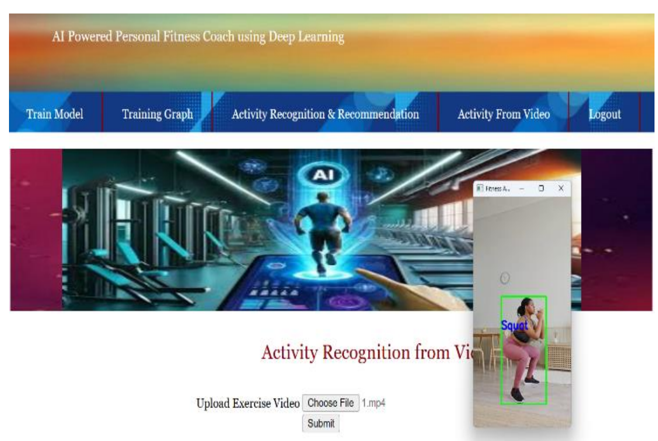

Fig. 12 Video activity recognition

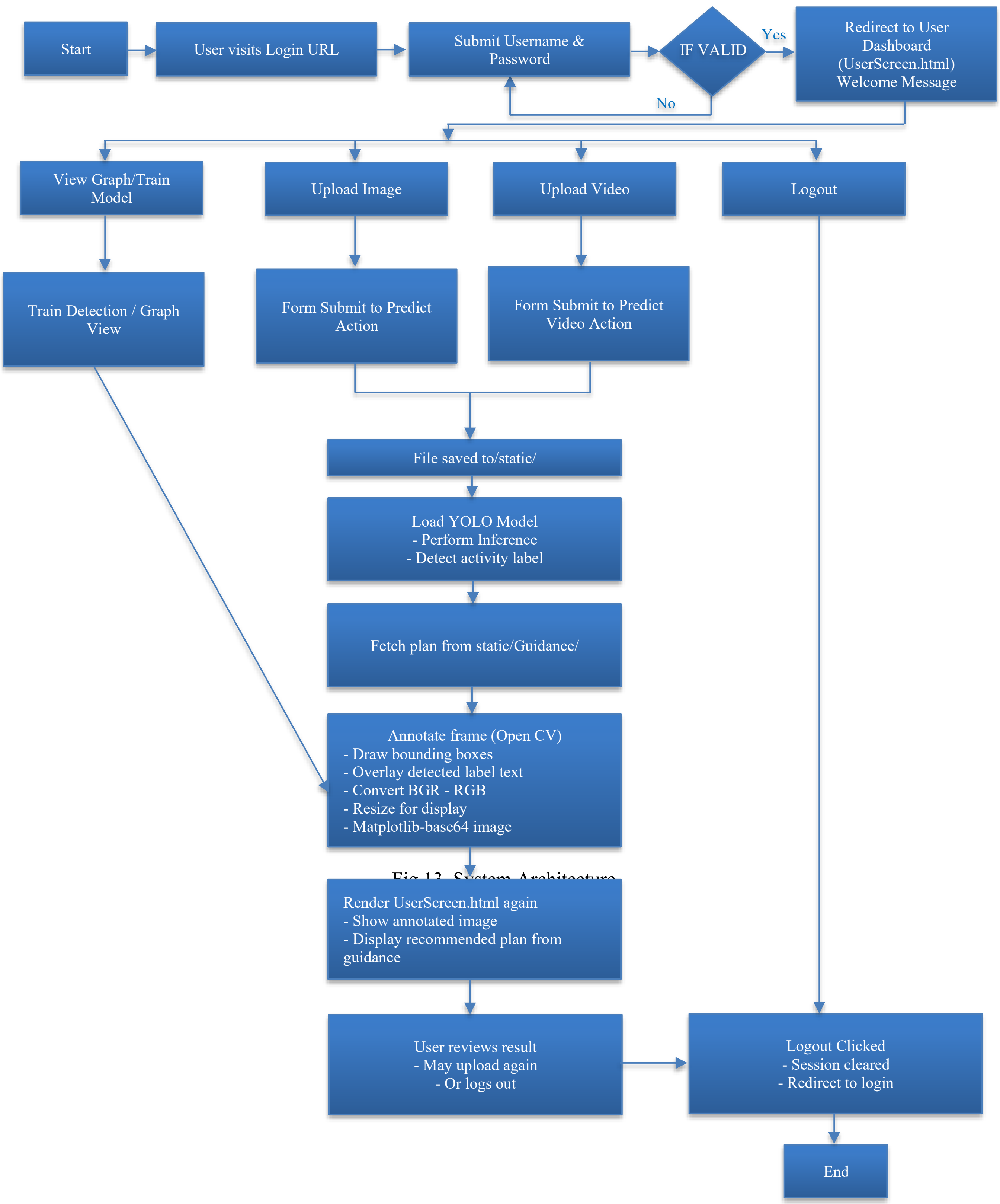

Fig. 13 System architecture

CNN Activity Recognition Accuracy Graph

YOLO11n summary (fused): 100 layers, 2,589,172 parameters, 0 gradients, 6.4 GFLOPs

Class	Images	Instances	Box(P	R	mAP50	mAP50-95): 100%
all	600	600	0.804	0.774	0.823	0.688
Bent Knee Crunch	20	20	0.881	0.9	0.937	0.757
Biceps Brachii Stretch	1	1	0	0	0	0
Bicycle Crunch	11	11	0.885	0.701	0.926	0.791
Boat Pose	18	18	0.988	1	0.995	0.881
BoundAnglePose	23	23	0.952	0.857	0.91	0.802
Bridge	19	19	0.97	0.842	0.981	0.821
Camel Pose	21	21	1	0.979	0.995	0.856
Cat Cow Pose	10	10	0.975	1	0.995	0.963
Child Pose	13	13	0.87	0.923	0.973	0.827
Claim Exercise	10	10	0.675	0.5	0.68	0.6
Clam Exercise	8	8	0.624	0.25	0.312	0.246
Cobra Pose	24	24	0.94	0.875	0.946	0.896
Cross Leg Forward Bend	21	21	0.896	0.619	0.864	0.694
Deltoid Muscle Stretch	21	21	0.95	0.857	0.945	0.781
Downward-Facing Dog Pose	16	16	0.995	1	0.995	0.847
Frog Pose	16	16	0.892	0.688	0.914	0.752
Iliopsoas Muscle Stretch	19	19	0.67	0.642	0.763	0.584
InnerThighLift	18	18	1	0.852	0.973	0.785
LegRaise0	12	12	1	0.735	0.89	0.753
LegRaise10	16	16	0.359	0.875	0.372	0.283
LegRaise30	60	60	0	0	0	0
LegRaise60	13	13	0.266	0.692	0.535	0.43
LegRaise90	32	32	1	0.69	0.953	0.781
Locust Pose	14	14	0.802	0.866	0.913	0.839
Lunge	23	23	0.709	0.652	0.761	0.547
Pigeon Pose	9	9	0.795	0.778	0.844	0.702
Plank	5	5	0.737	1	0.995	0.864
Raise Leg Crunch	9	9	0.371	0.556	0.47	0.327
Reverse Prayer Pose	12	12	1	0.937	0.995	0.741
Seated Side Bend	9	9	0.98	0.889	0.943	0.772
SidePlank	10	10	1	0.925	0.995	0.786
Squat	16	16	0.935	1	0.991	0.882
Standing Forward Bend	20	20	0.945	1	0.955	0.82
Super Men Pose	18	18	0.942	0.897	0.961	0.776
Triceps Stretch	20	20	1	0.877	0.981	0.725
Upper Trapezius Stretch	13	13	0.925	1	0.962	0.866

Speed: 0.3ms preprocess, 2.7ms inference, 0.0ms loss, 3.5ms postprocess per image

Results saved to **runs/detect/train**

Fig. 14 CNN Activity Recognition and Accuracy Metrics

5. Conclusion

This research presents an AI-powered personal fitness coaching system that utilizes deep learning and computer vision to recognize exercise activities and provide personalized workout recommendations. The proposed YOLOv11-based model achieved high Precision, recall, and mean Average Precision (mAP) across multiple exercise classes, demonstrating strong generalization capabilities.

By integrating activity recognition, posture evaluation, and adaptive plan recommendation into a single platform, the system addresses critical limitations of traditional fitness applications—namely, the lack of real-time feedback and personalization. The user-friendly web interface and fast inference time make this system suitable for home workouts, rehabilitation programs, and mobile fitness applications.

This study highlights AI's practical potential in enhancing personal health and wellness through intelligent automation. Future improvements could involve expanding the dataset, incorporating audio-based feedback, and integrating nutrition planning modules for a more holistic fitness experience.

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