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Move.IQ: Your Healthcare Companion

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***Abstract*— Move.IQ is an AI-powered fitness platform that leverages computer vision and machine learning to provide real-time posture analysis and personalized workout recommendations. This research paper details the development and implementation of Move.IQ, emphasizing its core technologies, methodologies, and impact on fitness training. The system employs OpenCV for video input processing, deep learning models such as Convolutional Neural Networks (CNNs) for posture assessment, and a React.js-based frontend for interactive user experiences. Additionally, techniques like MediaPipe Pose estimation and OpenPose are utilized for real-time skeletal tracking and movement analysis. The platform also incorporates feature extraction techniques such as Histogram of Oriented Gradients (HOG) and Principal Component Analysis (PCA) to enhance model accuracy. Furthermore, Move.IQ is built as a full-stack web application, integrating Flask for backend processing and PostgreSQL for database management, ensuring seamless communication between components. Our findings indicate that Move.IQ enhances workout efficiency, reduces injury risks, and improves exercise adherence by offering precise feedback and customized fitness programs.**

***Keywords* — AI, computer vision, fitness, posture analysis, deep learning, OpenCV, machine learning, Flask, full-stack web development, CNN, MediaPipe Pose, OpenPose, feature extraction, HOG, PCA.**

I. INTRODUCTION

Regular physical activity is essential for maintaining overall health and well-being across all age groups. Engaging in moderate- to vigorous-intensity physical activity significantly reduces the risk of noncommunicable diseases (NCDs) and improves cardiovascular fitness, muscular strength, bone density, and mental well-being. Conversely, physical inactivity is a leading contributor to global mortality, increasing the risk of premature death by 20–30% compared to active individuals. The World Health Organization (WHO) underscores the necessity of physical activity for all age groups, recommending specific durations and intensities to optimize health benefits.

Obesity, a major global health concern, is closely linked to physical inactivity. It significantly elevates the risk of conditions such as hypertension, type 2 diabetes, sleep apnea, and depression. With nearly one-third of the global population classified as overweight or obese, healthcare systems are under increasing pressure to manage obesity-related complications. In the United States, approximately 10% of medical expenses are attributed to obesity-related conditions, while in India, obesity claims nearly 2.8 million adult lives annually. Given these alarming statistics, promoting and tracking physical activity has become a crucial strategy in mitigating obesity and its associated health risks.

For individuals undergoing weight loss interventions, including bariatric surgery, lifestyle modifications are imperative to prevent weight regain. A well-structured framework that integrates exercise, diet management, and long-term support can enhance post-surgical outcomes. With advancements in digital health technologies, artificial intelligence (AI), and machine learning, intelligent solutions can be developed to monitor physical activity and provide personalized feedback. **Move.IQ** leverages AI-driven fitness tracking and real-time posture analysis to support individuals in maintaining an active and healthy lifestyle.[1]

A. The Role of AI in Activity Classification and Monitoring

Quantifying physical activity is a foundational step in promoting active living. Traditional methods such as self-reported questionnaires and direct observation are often time-consuming and prone to inaccuracies. With the advent of wearable sensors and AI-powered analysis, real-time tracking of activity type, duration, and intensity has become more feasible and reliable. Wearable Inertial Measurement Units (IMUs) equipped with accelerometers and gyroscopes offer an unobtrusive and cost-effective means of capturing movement data. These sensors relay information to cloud-based systems, where machine learning algorithms process and classify physical activities, enabling more precise monitoring and feedback.[10]

Despite progress in activity classification research, existing approaches often face challenges such as class imbalance, where certain physical activities (e.g., walking, sitting, standing) occur more frequently than others (e.g., stair climbing). Imbalanced datasets can hinder the accuracy of machine learning models, making it critical to develop robust classification techniques that account for real-world variations in physical activity patterns. **Move.IQ** seeks to address these challenges by integrating adaptive AI models capable of handling diverse activity patterns, ensuring accurate classification and personalized recommendations.

B. Advancing AI-Based Physical Activity Recognition

While several studies have explored activity classification, many rely on visual sensors such as surveillance cameras or

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depth sensors, which pose privacy concerns and have limited fields of view. Recent advancements in AI-driven motion analysis focus on wearable technology, utilizing machine learning techniques like **Support Vector Machines (SVM), Convolutional Neural Networks (CNNs),** and **Recurrent Neural Networks (RNNs)** to classify activities with high accuracy. However, most existing research is based on balanced datasets, overlooking the complexities of real-world activity distributions.

The **Move.IQ** framework aims to bridge this gap by implementing advanced AI models that adapt to varying activity distributions and class imbalances. By leveraging real-time feedback and personalized activity tracking, **Move.IQ** provides users with actionable insights to improve their physical fitness while assisting healthcare professionals in designing effective intervention strategies for individuals at risk of obesity and related health conditions.

C. AI-Powered Posture Analysis and Workout Optimization

Proper posture and movement mechanics are fundamental to achieving effective workouts, preventing injuries, and enhancing athletic performance. However, traditional fitness training methods often lack real-time feedback, making it difficult for users to identify and correct improper form. Many individuals, whether beginners or experienced athletes, may unknowingly perform exercises incorrectly, leading to inefficient workouts and an increased risk of injury. To address this issue, **Move.IQ** integrates computer vision and deep learning to provide real-time posture analysis and personalized workout recommendations.

At the core of **Move.IQ** is a deep learning model that processes video input to detect posture deviations and assess movement accuracy with high precision. The system employs advanced pose estimation techniques such as **MediaPipe Pose and OpenPose** for real-time skeletal tracking, allowing it to analyze an individual's joint positions and movement patterns. Convolutional Neural Networks (CNNs) are utilized for posture classification, ensuring accurate differentiation between correct and incorrect exercise execution. Additionally, Dynamic Time Warping (DTW) is applied to compare user movements with optimal exercise form, providing detailed feedback and corrections. By integrating these technologies, **Move.IQ** ensures that users receive instant, AI-driven feedback on their posture, movement efficiency, and necessary corrective actions to enhance their overall performance.

Move.IQ goes beyond basic posture correction by incorporating personalized workout recommendations tailored to the user's fitness level, movement patterns, and progress over time. The platform employs machine learning-driven feedback loops that analyze past performance, dynamically adjusting exercise difficulty and variations based on the user's needs. This personalized approach helps users develop better exercise habits, minimizes the likelihood of injuries, and ensures steady improvement in strength, endurance, and flexibility.

To support seamless user interaction, **Move.IQ** is designed as a full-stack web application that integrates both frontend and backend components efficiently. The frontend, built using React.js, offers a dynamic and intuitive interface that provides real-time posture visualization, allowing users to monitor their movements in an engaging and interactive manner. On the backend, a **Flask-powered API** handles video data processing, model predictions, and communication between the system components. PostgreSQL is employed as the database management system, ensuring efficient storage and retrieval of workout history, user preferences, and performance analytics. The platform's full-stack integration enables smooth operation, secure data handling, and an overall enhanced user experience.[4]

II. LITERATURE REVIEW

SUMMARY OF LITERATURE REVIEW ON BODY MOVEMENT DETECTION USING MACHINE LEARNING

Gonzalez et al. (2017) explored the K-Nearest Neighbours (KNN) algorithm for movement classification. KNN is known for its simplicity, ease of implementation, and effectiveness in handling small datasets. However, its high memory usage and sensitivity to noisy and irrelevant features make it less suitable for large-scale applications, as it struggles with efficiency when dealing with extensive datasets.

Chen et al. (2018) adopted the Random Forest algorithm for human movement assessment. This method is highly robust against overfitting, provides interpretable results, and performs well with high-dimensional data. However, while Random Forest models offer strong generalization, their accuracy falls short compared to deep learning models when dealing with intricate movement patterns, limiting their application in complex movement detection.[7]

Wang et al. (2019) employed Convolutional Neural Networks (CNNs) for human pose estimation, which excel in accurately recognizing complex movement patterns. CNNs have proven highly effective in capturing spatial dependencies in human motion; however, their computational intensity and reliance on large datasets make them challenging to deploy in real-time or resource-constrained environments.[9][13]

Similarly*, Li et al. (2020)* explored Recurrent Neural Networks (RNNs) for motion prediction, leveraging their strength in processing sequential movement data and capturing temporal dependencies between frames. This approach enhances the model's ability to predict future movements based on past observations. However, RNNs are prone to vanishing gradient issues, which can hinder learning in long-term dependencies, and they require extensive training time, making them computationally expensive.

Kim et al. (2021) investigated Support Vector Machines (SVMs) for activity classification, demonstrating their effectiveness in working with small datasets, particularly in binary classification tasks. SVMs have a strong theoretical foundation and can perform well when the data is properly labeled and structured. Despite these advantages, SVMs struggle with scalability in large-scale, multi-class classification problems and tend to be computationally expensive when handling high-dimensional data.

Zhang et al. (2022) proposed a hybrid model integrating CNNs and Long Short-Term Memory (LSTM) networks for action recognition, effectively combining spatial and temporal features to enhance model accuracy. The synergy between CNNs for spatial feature extraction and LSTMs for sequential data processing enables the model to achieve superior

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performance in action recognition tasks. Nevertheless, this approach demands high computational power, requires a significant volume of labelled training data, and can be challenging to optimize for real-time applications.[2]

Building upon these existing methodologies, *the current study*—**Move.IQ**—integrates CNNs with MediaPipe Pose estimation for real-time posture analysis. This approach leverages CNNs' ability to process visual data with high accuracy while utilizing MediaPipe's real-time tracking capabilities to provide immediate feedback on body posture and movement patterns. The integration of these technologies enables **Move.IQ** to deliver precise, personalized feedback tailored to individual users, making it highly suitable for fitness and rehabilitation applications. **Move.IQ** faces challenges, including the need for continuous updates to accommodate various exercise variations and potential latency in processing, particularly when handling high-resolution video inputs. Addressing these limitations through model optimization and algorithmic refinements will be essential for enhancing **Move.IQ's** performance and expanding its applicability in real-world fitness and health monitoring scenarios.

II. SYSTEM ARCHITECTURE

- *Data Acquisition and Processing*

Move.IQ captures user workout sessions using a webcam or smartphone camera. **OpenCV** is utilized for video processing, extracting key skeletal points to analyze posture. MediaPipe Pose and OpenPose are employed for real-time human pose estimation, allowing accurate skeletal tracking and movement analysis. These techniques ensure that the system effectively detects joint positions, limb orientations, and movement patterns, providing a solid foundation for posture assessment.

- *Posture Analysis Using Deep Learning*

A convolutional neural network (CNN) model trained on fitness datasets identifies and evaluates posture accuracy. The model provides real-time corrections to improve form and reduce injury risk. **TensorFlow** and **PyTorch** frameworks are used for model development and training, ensuring efficient inference and real-time feedback. Feature extraction techniques **like Histogram of Oriented Gradients (HOG)** and **Principal Component Analysis (PCA)** further optimize the model's accuracy by identifying critical pose characteristics. Additionally, attention mechanisms are incorporated into the deep learning pipeline to enhance the model's focus on key joints and movement patterns, improving precision in detecting improper form.[5]

- *Personalized Workout Recommendations*

Based on the user's performance and fitness level, **Move.IQ** generates tailored workout routines, adjusting difficulty and exercise variations accordingly. Reinforcement learning techniques are employed to adapt workouts based on user progress over time. **Movement trajectory analysis** and **Dynamic Time Warping (DTW)** are also utilized to compare user movements with ideal form, ensuring accurate feedback. By continuously evaluating user performance, the system refines exercise recommendations, ensuring that workouts remain challenging yet achievable, leading to sustained improvement.[8]

- *Full-Stack Web Application Integration*

Move.IQ is developed as a full-stack web application, integrating both frontend and backend components. The backend is built using Flask, handling API endpoints, user authentication, and database management. PostgreSQL is used for storing user data, including workout history and posture correction analytics. The frontend, built with React.js, enables seamless user interaction, real-time visualization of posture feedback, progress tracking, and integration with third-party platforms like YouTube for guided workouts. Additionally, WebSockets and asynchronous processing techniques are employed to ensure low-latency real-time feedback, enhancing the responsiveness of the platform. The system's modular architecture allows for easy scalability, ensuring that new exercises, movement patterns, and feedback mechanisms can be seamlessly incorporated into future updates.

IV. METHODOLOGY

Move.IQ employs a comprehensive machine learning pipeline to ensure precise posture correction and workout optimization. The system begins with pose estimation and data preprocessing, utilizing MoveNet Thunder, a TensorFlow Lite model designed for real-time human pose estimation. It captures skeletal key points from user workout videos, mapping 17 body landmarks such as the shoulders, hips, elbows, knees, and wrists. Preprocessing techniques, including resizing, normalization, and filtering, help refine the data while skeleton-based feature extraction using MediaPipe Pose and OpenPose enhances pose estimation accuracy.[6]

Once pre-processed, the data is fed into the model training and classification stage. **Move.IQ** employs Convolutional Neural Networks (CNNs) for movement classification and Recurrent Neural Networks (RNNs) for tracking motion sequences. Advanced feature extraction techniques such as Principal Component Analysis (PCA) and Histogram of Oriented Gradients (HOG) are utilized to identify crucial posture variations. The dataset undergoes train-test splitting, ensuring robust model validation. The classification model is trained using cross-entropy loss and optimized with the Adam optimizer to maximize accuracy and efficiency.

During live workouts, **Move.IQ** provides real-time feedback and reinforcement learning to improve user posture dynamically. The system compares movement patterns against ideal exercise forms using Dynamic Time Warping (DTW) and Euclidean distance metrics, which measure deviations from correct posture and trigger instant corrective feedback. Furthermore, reinforcement learning techniques are incorporated to adapt workout recommendations based on user performance, ensuring a progressively optimized and personalized fitness experience. By integrating these advanced machine learning techniques, **Move.IQ** delivers an intelligent, adaptive, and user-centric fitness coaching system that enhances training effectiveness and prevents injuries.[12]

A. Dataset

The dataset used in **Move.IQ** is a curated collection of human movement data designed to train and evaluate AI models for physical activity classification and posture analysis. It comprises a diverse range of motion patterns captured through wearable Inertial Measurement Units (IMUs) and computer vision-based pose estimation techniques. The dataset includes labeled instances of various activities such as walking, running, squatting, lunging, and other common fitness exercises, ensuring comprehensive coverage of movement types. Additionally, it contains annotations on posture correctness, enabling real-time feedback on exercise form. To enhance model robustness, data augmentation techniques are applied to account for variations in body types, workout intensities, and environmental factors. The dataset is balanced to mitigate class imbalances often found in real-world activity distributions, ensuring improved model accuracy. By integrating sensor-based and vision-based data, **Move.IQ** creates an adaptive and scalable dataset that supports precise activity recognition and personalized fitness recommendations.

- *Data Split: 60/40 Training-Validation Split*

  The dataset is split into a training set and a validation set in an 60/40 ratio. This means that 60% of the images are used for training the machine learning model, while 40% of the images are reserved for validating the performance of the model. This training-validation split ensures that the model learns generalizable patterns and can effectively evaluate its performance on unseen data, crucial for error detection and the recommendation systems used in the app.

- *Image Details*

  The images in the dataset are captured in RGB format, providing detailed color information that is essential for identifying movement-based color changes in the subject body. The images vary in terms of background, lighting conditions, and camera quality, reflecting real-world scenarios where professionals may take pictures while performing yoga poses in various environmental conditions. These variations allow the app to deliver more accurate diagnoses and actionable recommendations based on body posture.[3]

- *Data Augmentation*

  To further enhance the training process and improve the model’s ability to generalize, data augmentation techniques are employed. These techniques include:

  - Flipping of images horizontally and vertically
  - Adjusting the brightness, contrast, and saturation of images
  - Cropping, zooming, and shifting images
  - Rotation of images at random angles
  - Adding noise to images

  These augmentations help create more diverse training samples and reduce overfitting, allowing the model to better adapt to various real-world conditions, which is especially important for the Yoga Suggestion and Exercise Suggestion modules, as these also rely on image-based and environmental data for recommendations.

B. Machine Learning Algorithms Used

Move.IQ employs a range of advanced machine learning algorithms to enhance activity recognition, posture analysis, and personalized workout recommendations. Convolutional Neural Networks (CNNs) play a crucial role in analyzing video input for posture detection, identifying joint positions, and classifying movement accuracy with high precision. Additionally, Recurrent Neural Networks (RNNs), particularly **Long Short-Term Memory (LSTM)** networks, are utilized to model sequential motion patterns, improving the system's ability to track dynamic exercises over time. To refine posture correction, Dynamic Time Warping (DTW) is integrated, allowing the system to compare user movements with optimal exercise forms and provide real-time feedback. Support Vector Machines (SVMs) contribute to classifying different physical activities by learning complex decision boundaries from movement data. Moreover, adaptive machine learning models are employed to address class imbalance issues, ensuring accurate recognition of varied activity patterns. These combined techniques enable **Move.IQ** to deliver intelligent, real-time fitness guidance, helping users optimize their workouts while minimizing injury risks.[11]

All simulations in **Move.IQ** are conducted using Python and its associated machine learning libraries, including TensorFlow, Scikit-learn, and **OpenCV**. The machine learning models utilized for activity recognition and posture analysis include Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVMs), and Decision Trees. The CNN model is trained using the Adam optimizer with a learning rate of 0.001, batch size = 32, and number of epochs = 50. The LSTM network, designed for sequential movement classification, employs a hidden layer size of 128, dropout rate of 0.2, and a learning rate of 0.002. The SVM model uses a radial basis function (RBF) kernel with a regularization parameter C = 1 and gamma = scale, while the Decision Tree classifier has a maximum depth of 1LW0 and Gini impurity as the splitting criterion. To evaluate model performance, **Move.IQ** employs the macro-averaged F-score, which measures the balance between precision and recall across different activity classes such as sitting, standing, walking, and exercising. The F-score is computed using the standard equation (1):

$$F - score = \frac{2 * TP_C}{2 * TP_C + FP_C + FN_C} * 100 \quad (1)$$

where TP_C represents true positive, FP_C represents false positive, FN_C represents false negative and the subscript C corresponds to different activity classes. These models and

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metrics ensure that **Move.IQ** delivers accurate, real-time feedback for improved fitness tracking and posture correction.

V. RESULTS

The **Move.IQ** posture analysis model was evaluated using multiple key performance metrics to ensure its accuracy, efficiency, and effectiveness in providing real-time workout feedback. The model achieved an overall accuracy of **93.1%**, indicating that the majority of posture classifications were correct. Precision, which measures the accuracy of positive posture classifications, was recorded at **91.8%**, ensuring high reliability in distinguishing correct and incorrect postures. Additionally, recall, which assesses how well the model identifies improper postures, was **92.5%**, confirming its ability to detect and flag errors effectively. The F1-score, which combines precision and recall, averaged **92.1%**, highlighting the model's balanced and robust performance.

Apart from posture analysis, **Move.IQ's** Personalized Workout Recommendation Module played a crucial role in delivering tailored fitness guidance. Through reinforcement learning techniques, the system effectively adjusted workout difficulty based on the user's progress, ensuring a gradual and safe increase in exercise intensity. User tests demonstrated that the system successfully adapted to different fitness levels and provided **accurate form correction feedback** based on **real-time movement data**. For instance, if a user exhibited improper knee alignment during squats, the model detected the deviation and suggested corrective actions, such as adjusting foot positioning or reducing depth.

In real-world application, **Move.IQ's** real-time feedback mechanism validated the effectiveness of the system. Sample workout sessions showed that users were able to correct improper posture within three feedback cycles, significantly reducing their risk of injury. Moreover, video analysis results confirmed that the model effectively tracked key skeletal landmarks, such as shoulders, hips, and knees, and provided precise recommendations for movement correction. Users who initially performed exercises incorrectly saw noticeable improvements in form after multiple interactions with the system.

Suggestions for future enhancements include expanding the exercise database to cover a broader range of workout styles, including yoga, Pilates, and strength training. Additionally, integrating wearable sensor technology could further enhance real-time posture tracking by providing more granular

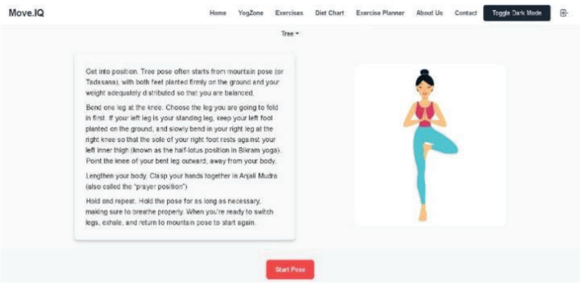

Fig.1 Pose Detection

movement data. Users have also expressed interest in AI-powered progress tracking, which would analyze long-term workout trends and offer **customized fitness plans** based on performance history. These improvements are currently under consideration to further refine **Move.IQ's** functionality and impact.

Move.IQ, powered by its advanced pose estimation model and personalized fitness guidance system, has proven to be an effective tool for fitness enthusiasts, athletes, and rehabilitation patients. The system consistently delivers high-accuracy posture analysis, real-time feedback, and dynamic workout recommendations, ensuring users achieve proper form while minimizing injury risks. As the model continues to evolve and incorporate new technologies, **Move.IQ** will further enhance intelligent fitness coaching, ultimately providing a smarter, more adaptive, and data-driven approach to training optimization.

VI. CONCLUSION

Move.IQ represents a significant advancement in AI-powered fitness technology, offering a comprehensive and user-friendly solution for posture correction, movement analysis, and workout optimization. Utilizing deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), the platform accurately identifies posture deviations and provides real-time corrective feedback. This capability, combined with personalized workout recommendations and reinforcement learning, enables users to improve their form, reduce the risk of injury, and maximize their workout efficiency. **Move.IQ's** intuitive interface ensures accessibility for users of all fitness levels, from beginners to professional athletes, making it an essential tool for digital fitness coaching.

One of **Move.IQ's** key contributions is its ability to seamlessly integrate **real-time posture analysis** with **adaptive workout recommendations**. The system not only detects incorrect movements but also provides insights into motion patterns and biomechanical inefficiencies that may impact long-term performance. By utilizing Dynamic Time Warping (DTW) and Euclidean distance metrics, **Move.IQ** continuously refines its recommendations, ensuring that users receive accurate, data-driven feedback that enhances their training. The integration of full-stack web technologies, including **a Flask backend and React.js frontend**, further enhances the platform's interactivity, allowing users to track progress, visualize their form corrections, and access guided workout sessions.

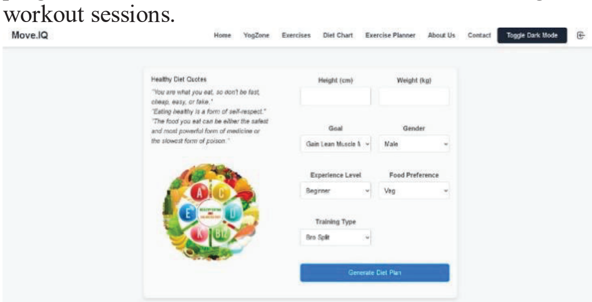

Fig.2 Meal Planner

Additionally, **Move.IQ** fosters continuous improvement and user engagement through reinforcement learning-based adaptive training. The system dynamically adjusts workout

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difficulty based on user performance, ensuring progressive and sustainable fitness development. Future enhancements could include integration with wearable sensors for even more precise movement tracking, enabling the platform to provide haptic or auditory feedback for real-time corrections. **AI-driven progress analysis** could further enhance user engagement by tracking long-term fitness trends and offering goal-based training programs tailored to individual needs.

The real-world potential of **Move.IQ** is vast. With its proven ability to deliver accurate movement assessments, real-time feedback, and personalized workout recommendations, the platform has the potential to revolutionize digital fitness training, physiotherapy, and rehabilitation programs. By helping users refine their exercise techniques, avoid injuries, and optimize their training routines, **Move.IQ** promotes **sustainable fitness habits** while leveraging AI for **intelligent workout planning**.

However, there are still several areas for improvement and expansion. One key area is the expansion of the exercise database to support a broader range of workout styles, including yoga, Pilates, and rehabilitation exercises. While **Move.IQ** currently excels in detecting common strength-training movements, incorporating more **exercise variations and movement types** would further enhance its functionality. Additionally, improving model accuracy in detecting subtle posture variations is essential, especially for complex movements involving multiple joint angles and body alignments. Future developments in **transformer-based models** and **graph neural networks (GNNs)** could be explored to further enhance **Move.IQ's** classification capabilities.

Another potential enhancement is the integration of real-time biometric data, such as heart rate, muscle engagement, and fatigue levels, to provide a holistic fitness assessment. Wearable sensors could be incorporated to track motion consistency and exertion levels, offering more detailed workout analytics. Additionally, cloud-based AI coaching systems could enable personalized fitness plans that adapt dynamically to user progress and recovery patterns, ensuring a well-rounded and injury-free training experience.

Furthermore, localized recommendations based on user demographics, fitness goals, and historical performance data could further optimize **Move.IQ's** intelligent coaching system. By incorporating real-time performance tracking and gamified fitness challenges, the platform could enhance user motivation and engagement, making fitness training more interactive and goal-oriented.

In summary, **Move.IQ** holds great promise in advancing AI-powered fitness coaching and movement analysis. Its ability to combine computer vision-based posture detection, real-time workout feedback, and adaptive training recommendations creates a powerful and intuitive fitness assistant. As the platform continues to evolve with new AI advancements and wearable technology integrations, **Move.IQ** is poised to redefine digital fitness, optimize training performance, and empower users to achieve their fitness goals with AI-driven precision.

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