PHYSIOGURU: A VIRTUAL REHAB ASSISTANT USING POSE DETECTION WITH CNN-LSTM

***Project Reference No.:** 49S_BE_4073*

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Keywords:

AI-based Physiotherapy, Human Pose Estimation, CNN-LSTM, Tele-Rehabilitation, Real-Time Feedback System.

Introduction:

The increasing prevalence of musculoskeletal disorders and post-operative conditions has created a growing demand for effective physiotherapy and rehabilitation services. Traditional physiotherapy often requires frequent hospital visits, making it costly, time-consuming, and inconvenient for many patients. As a result, patients tend to rely on home-based exercise routines, which lack proper supervision and real-time feedback. This often leads to incorrect posture, reduced effectiveness of exercises, and even risk of further injury.

With the advancement of Artificial Intelligence and Computer Vision, there is an opportunity to transform rehabilitation into a more accessible and intelligent process. AI-driven systems can analyze human movements and provide instant feedback, enabling patients to perform exercises correctly without constant physical supervision. However, existing solutions are either dependent on expensive hardware or provide only static guidance without personalization.

To address these challenges, this project introduces **PhysioGuru**, an AI-based virtual rehabilitation assistant that leverages pose detection and deep learning techniques. The system uses a standard webcam to capture user movements and applies MediaPipe-based pose estimation to extract skeletal landmarks. A hybrid CNN-LSTM model is employed to recognize exercises and analyze motion patterns over time, ensuring accurate activity detection.

The system further enhances user experience by incorporating real-time feedback mechanisms, automated repetition counting, and posture correction. Additionally, it integrates Generative AI to provide personalized rehabilitation plans and progress tracking, making the system adaptive to individual needs. By eliminating the need for specialized equipment and enabling remote monitoring, the proposed solution aims to democratize access to physiotherapy.

Overall, this project contributes to the growing field of digital healthcare by offering a scalable, cost-effective, and intelligent rehabilitation platform that bridges the gap between clinical supervision and home-based recovery.

Objectives:

1. To design an AI-powered virtual rehabilitation assistant using pose detection and CNN-based models.
2. To provide real-time posture correction through visual and voice feedback using a standard webcam.
3. To accurately analyze and count exercise repetitions, improving overall rehabilitation quality.
4. To generate adaptive exercise and nutrition plans based on individual user progress using machine learning and create detailed performance reports for users and physiotherapists for continuous monitoring and improvement.

Methodology:

The proposed system follows a structured methodology combining computer vision, deep learning, and web technologies to deliver real-time rehabilitation assistance. The process begins with capturing live video input from the user through a standard webcam integrated into a browser-based interface. These video frames are transmitted to the backend server using a low-latency WebSocket connection for continuous real-time processing.
The first stage of processing involves **pose detection using MediaPipe (BlazePose)**, which extracts 33 key body landmarks from each frame. These landmarks represent joints such as shoulders, elbows, hips, and knees. The extracted coordinates are then normalized to ensure scale invariance and used to compute joint angles required for biomechanical analysis.
Next, the processed landmark data is fed into a **CNN-LSTM hybrid model**, where the CNN component captures spatial relationships between joints, and the LSTM component analyzes temporal movement patterns across multiple frames. This enables accurate classification of physiotherapy exercises and ensures robustness against noise and variations in movement.

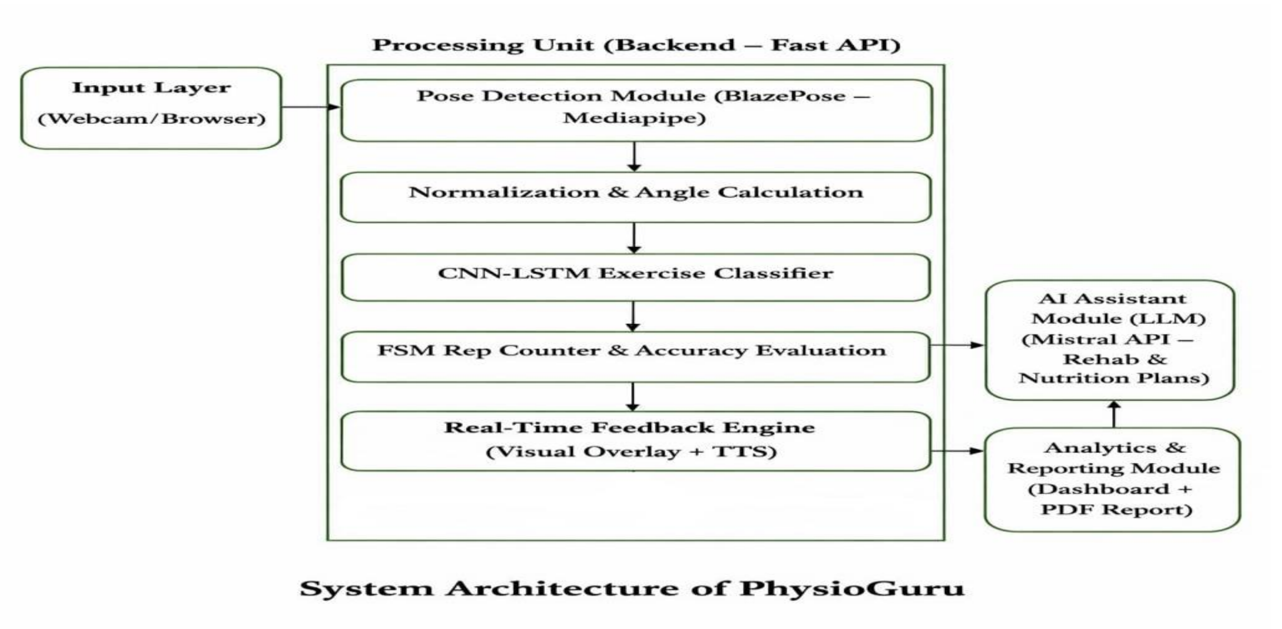

Figure 1: System Architecture of PhysioGuru

Following exercise recognition, a **Finite State Machine (FSM)** is applied to track different phases of motion (start, mid, and end positions). This ensures precise repetition counting by validating only complete and correct movements. Simultaneously, geometric heuristics are used to compare joint angles with predefined thresholds to detect posture deviations.
The system then generates **real-time feedback** through visual overlays and text-to-speech guidance, helping users correct their posture instantly. All session data, including repetition count, accuracy, and duration, is stored in a PostgreSQL database for further analysis.
An additional **Generative AI module** is integrated to provide personalized rehabilitation plans and dietary recommendations based on user-specific data such as injury type and performance history. The system also includes an analytics module that generates dashboards and downloadable PDF reports for tracking recovery progress.
The overall architecture, as illustrated in the system diagram, demonstrates the end-to-end workflow from video input to intelligent feedback and reporting.
This methodology ensures a scalable, efficient, and user-friendly solution for delivering remote physiotherapy using AI-driven techniques.

Result and Conclusion:

The implementation of PhysioGuru demonstrates the effectiveness of integrating computer vision and deep learning techniques for virtual rehabilitation. The system successfully captures real-time video input and accurately detects human body landmarks using MediaPipe, enabling reliable pose estimation under standard indoor conditions. The CNN-LSTM model effectively classifies different physiotherapy exercises by learning both spatial and temporal patterns, achieving high accuracy in distinguishing movements.
The Finite State Machine-based repetition counting mechanism ensures that only complete and biomechanically correct movements are counted, improving the reliability of exercise tracking. Additionally, the geometric analysis of joint angles enables precise posture correction, providing users with immediate feedback through visual overlays and audio cues. This real-time feedback loop significantly enhances user engagement and reduces the chances of performing incorrect exercises.
The integration of a Generative AI module allows the system to provide personalized rehabilitation and dietary plans, making the platform adaptive to individual user needs. The analytics module further supports users by offering detailed progress tracking through dashboards and downloadable reports, enabling data-driven monitoring of recovery.
Testing results indicate that the system performs efficiently with low latency, ensuring smooth real-time interaction. The use of a standard webcam without requiring specialized hardware makes the solution cost-effective and accessible to a wide range of users.
In conclusion, PhysioGuru successfully bridges the gap between clinical physiotherapy and home-based rehabilitation by providing an intelligent, scalable, and user-friendly solution. The project demonstrates strong potential for real-world applications in digital healthcare, particularly in tele-rehabilitation, and can significantly improve accessibility, adherence, and effectiveness of physiotherapy practices.

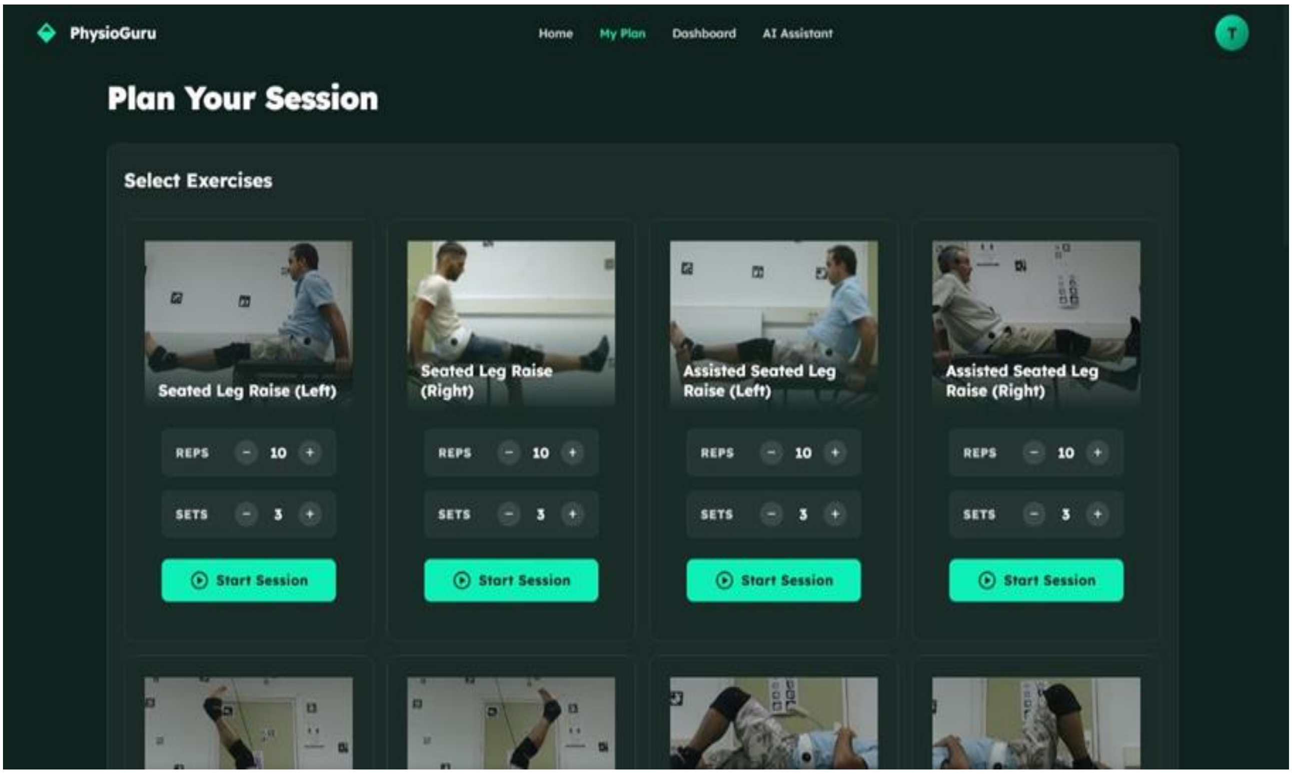

Figure 2: My Plan Page

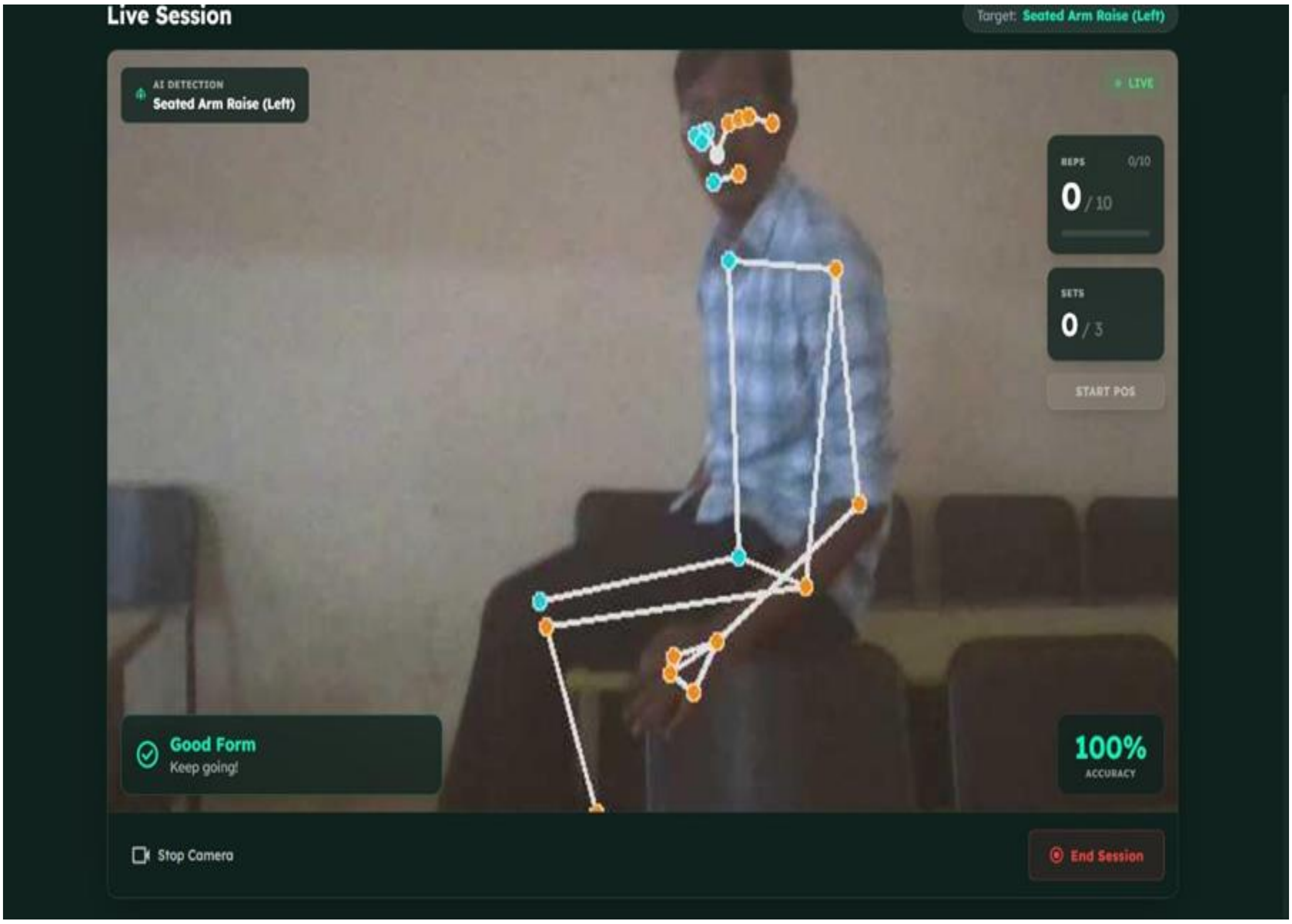

Figure 3: Live Session Page

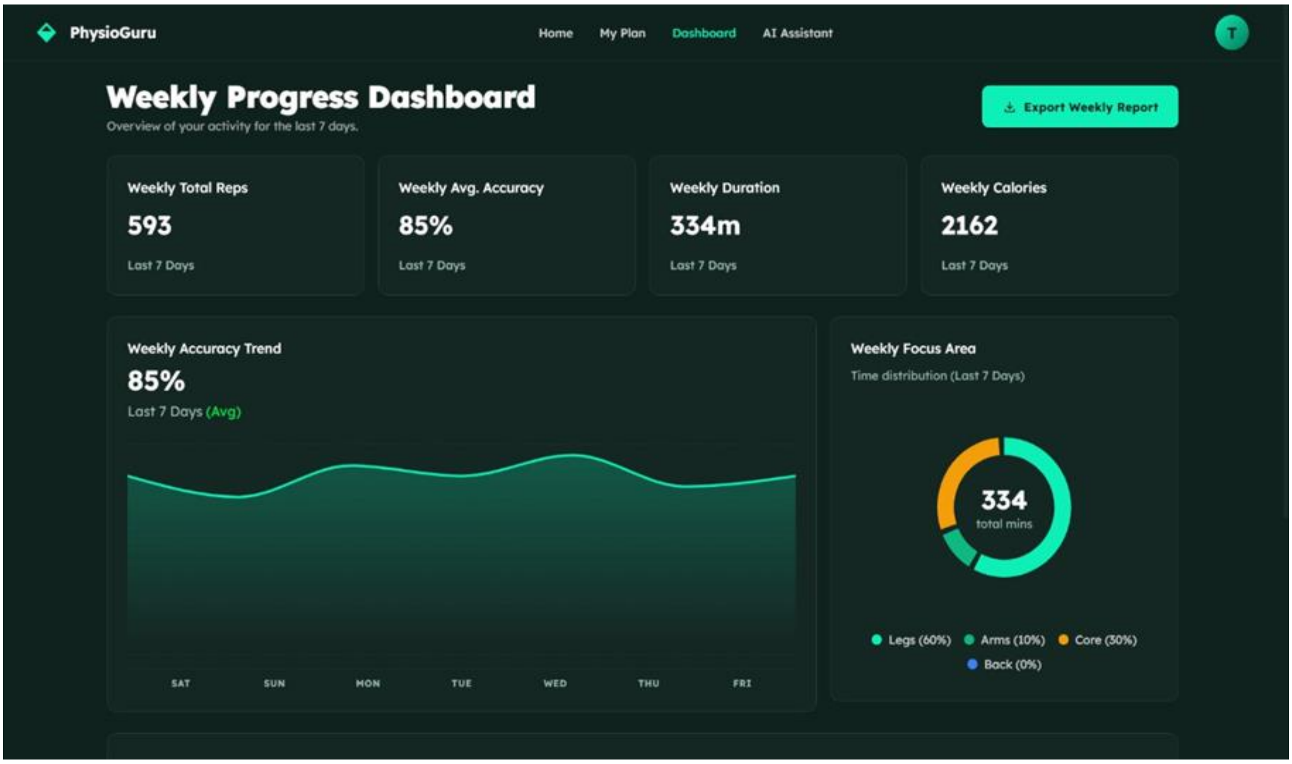

Figure 4: Dashboard Page

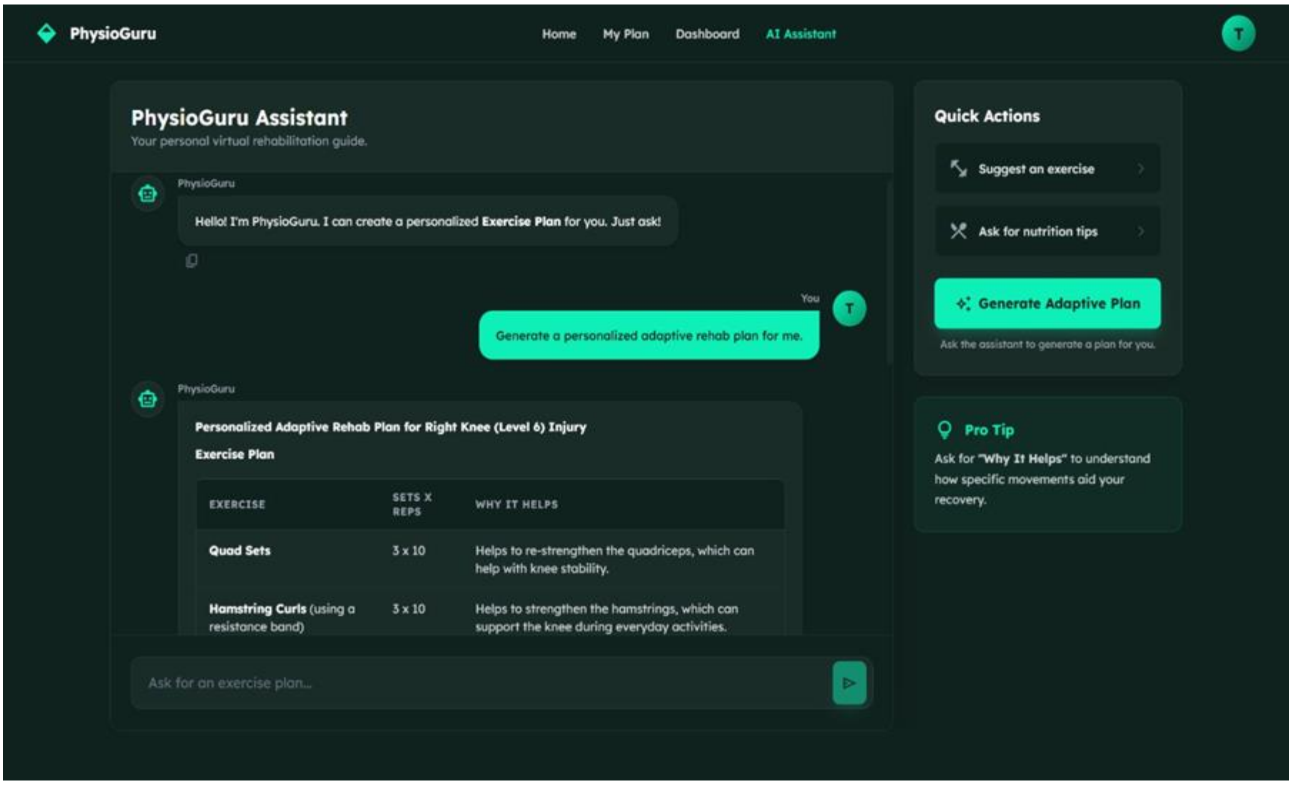

Figure 5: AI Assistant Page

Project Outcomes & Industry Relevance:

1. Provides a cost-effective and accessible physiotherapy solution using only a webcam and browser.

2. Enables real-time posture correction and exercise monitoring, improving accuracy of rehabilitation.
3. Reduces dependency on in-person physiotherapy sessions, saving time and cost for patients.
4. Enhances patient engagement and adherence through instant feedback and progress tracking.
5. Supports remote healthcare (tele-rehabilitation), especially beneficial in rural or underserved areas.
6. Integrates AI to deliver personalized rehabilitation and diet plans, improving recovery outcomes.
7. Generates data-driven reports, helping physiotherapists monitor patient progress remotely.
8. Demonstrates practical application of Computer Vision and Deep Learning in healthcare.
9. Can be deployed in hospitals, rehabilitation centers, and fitness clinics as a support tool.
10. Useful for post-surgery recovery, sports injury rehabilitation, and elderly care.
11. Scalable into a commercial healthcare product or SaaS platform.
12. Contributes to the advancement of digital health and AI-assisted medical systems.
13. Opens opportunities for integration with wearables, mobile apps, and smart healthcare devices.

Working Model vs. Simulation/Study:

1. The project involves the development of a functional working model in the form of a full-stack web application.
2. It is not a theoretical study or simulation, but an implemented system that operates in real time.
3. The system uses a webcam to capture live video and processes it using computer vision and deep learning models.
4. Key components such as pose detection (MediaPipe), CNN-LSTM model, and repetition counting (FSM) are fully implemented and tested.
5. The application provides real-time feedback, posture correction, and exercise recognition, demonstrating practical functionality.
6. It also includes user interface, database integration, and AI-based recommendation modules, making it a complete working prototype.
7. The model has been tested under real-world conditions such as different lighting and user environments.

Project Outcomes/ Learnings:

1. Developed a fully functional AI-based rehabilitation system capable of real-time pose detection, exercise recognition, and posture correction.
2. Successfully integrated Computer Vision and Deep Learning (CNN-LSTM) into a real-time application, bridging theory with practical implementation.
3. Achieved efficient low-latency processing and real-time feedback, ensuring smooth user interaction and accurate monitoring.

4. Gained hands-on experience in full-stack development and system integration, including frontend, backend, database, and AI modules.
5. Learned to solve real-world challenges such as model accuracy, synchronization, and user adaptability, while building a scalable healthcare solution.

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Future Scope:

The future scope of this project includes:

1. The system can be extended to support multi-user and multi-person tracking, enabling use in physiotherapy clinics and group rehabilitation sessions.
2. Integration with mobile applications (Android/iOS) can improve accessibility and allow users to perform exercises anytime, anywhere.
3. Future versions can incorporate wearable sensors (IoT devices) to enhance accuracy by combining vision-based and sensor-based data.
4. The platform can be upgraded with advanced AI models (Transformers or 3D pose estimation) to improve precision in complex movements and low-light conditions.
5. Integration with Augmented Reality (AR) or Virtual Reality (VR) can provide immersive rehabilitation experiences with guided visual assistance.
6. A dedicated doctor/physiotherapist dashboard can be developed for remote patient monitoring, prescription of exercises, and real-time intervention.
7. The system can be scaled into a commercial SaaS healthcare platform, integrated with hospitals, fitness centers, and telemedicine services, expanding its real-world impact.