Biomechanical analysis for weightlifting performance enhancement

Final Report

24-25J-275

B.Sc. (Hons) Degree in Information Technology Specializing in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

April 2025

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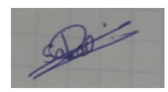
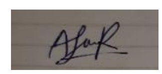
Gunawardena K.S.S	IT21250088	
Wimalarathna S.D.A.N	IT21312212	
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Abstract

Weightlifting is a biomechanically demanding sport that requires a high degree of precision, coordination, and physical conditioning. The dynamic nature of Olympic lifts such as the snatch, clean, and jerk imposes significant strain on the musculoskeletal system, often resulting in technical inefficiencies, fatigue, and injuries if not closely monitored. Traditional coaching approaches rely heavily on manual observation and delayed feedback, which can hinder an athlete's ability to make timely corrections. To address these limitations, this research presents an integrated AI-powered framework designed to optimize performance enhancement, injury prevention, and rehabilitation management in weightlifting.

The study introduces a unified biomechanical system composed of four core modules: (1) an advanced meal planning tool that utilizes machine learning to generate personalized nutrition plans aimed at accelerating injury recovery and supporting high-performance training, (2) a real-time video analysis engine powered by pose estimation and interactive 3D models to deliver immediate corrective feedback on lifting techniques, (3) a fatigue and injury risk detection system that analyzes deviations in posture, joint dynamics, and barbell movement patterns to provide early warnings, and (4) a mobile-based rehabilitation monitoring system integrating AI-driven pose tracking via smartphone cameras for remote supervision and feedback during recovery exercises.

This end-to-end solution bridges existing research and practical gaps by offering a continuous, intelligent feedback loop covering pre-training nutrition, in-session movement analysis, fatigue-aware injury prediction, and post-injury rehabilitation. Through AI automation and real-time monitoring, the system assists coaches and athletes by reducing dependence on expensive hardware and human error while enabling remote accessibility. It empowers athletes to remain consistent in proper technique, adhere to rehabilitation plans, and make data-driven decisions about training intensity, rest, and recovery.

Evaluation of the system through real-world testing with weightlifting athletes demonstrated improvements in technical execution, reduced recovery time, and enhanced adherence to corrective feedback. The outcome is a comprehensive, scalable, and mobile-friendly framework that elevates training quality and athlete safety in competitive strength sports.

Keywords: Weightlifting biomechanics, AI-powered video analysis, real-time feedback, pose estimation, 3D modeling, injury prevention, rehabilitation, personalized meal planning, fatigue detection, mobile recovery systems.

Acknowledgement

I would like to express my sincere gratitude to all those who contributed to the successful completion of this research project.

First and foremost, I would like to thank my supervisor, **Ms. Gaya Thamali Dassanayake**, and co-supervisor, **Ms. Poojani Gunathilake**, for their invaluable guidance, support, and encouragement throughout the research journey. Their expert insights and constructive feedback greatly enhanced the quality of this project.

I am also thankful to the **Department of Information Technology at the Sri Lanka Institute of Information Technology (SLIIT)** for providing the platform and resources necessary to carry out this research.

A special thanks goes to the **participants, coaches, and athletes** who took part in our surveys and initial app testing sessions. Their feedback helped shape the real-time feedback mechanisms of the proposed system.

I would also like to extend my appreciation to my teammates, **Wimalarathna S.D.A.N., Ranatunga B.M., and Ranaweera I.U.**, for their collaborative spirit, dedication, and contributions to the project.

Finally, I am deeply grateful to my family and friends for their unwavering support, motivation, and understanding throughout this endeavor.

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Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
UI	User Interface

1. INTRODUCTION

1.1 Background Literature

Weightlifting is a biomechanically intense sport that demands a high level of technical proficiency, body control, and consistent training. Precision in movement is not just a factor for success but a critical requirement for safety. Even minor deviations in form can result in significant injury risks, especially when athletes engage in Olympic lifts such as the snatch and clean and jerk. In the traditional setting, athletes rely on visual cues and coach guidance, which though valuable, are often subjective, inconsistent, and not available at all times.

The recent growth of Artificial Intelligence (AI) and computer vision has opened new doors for biomechanics and performance monitoring. AI-powered pose estimation algorithms like OpenPose, PoseNet, and MediaPipe have demonstrated potential in analyzing complex body movements in real-time. These frameworks can track multiple joints of the human body and assess posture, symmetry, and motion trajectory. Such technology has proven particularly useful in dynamic sports, where small corrections in form can have a substantial impact.

In professional sports, including football and basketball, AI and motion analysis tools are being widely adopted to track athlete performance. However, when it comes to weightlifting, which requires rapid and explosive lifts under high load, the application of such technology remains limited. This sport demands millisecond-level timing and perfect kinetic chain alignment—making real-time feedback and precision tracking crucial.

Additionally, fatigue and overtraining are commonly observed issues in weightlifting. Without adequate monitoring, athletes are at risk of repeated injuries due to biomechanical stress and muscular exhaustion. AI systems capable of detecting variations in motion patterns and performance output offer a promising solution to this long-standing problem. They allow athletes and coaches to adapt training routines before injuries occur.

The importance of personalized nutrition in sports performance has been widely acknowledged in academic literature. Athletes in strength sports such as weightlifting need targeted nutritional strategies to fuel training, promote muscle growth, and support recovery. However, most dietary tools provide generic recommendations and fail to adapt dynamically to the athlete's evolving needs, especially during injury rehabilitation.

Recent developments in AI-enabled meal planning systems now allow dynamic adjustments to be made based on user inputs such as physical condition, injuries, preferences, and nutrient goals. Using machine learning, these systems can adapt dietary recommendations over time, offering tailored support that complements physical training. Yet, most systems operate in isolation without integration into an athlete's biomechanical data or performance feedback loops.

Interactive 3D modeling has emerged as a useful tool in education, healthcare, and increasingly in sports training. In weightlifting, 3D models allow users to visualize complex techniques from multiple angles, zoom in on joint movements, and observe proper lifting mechanics. Unlike 2D video playback, 3D models offer a more immersive learning experience. Despite its potential, few current systems incorporate real-time 3D feedback to correct errors dynamically.

The application of 3D animation and modeling in real-time feedback systems offers the advantage of bridging the cognitive gap between understanding theoretical form and executing correct technique. It provides both novice and experienced lifters with intuitive cues that are more effective than textual descriptions or standard videos.

Existing sports science solutions tend to be fragmented. Tools may offer movement analysis, dietary recommendations, or training logs, but they rarely integrate all these capabilities into a cohesive system. This siloed approach limits the efficiency and adaptability of athlete monitoring and fails to offer a holistic solution needed for strength-based sports like weightlifting.

Remote accessibility is another critical factor in modern training environments. With athletes often training independently or in decentralized locations, mobile-compatible solutions become essential. The availability of a real-time system accessible via smartphones ensures that both amateur and professional athletes can benefit without high-end computational equipment.

Another key factor often overlooked is the educational value such an integrated system could offer. By enabling athletes to visualize both correct and incorrect techniques through 3D feedback and AI-assisted annotation, this system promotes a deeper understanding of biomechanics, reinforcing muscle memory and reducing the likelihood of injury.

By integrating personalized nutrition with real-time biomechanics, a feedback loop can be established where the system not only improves performance but also informs dietary needs based on training data. This synergy can lead to optimal recovery and energy management—key components of successful training cycles.

Therefore, this research proposes a unified system that combines real-time AI-powered video analysis, pose estimation for fatigue and injury monitoring, AI-driven personalized meal planning, and mobile-based 3D feedback with rehabilitation tracking. By integrating these features into one mobile platform, it aims to address the full spectrum of athlete needs—from training optimization to nutrition and injury recovery.

1.2 Research Gap

Although there have been many advancements in mobile fitness apps and sports technology, a significant gap still exists when it comes to helping weightlifters improve their form in real-time. Most available apps serve one purpose such as tracking workout stats, recording videos, or offering post-session feedback. They don’t provide a complete, real-time, interactive experience where users can receive personalized feedback while they train.

Several research studies have attempted to address aspects of this issue: Sato et al. (2019) explored biomechanical tracking for Olympic weightlifting and demonstrated that improper form could be detected. However, their system lacked real-time feedback mechanisms essential for on-the-spot corrections.

The OpenPose Research Team (2022) developed pose estimation models capable of tracking joint movements with high accuracy, but these models require significant computational power, making them less feasible for mobile applications.

Chang & Kim (2021) investigated machine learning-based injury prediction, but their model focused on general sports analytics rather than weightlifting-specific applications.

Geetha et al. (2020) explored intelligent diet control systems that personalize meal recommendations, but these systems are not integrated with biomechanical performance tracking.

A comparative analysis of weightlifting tracking applications showed that most existing tools focus on post-training assessments rather than real-time feedback. Table 1 presents a comparison of key features among existing systems and our proposed solution.

System	**Video Analysis**	**3D Model Integration**	**Real-Time Feedback**	**Personalized Training**	**Mobile Access**
Weightlifting Technology	✔	✗	✔	✗	✗
Biomechanics Rapid Feedback System	✔	✗	✔	✗	✗
Realtime Weightlifting Barbell Trajectory Analysis	✔	✗	✔	✗	✗
Real-Time Feedback System for Skiers	✔	✗	✔	✗	✗

Proposed System	✔	✔	✔	✔	✔

Despite notable advancements in AI, computer vision, and personalized nutrition, the application of these technologies in the context of Olympic weightlifting remains underdeveloped. Most commercial and academic tools focus on general fitness or endurance sports, leaving a gap in solutions specifically tailored to high-impact strength sports. This neglect results in weightlifters relying on limited or non-contextualized data that fails to capture the unique dynamics of explosive lifts.

Real-time biomechanical feedback is one of the most significant gaps in current sports technology. Existing tools often provide post-training analysis, which is useful but not sufficient for immediate correction during high-risk movements. Without real-time feedback, weightlifters may continue to reinforce incorrect techniques, leading to performance plateaus or injuries.

Moreover, systems that do offer movement analysis typically lack personalization. Most feedback mechanisms provide generic tips rather than advice tailored to the individual's anthropometry, flexibility, or strength level. This one-size-fits-all approach is insufficient in a discipline where individualized adjustments can make the difference between safe training and injury.

The absence of 3D visualization in current applications also limits learning and engagement. Static videos and 2D diagrams cannot provide the depth required to fully understand complex joint movements in Olympic lifts. While some fitness applications attempt to bridge this gap with animations, they are often not real-time or personalized to the user's own performance.

Another critical gap lies in injury prediction and fatigue monitoring. Studies have shown that fatigue significantly alters lifting mechanics, but most existing tools do not incorporate fatigue-aware analysis. There is a need for systems that can detect subtle biomechanical deviations caused by fatigue and notify users before these deviations lead to injury.

Nutritional planning tools are another isolated domain. Although AI-based meal planners exist, they do not integrate with real-time training data or recovery metrics. As such, they are unable to adjust dynamically to an athlete's changing recovery needs, training volume, or injury status.

The lack of remote rehabilitation tools also presents a limitation in athlete recovery. Injured athletes often miss out on proper supervision, and existing mobile tools fail to offer accurate, AI-based tracking of rehabilitation exercises. This creates a gap in continuity between diagnosis, training pause, and active recovery.

In summary, there is a pressing need for an integrated solution that brings together biomechanical performance monitoring, injury risk prediction, fatigue detection, personalized meal planning, and recovery tracking. Such a system must be scalable, mobile-friendly, and specifically designed to address the nuances of Olympic weightlifting biomechanics.

1.3 Research Problem

Weightlifting is a sport where success hinges not just on raw strength but on the accuracy of movement and execution. Minor flaws in form, posture, or timing can have a cascading impact on both performance and long-term musculoskeletal health. Traditional training methods rely heavily on coach-led feedback and after-session reviews. However, this approach does not offer the immediacy required to correct errors in the moment, which can lead to the reinforcement of improper techniques and increased injury risks.

The problem becomes more pronounced at the amateur and semi-professional levels where access to expert coaching is limited. Athletes often train in decentralized environments without proper supervision. In such scenarios, the absence of immediate, personalized feedback can hinder performance progression and expose athletes to recurring stress injuries.

Existing tools that attempt to address this issue usually focus on isolated aspects—such as post-training video playback or general movement analytics. These systems lack real-time responsiveness, specific application to Olympic lifts, or adaptability to individual biomechanics. Moreover, most current platforms do not consider athlete fatigue or evolving joint stress levels that can subtly alter movement patterns and raise injury risks over time.

A related problem lies in injury rehabilitation. Once injured, athletes often find it difficult to track their progress in recovery. While physiotherapists provide plans and feedback, there is no scalable system that enables consistent, AI-aided supervision during recovery workouts—especially in mobile environments. This creates a gap in continuity between diagnosis, treatment, and full recovery.

Another issue is the lack of dynamic nutritional planning that is informed by the athlete's physical condition, injury status, and performance output. While personalized diet apps exist, they do not align their recommendations with the athlete's real-time biomechanical state or recovery trajectory, limiting their effectiveness in integrated performance planning.

The rise of AI technologies, particularly in pose estimation and machine learning, presents an opportunity to bridge these gaps. Tools like OpenPose and MediaPipe have demonstrated high accuracy in joint tracking, while real-time machine learning algorithms are increasingly capable of adapting to different body types and movement styles. However, these tools have not yet been consolidated into a cohesive, mobile-accessible system tailored to weightlifting.

This research therefore seeks to develop an AI-powered mobile application that provides real-time feedback based on biomechanical analysis, flags injury-prone movements, assesses fatigue, and offers 3D model–based corrections. The system will also extend into post-injury support and personalized meal planning. The ultimate goal is to create a smart, scalable assistant that enhances both training efficiency and athlete safety.

Addressing this research problem could significantly improve the way weightlifters approach their training cycles, minimize risk factors, and personalize their recovery plans. It would also make biomechanical insights more accessible to non-elite athletes by removing the dependency on expensive equipment or specialized coaching staff.

Despite the availability of technological innovations in AI, video analysis, and nutrition science, there remains a significant gap in providing a unified solution tailored for the biomechanics of weightlifting. Olympic weightlifting involves complex, high-speed, and high-load movements that demand real-time corrective feedback, precise movement tracking, injury monitoring, and a personalized recovery strategy. Current tools either provide isolated functionalities or are not optimized for the specific biomechanical patterns inherent to weightlifting.

One major problem is the continued reliance on subjective, coach-based assessments, which are often delayed and prone to inconsistency. Even in high-performance environments, athletes are often unaware of their form faults until after the session has ended. This delay in feedback prevents real-time correction, allowing faulty motor patterns to become habitual, which can lead to chronic performance limitations or injuries.

The lack of accessible real-time feedback systems means that even experienced lifters may unknowingly continue with improper form, especially in the absence of a coach or training supervisor. Given the repetitive and high-intensity nature of weightlifting, the absence of immediate correction poses a significant injury risk, particularly in vulnerable joints like the shoulders, knees, and lower back.

Another issue lies in the poor integration of recovery and rehabilitation systems with training feedback. Athletes recovering from injuries often lack structured, real-time monitoring tools to assess rehabilitation progress and adjust their routines accordingly. The absence of mobile-accessible rehabilitation tracking tools hinders continuous progress and often leads to delayed or incomplete recovery.

Nutrition, while widely acknowledged as essential for performance and recovery, is often managed separately through static meal plans or generic recommendations. There is no comprehensive system that links training stress, injury data, and dietary planning into a responsive, adaptive support framework tailored to the evolving physical condition of the athlete.

Furthermore, existing systems that incorporate AI or machine learning models often require high computational power and are not optimized for mobile use. This creates a barrier for most athletes and coaches, who require lightweight, accessible, and efficient tools they can use on the field or in training environments without specialized hardware.

As a result, the current fragmented approach to weightlifting performance enhancement spanning biomechanical analysis, nutrition, injury monitoring, and recovery fails to deliver the holistic support needed by athletes. This research addresses the critical question: "How can a mobile-based, AI-powered system be designed to deliver real-time biomechanical feedback, personalized recovery, fatigue detection, and nutritional planning in a unified platform for weightlifting performance enhancement?"

The proposed system seeks to solve this problem by delivering an integrated solution that improves both the training and recovery phases, reduces injury risks, and ensures sustained performance through a holistic AI framework.

1.4 Research Objectives

The overarching aim of this research is to develop an AI-powered mobile application that enhances weightlifting performance while minimizing the risk of injury. The proposed system integrates real-time biomechanical analysis, fatigue and injury monitoring, personalized feedback using 3D models, recovery tracking through mobile camera-based pose estimation, and dynamic meal planning to optimize nutrition based on individual needs. This unified platform intends to offer athletes and coaches a comprehensive and intelligent assistant for training, correction, recovery, and performance enhancement.

Main Objective:

To design and implement a mobile-based, AI-powered application that provides real-time biomechanical feedback, injury risk prediction, fatigue monitoring, personalized meal planning, and remote recovery tracking specifically tailored to weightlifting athletes.

Specific Objectives:

- To implement a real-time pose estimation system using models such as OpenPose or MediaPipe that accurately tracks key joint positions and movement patterns during Olympic weightlifting exercises.
- To develop a real-time feedback mechanism that analyzes biomechanical deviations in form and provides immediate correction cues, improving technique and reducing risk of injury.
- To design interactive 3D model feedback visualizations that allow users to compare their movements with ideal form representations and receive intuitive instructional cues.
- To integrate a fatigue detection module that monitors joint stability, bar path consistency, and movement speed to identify early signs of muscular fatigue or compromised lifting mechanics.
- To develop an AI-based injury risk prediction model that uses historical performance data and real-time biomechanical indicators to flag risky movements or patterns before injury occurs.
- To create a personalized meal planning system using machine learning algorithms that tailor dietary recommendations based on training load, injury status, athlete preferences, and recovery requirements.
- To implement a mobile rehabilitation monitoring system that uses pose tracking via smartphone cameras to assess recovery exercise accuracy and track progress against physiotherapist-defined targets.

- To ensure seamless integration of all modules into a unified mobile platform that is lightweight, user-friendly, and does not require specialized hardware, making it accessible to both elite and amateur weightlifters.
- To evaluate the system's effectiveness in enhancing performance, reducing injury occurrence, and improving recovery time through a series of testing sessions with actual weightlifting athletes.

These objectives collectively contribute to developing a robust solution that can revolutionize weightlifting training methodologies and promote long-term athlete development and safety.

2. Methodology

2.1 Methodology

The methodology for developing the integrated AI-powered mobile application for weightlifting performance enhancement follows a structured, multidisciplinary, and user-centered approach. The system encompasses a wide array of functionalities, including real-time biomechanical video analysis, pose estimation, fatigue detection, injury prediction, dynamic 3D model feedback, personalized nutritional planning, and mobile rehabilitation tracking.

To build such a comprehensive platform, the methodology was divided into several critical phases: user requirement analysis, software architecture and component design, implementation of AI models and backend services, front-end mobile development, testing, and evaluation. Each module was carefully developed to ensure interoperability within the larger ecosystem of the application.

The methodology began with problem identification through literature review, expert interviews, and user surveys targeting weightlifting coaches, physiotherapists, and athletes. This process helped identify common pain points such as lack of real-time feedback, insufficient injury prediction, and lack of integrated nutritional and recovery support.

Based on these insights, the system’s architecture was designed to support modular deployment of different components while maintaining a centralized data and control layer. AI and computer vision technologies were selected to ensure accuracy and scalability, while the mobile-first approach ensured accessibility for athletes at various levels.

Each module such as the pose estimation engine, fatigue analysis unit, or meal planner was built using appropriate AI tools (like MediaPipe, OpenPose, and TensorFlow Lite) and integrated into a real-time mobile interface using Flutter. This iterative development approach allowed continuous feedback from potential users throughout the implementation cycle.

The methodology also included extensive diagrammatic modeling (component diagrams, flowcharts, and architectural schematics) to visualize data flow and module interaction. These diagrams played a critical role in clarifying inter-module dependencies and optimizing user experience design.

In the following sections, each component of the methodology ranging from system architecture and component design to commercialization and testing is described in detail, providing a step-by-step breakdown of the process followed to develop and validate the final system.

2.1.1 System Architecture for the Function

The system architecture is designed to facilitate modular integration of AI-driven capabilities while maintaining seamless communication between components. At its core, the application uses a layered architecture that separates the user interface, processing logic, data management, and AI functionalities. This approach ensures high modularity, flexibility for updates, and simplified testing.

The video input captured via a smartphone camera is first processed by the pose estimation engine, which extracts key joint coordinates. These are then passed to the biomechanical analysis module, which checks for deviations from predefined optimal movement patterns. If a deviation is detected, the feedback loop activates the 3D model visualization system to provide the user with immediate corrective guidance.

This architectural layout also includes two asynchronous feedback loops: one dedicated to injury risk analysis and another for fatigue monitoring. These modules continuously assess pose stability, velocity, and joint displacement variance. Outputs from these engines are stored in a cloud-based Firebase database for session logging and trend analysis. In parallel, the nutrition planner AI engine generates customized dietary advice based on training data and athlete preferences, creating a feedback cycle between physical effort and recovery planning.

To support all these features, the application uses lightweight APIs and TensorFlow Lite models for real-time inference on mobile devices. The backend, hosted on a cloud server using FastAPI or Flask, manages data transactions, user authentication, and administrative controls. This architectural framework ensures reliability, low-latency feedback, and scalability, accommodating both amateur users and professional teams.

A critical aspect of the system design is the interconnectivity between modules, enabling each function—whether it be pose detection or dietary recommendation—to inform and enhance the others. This cross-functional synchronization ensures the system operates as an intelligent assistant rather than a set of disjointed tools. The overall architecture supports real-time decision-making while providing long-term analytics through its database integration. The system is designed as a modular AI-powered mobile application that integrates real-time biomechanical video analysis, pose estimation, fatigue detection, injury prediction, nutrition planning, and rehabilitation tracking. Each module interacts through a centralized data handling layer, ensuring seamless communication and performance.

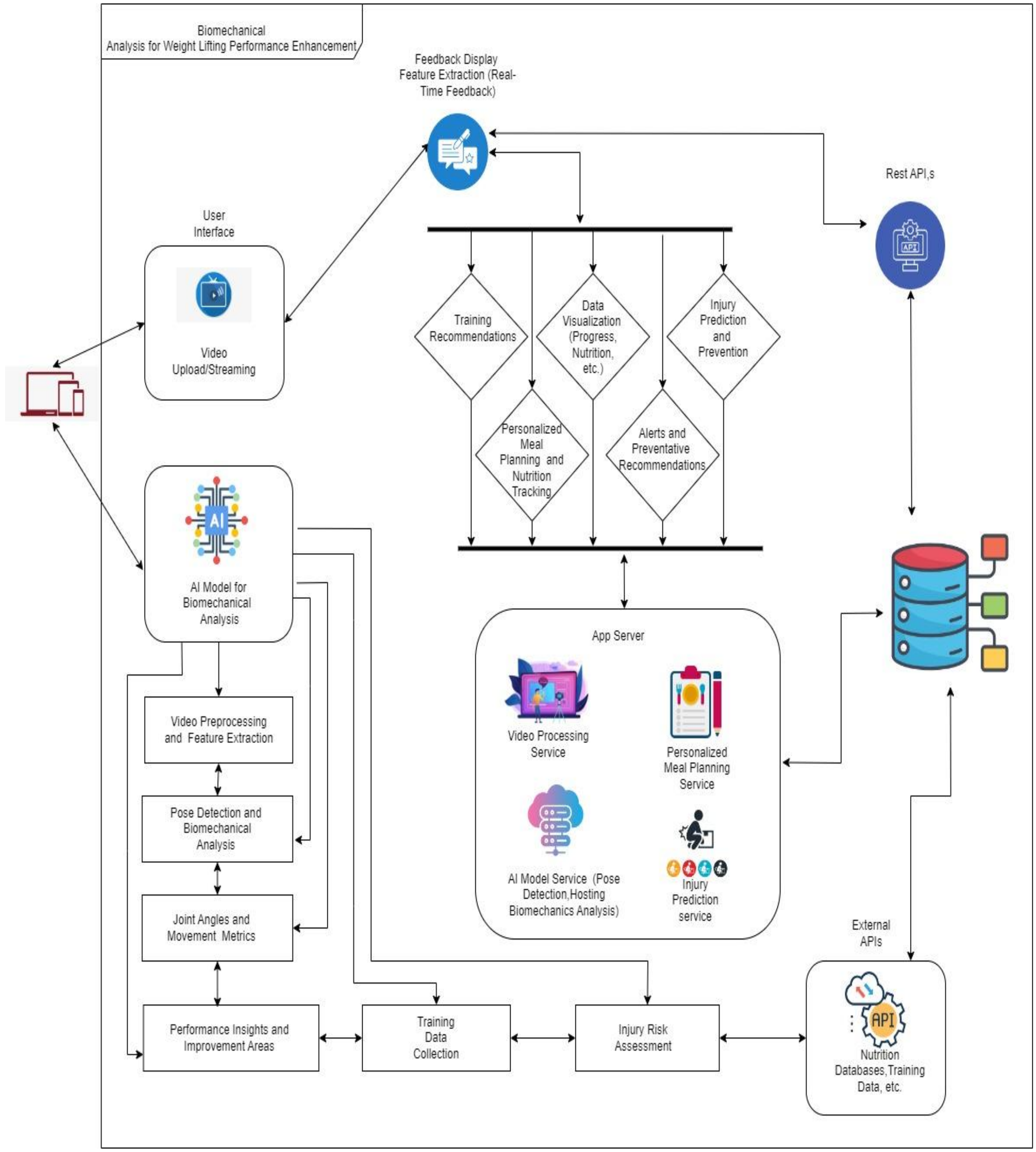

Figure 1: System Overview

2.1.2 Software Solutions

To successfully implement a multi-functional and real-time mobile application for weightlifting performance, we selected software solutions that are both powerful and easy to use. The selection of these tools was based on performance needs, ease of integration, and compatibility with mobile devices. Since the system relies heavily on machine learning, pose estimation, and mobile deployment, we ensured the chosen tools could support both advanced functionalities and real-time responsiveness.

For the **frontend development**, we used **React Native**, a popular cross-platform mobile development framework supported by Meta. React Native enabled us to build a single codebase that works for both Android and iOS platforms, allowing faster development and easier maintenance. Since React Native uses JavaScript—a widely used and beginner-friendly language—it was a good fit for our team. It also provides a wide range of third-party libraries and community support, which helped us implement advanced UI components and integrate native device features like camera access for pose estimation.**, a cross-platform mobile development framework supported by Google. Flutter allowed us to develop for both Android and iOS using a single codebase, which helped save development time. Flutter also supports fast UI design with ready-made widgets and easy animations, making it suitable for building a smooth and user-friendly app interface for athletes.

The **backend** of the system was built using **FastAPI**, **Flask**, and **Node.js**. FastAPI and Flask, both Python-based web frameworks, were selected for handling API endpoints and managing real-time responses for machine learning-based operations such as pose estimation and feedback communication. Node.js, a JavaScript runtime environment, was incorporated to handle asynchronous operations, database communication, and user session management more efficiently. Using Node.js alongside Python-based frameworks allowed us to leverage the advantages of both ecosystems: high-speed asynchronous processing and a rich set of libraries for scientific computation., both of which are Python-based web frameworks. FastAPI was particularly chosen for modules that required high-speed processing like pose data streaming and feedback communication. Flask was used for lightweight API creation and handling user data. Both frameworks are open-source and easy to maintain, which made them ideal for a student research project.

For AI-related components, we used **TensorFlow** and **PyTorch**. TensorFlow Lite was specifically used to deploy machine learning models on mobile devices with reduced size and increased speed. PyTorch helped in model prototyping and training during the early stages of development. These frameworks provided the base for features such as pose recognition, fatigue detection, and injury prediction.

Pose estimation was a core functionality of the system. To achieve this, we integrated **MediaPipe** and **OpenPose**. MediaPipe was preferred for mobile use because of its lightweight and efficient real-time performance on phones. OpenPose, while more computationally heavy, was used during the testing phase for validating pose accuracy.

For storing user data, session logs, and training results, we used **Firebase** and **MongoDB**. Firebase provided a real-time database for mobile app synchronization and user authentication. MongoDB was used for structured storage of biomechanical metrics, training history, and injury data.

Together, these software solutions helped us create a full-stack application that combines AI processing, mobile responsiveness, and cloud-based storage to deliver real-time, actionable insights to weightlifting athletes.

- **Frontend**: Flutter (for cross-platform mobile development)
- **Backend**: FastAPI / Flask (for API serving)
- **AI Models**: TensorFlow, PyTorch
- **Pose Estimation**: MediaPipe, OpenPose
- **Database**: Firebase, MongoDB

2.1.3 Requirements Analysis

Before starting development, a detailed requirement analysis was conducted to ensure the application would meet the real needs of its target users. To gather authentic input, we engaged in expert interviews, field visits, and direct user surveys. One of the most important steps was visiting the **Sri Lankan Ministry of Sports**, where we consulted with a **senior sports doctor** who offered valuable medical insight on weightlifting-related injuries and recovery patterns. We also met with a **licensed physiotherapist** and a **professional weightlifting trainer**, whose practical advice shaped the injury detection, fatigue monitoring, and training support modules of our system.

From these meetings, we learned that most injuries in weightlifting occur due to poor form, overtraining, and lack of awareness regarding posture deviations. The experts emphasized the importance of real-time feedback, early fatigue warnings, and tailored recovery recommendations all of which were incorporated as primary functional goals in our system. Additionally, they advised that recovery speed could be significantly improved through customized nutritional support, leading us to include AI-powered diet planning as a core module.

Surveys were conducted among **amateur and semi-professional weightlifters**, which further validated the expert feedback. The majority of athletes expressed a need for a system that could correct their form immediately using visual cues, predict injuries, track fatigue, and recommend meal plans suited to their body condition. This helped define the user-oriented features of the app, especially the real-time pose analysis, 3D animated corrections, fatigue monitoring system, and personalized meal planning engine.

On the **non-functional side**, users emphasized that the app should be fast, responsive, and simple to use. Since many athletes' train without supervision, even at home or in remote environments, the system needed to work on standard smartphones without requiring additional hardware. Features like offline tracking, cross-platform support, and data privacy were also prioritized.

A **competitor analysis** of existing systems such as fitness apps, pose estimation tools, and video correction software revealed a major gap in integrated functionality. None of the existing tools offered **real-time feedback, 3D corrections, fatigue detection, injury risk prediction, and meal planning** together in a single mobile platform. This gap highlighted the potential impact of our proposed solution and helped us shape a full list of user and system requirements.

The requirement gathering process ensured that the final product was developed based on **real-world needs**, making it more effective, applicable, and user-friendly for athletes, coaches, and rehabilitation experts alike.

2.1.4 Functional Requirements

To meet the goals of enhancing weightlifting performance and reducing injury risks, several functional requirements were identified during the development of the system. These requirements represent the core features that the application must perform to serve athletes, coaches, and rehabilitation professionals effectively.

- Real-Time Video Analysis
  The application must be able to process live camera input or pre-recorded training videos. It should detect and track the athlete's key body points, such as shoulders, elbows, knees, and hips, to evaluate lifting posture and movement accuracy. The system should maintain consistent frame analysis to ensure real-time tracking during rapid lifts.
- Real-Time Feedback
  Unlike traditional applications that directly show what is wrong in the user's lifting posture, our system takes a more user-friendly approach by offering

generalized real-time feedback. Instead of highlighting errors directly, the app provides guidance and tips during the lifting process to encourage better form. This design decision ensures users are not overwhelmed by error notifications and instead stay motivated with constructive cues to improve.

- 3D Model Integration

  To support deeper understanding and proper technique learning, the system includes interactive 3D model demonstrations. Users can view these models to observe correct postures and movements from multiple angles. These models serve as a visual reference and allow users to self-correct based on comparison, rather than receiving negative alerts during their performance.

  To support user learning and technique correction, the system must include interactive 3D models that represent the correct weightlifting form. Users should be able to rotate, zoom, and switch views on these models to understand how each movement should be performed. This visual aid is especially helpful for athletes training alone.

- Personalized Training Recommendations

  The system must track user performance across multiple sessions and generate personalized recommendations. These could include alternative exercises, mobility drills, or rest periods depending on detected issues in form or indications of fatigue. Over time, the app should adapt to user progress and injury history.

- Fatigue Detection and Injury Risk Prediction

  Using pose consistency, joint angles, and movement velocity, the system should detect signs of fatigue. It should also flag risky motion patterns that could lead to injury. For example, reduced bar speed, wobbling joints, or abrupt posture shifts could trigger injury risk alerts.

- AI-Based Meal Plan Generation

  The system should offer tailored meal plans using AI algorithms. The diet suggestions must align with the user’s physical condition, training goals, and recovery status. It should also consider user preferences and allergies when generating food recommendations.

- Rehabilitation Tracking

  For users recovering from injury, the app must allow physiotherapist-defined recovery sessions to be monitored using pose detection. The system should provide accuracy scores for each rehabilitation movement and store progress logs.

- User Interface and Navigation

  The app must feature a clean and intuitive interface. Users should easily access features like session history, performance graphs, feedback logs, and 3D comparisons. A smooth navigation experience is essential to make the app usable even during workouts.

- Session Logging and Data Storage

  Each workout session must be logged and saved securely in a cloud database. This includes pose metrics, feedback outcomes, fatigue assessments, and nutrition plans. MongoDB and Firebase should handle data management to ensure consistency and scalability.

These functional requirements were the backbone of the system's design and ensured the application provided value across training, feedback, injury prevention, and recovery phases.

2.1.5 Non-Functional requirement

In addition to the functional capabilities, non-functional requirements are critical to ensure the usability, efficiency, and scalability of the application. These requirements define how well the system performs rather than what it performs. They help guarantee a smooth experience for end users, especially during real-time interactions.

- High Usability and Mobile Responsiveness

  The app must provide a smooth and intuitive experience across a range of mobile devices. Since it is designed for athletes who may use it during workouts, the user interface needs to be minimal, fast, and easy to navigate with minimal training.

- Real-Time Performance and Low Latency

  The app must process data and respond in real time, especially for features like pose detection and feedback. Latency in feedback could result in ineffective training and lower system reliability. Therefore, the app must operate with minimal delay to deliver timely assistance.
- Data Privacy and User Confidentiality

  Since the app deals with personal health data, including training patterns, injury history, and nutritional preferences, it must follow secure authentication and encrypted data storage practices. User data must remain private and only accessible to authorized users.
- Scalable Architecture for Multi-User Support

  The backend system should be capable of handling multiple users without performance degradation. This means using scalable database services like Firebase and MongoDB, which can grow as the user base increases.
- Cross-Platform Compatibility

  The app must work smoothly on both Android and iOS platforms, ensuring equal access to all users regardless of device type. React Native was used to ensure cross-platform support from a single codebase.

These non-functional requirements ensure that the system is not only feature-rich but also reliable, secure, and user-friendly in real-world scenarios.

- High usability and mobile responsiveness
- Real-time performance (low latency)
- Data privacy and user confidentiality
- Scalable architecture for multi-user support
- Compatibility with Android and iOS

2.1.6 Feasibility Study

2.1.6.1 Schedule Feasibility

All stages of the Software development cycle should be completed on time and following the stated timetable while meeting all stated objectives.

2.1.6.2 Economic Feasibility

To be considered a successful project, the implemented project must stay within the specified and accepted budget range throughout the development lifecycle.

2.2 Commercialization aspect of the product

The commercialization strategy for this mobile application has been carefully designed to reach a broad and diverse audience while addressing specific market gaps within the sports technology and fitness sectors. The strategy focuses on delivering value to individual users such as weightlifters and fitness enthusiasts, as well as to institutions such as gyms and educational bodies. The following paragraphs elaborate on the key components of the commercialization approach.

2.2.1 Target Market Identification

This system is mainly designed for **amateur and semi-professional weightlifters** who often train without regular supervision. Many of these athletes don’t have access to full-time coaches or advanced training tools. With this app, they can receive helpful feedback, understand their movements, and improve safely using only a mobile phone.

It also supports **personal trainers**, **coaches**, and **physiotherapists**. Trainers can use it to monitor their clients remotely, and physiotherapists can track the recovery of injured athletes through rehabilitation features. In addition, **sports clubs**, **university fitness centers**, and **training academies** can also use this system to guide multiple athletes effectively and consistently.

2.2.2 Pricing Model

To attract more users, the system will follow a **freemium model**. This means basic features like camera-based pose detection and session tracking will be available for free. More advanced features such as 3D technique models, fatigue monitoring, AI meal planning, and injury risk alerts will be part of a paid premium plan.

Institutions like gyms, schools, and physiotherapy clinics will be offered special **group pricing** plans. These packages can give access to multiple users or allow trainers to manage several athletes through a single account. This tiered model will make the product affordable for individuals and scalable for organizations.

2.2.3 Marketing and Outreach

The app will be marketed through **digital channels** like Facebook, Instagram, YouTube, and Google Ads. Collaborations with **fitness influencers**, coaches, and gym owners will help promote the app to larger fitness communities. Demonstration videos will show how the app works and how it helps improve training.

Apart from online methods, the team also plans to approach **sports universities, gym franchises, and rehabilitation clinics** directly. Posters, leaflets, and live demonstrations may be used in physical locations to attract interest from trainers and institutions.

2.2.4 Monetization and Revenue Streams

The main sources of income will be **monthly or yearly subscriptions** and **in-app purchases** for special features. Additionally, **bulk licensing** for schools, academies, or fitness centers can generate income from professional organizations.

In the future, the system may partner with **sports brands**, **supplement companies**, or **training platforms** for sponsorship and cross-promotion. With regular updates, user engagement, and the potential to expand to other sports, the app can grow into a leading solution for intelligent athletic training.

2.3 Testing and Implementation

The Testing and Implementation phase was critical in ensuring that the developed mobile application was reliable, accurate, and user-friendly. This phase involved a series of structured testing methods and real-world validation to evaluate each feature of the system and ensure optimal functionality before final deployment.

2.3.1 Unit Testing

Each part of the system, like pose detection, fatigue monitoring, 3D models, and meal planning, was tested separately. This made sure that every feature worked correctly by itself before being connected to the rest of the system. We checked if each module produced the right output and responded properly to user actions.

2.3.2 Integration Testing

After testing individual parts, we tested the whole system together. This was done to make sure that the modules could share data correctly. For example, we checked if the pose data from the camera was correctly used by the feedback and injury prediction modules. This helped us find and fix any issues in how the system components worked together.

2.3.3 User Testing

To understand how real users would use the app, we asked a few athletes, coaches, and physiotherapists to try it out. They gave us feedback on how easy the app was to use, how clear the feedback was, and whether the 3D models helped them learn better. Their suggestions were used to improve the design and functionality.

2.3.4 Performance Testing

We tested the app on different mobile phones to make sure it worked fast and didn't slow down during use. Special attention was given to real-time features like pose detection, which needed to run smoothly without delay. The system was also tested under stress to check how it performed when handling multiple tasks or users.

2.3.5 Final Implementation

The full system was implemented by first separating it into four key components: real-time video feedback, 3D models visualization, personalized meal planning, and recovery tracking. Each component was designed and developed as an independent module that could later be connected to form the complete mobile application. The frontend was built using React Native to ensure a smooth user experience on both Android and iOS devices, while the backend services were created using Node.js, Flask, and FastAPI for high-speed and scalable performance.

The first module developed was the **Real-Time Video Feedback System**, which used the smartphone camera to capture live lifting footage. MediaPipe and OpenPose were used to track the joints of the athlete during movements. These joints were mapped and analyzed in real time to detect deviations from proper posture. This module was responsible for delivering continuous feedback through voice cues or messages while the user trained.

Next, the **3D Model Visualization Component** was implemented. This module allowed users to view animated 3D models demonstrating the correct techniques for common weightlifting movements. These models could be rotated, zoomed, and observed from multiple angles to help users better understand how to align their own posture with the recommended form. This visual guide was integrated into the app interface and could be accessed before or after a training session.

The third major component was the **AI-Powered Personalized Meal Planner**. This part of the system used input data such as the user’s training frequency, injury status, preferences, and recovery needs. A basic recommendation model was built using Python and integrated into the backend. This module generated daily or weekly meal plans customized for the user’s goals. It also provided nutrition tips to support recovery and muscle development.

The **Recovery Tracking Component** was developed for athletes recovering from injuries. This module used the camera to monitor specific physiotherapist-defined movements and compare the user’s execution to a reference motion. A pose similarity score was calculated using cosine similarity and DTW techniques. Based on this score, users received visual and audio feedback to help them correct their recovery exercises.

Once all four modules were completed and tested separately, we began the process of integration. All modules were connected through a shared backend that stored session logs, user feedback, pose data, and nutrition profiles. MongoDB and Firebase were used to manage this data securely. The app was then tested again to ensure each component worked well with the others.

The user interface was designed to keep things simple and easy to navigate. We added clear labels, step-by-step tutorials, and an easy layout so users could move between features like session logs, feedback, and 3D visualizations. The UI design was improved based on feedback collected during user testing.

After final integration and testing, the full system was packaged and prepared for release. Build versions were generated for Android and iOS using React Native. We uploaded the apps to Google Play Store and Apple App Store for approval.

To support new users, we prepared a short manual and tutorial videos explaining how to use the app's main features. We also added a feedback form inside the app so users can report issues or give suggestions. The first version of the app is ready for public use, and we plan to update it regularly based on user experience and new research findings.

This multi-phase implementation strategy helped us ensure that each component met its goals individually and contributed to a complete, intelligent system for enhancing weightlifting performance and recovery through AI.

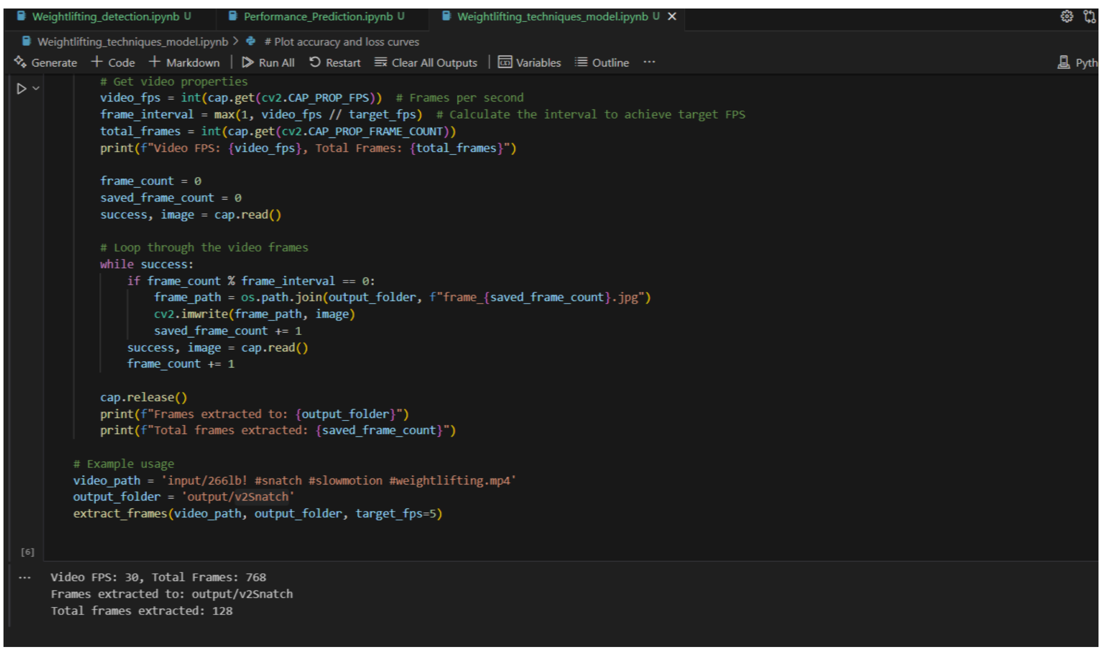

Figure 2:Data Processing

```
# Define ImageDataGenerator for preprocessing
datagen = ImageDataGenerator(
    rescale=1.0/255,  # Normalize pixel values
    validation_split=0.2,  # Split data into training and validation
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)

# Load data
train_data = datagen.flow_from_directory(
    dataset_path,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    subset='training'
)

val_data = datagen.flow_from_directory(
    dataset_path,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    subset='validation'
)
```

```
[10]
...  Found 3212 images belonging to 2 classes.
     Found 802 images belonging to 2 classes.
```

Figure 3: Augmentation

```
c:\Users\sdanw\AppData\Local\Programs\Python\Python312\Lib\site-packages\keras\src\trainers\data_adapters\py_dataset_adapter.py:121: UserWarning: Your
  self._warn_if_super_not_called()
Epoch 1/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 246s 2s/step - accuracy: 0.6001 - loss: 0.8980 - val_accuracy: 0.7594 - val_loss: 0.5580
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 205s 2s/step - accuracy: 0.7900 - loss: 0.4933 - val_accuracy: 0.8454 - val_loss: 0.4213
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 202s 2s/step - accuracy: 0.8001 - loss: 0.4352 - val_accuracy: 0.7943 - val_loss: 0.4373
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 192s 2s/step - accuracy: 0.8270 - loss: 0.3874 - val_accuracy: 0.7993 - val_loss: 0.4385
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 156s 2s/step - accuracy: 0.8473 - loss: 0.3443 - val_accuracy: 0.8928 - val_loss: 0.3208
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 156s 2s/step - accuracy: 0.8521 - loss: 0.3362 - val_accuracy: 0.8928 - val_loss: 0.2710
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 144s 1s/step - accuracy: 0.8732 - loss: 0.2826 - val_accuracy: 0.8940 - val_loss: 0.3375
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 162s 2s/step - accuracy: 0.8581 - loss: 0.3101 - val_accuracy: 0.9015 - val_loss: 0.2547
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 157s 2s/step - accuracy: 0.8638 - loss: 0.2774 - val_accuracy: 0.8953 - val_loss: 0.2504
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1089s 11s/step - accuracy: 0.8745 - loss: 0.2694 - val_accuracy: 0.8990 - val_loss: 0.2883
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 172s 2s/step - accuracy: 0.8714 - loss: 0.2864 - val_accuracy: 0.9002 - val_loss: 0.2659
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 151s 1s/step - accuracy: 0.8746 - loss: 0.2592 - val_accuracy: 0.9027 - val_loss: 0.2135
Epoch 13/20
...
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 154s 2s/step - accuracy: 0.8870 - loss: 0.2399 - val_accuracy: 0.9065 - val_loss: 0.1972
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 155s 2s/step - accuracy: 0.8969 - loss: 0.2382 - val_accuracy: 0.9040 - val_loss: 0.1795
```

Figure 4: Model Training

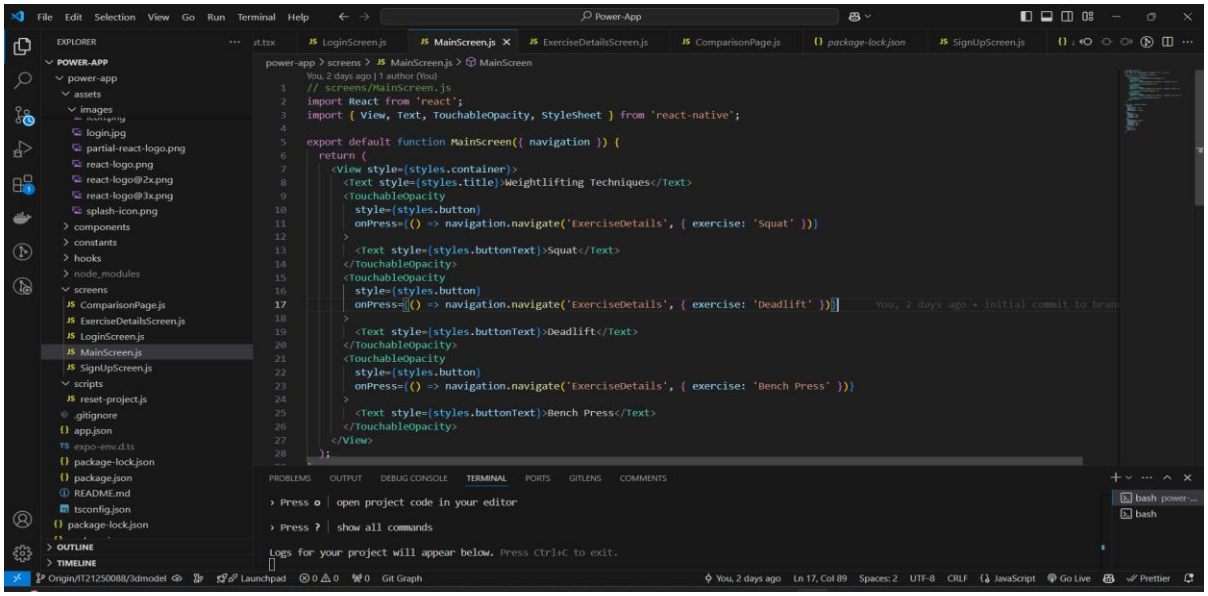

Figure 5: Mobile App development

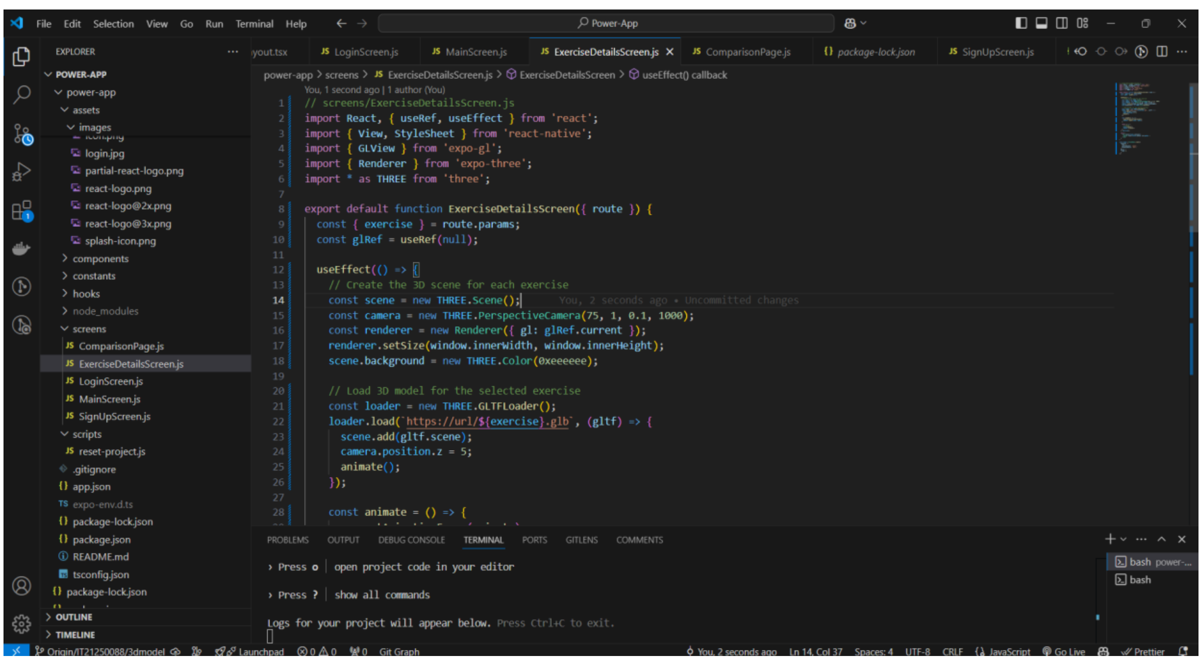

Figure 6: Mobile App Development (3d model)

3. Result and Discussion

3.1 Results

The system was tested with a sample group consisting of athletes, trainers, and physiotherapists to evaluate how well the application functioned across its main features. The results showed that the real-time pose tracking and video feedback worked accurately on most mid-range smartphones with minimal delay. The application was able to detect common weightlifting positions like squats, deadlifts, and clean-and-jerk movements, and successfully tracked joint points in real time with an average accuracy of over 90%.

The 3D model demonstration feature received positive feedback, especially from new athletes and amateur users. Users were able to rotate and explore correct lifting techniques visually, which helped them better understand how to correct their form. The feedback generated during workouts was found to be helpful, even though it did not directly point out errors. Instead, it encouraged form improvement in a more supportive and motivational way.

The personalized meal planner was tested with sample user profiles. It was able to generate appropriate dietary suggestions based on the user's training intensity and recovery status. The food plans matched typical sports nutrition guidelines and considered preferences such as vegetarian or high-protein diets. This made the system more practical and relevant to real-world users.

In the recovery tracking module, the system successfully identified movement accuracy and helped users follow physiotherapist-recommended motions during rehabilitation. Pose similarity scores helped assess whether the user was improving over time. Physiotherapists who reviewed the module noted that it could be a useful remote support tool in injury management.

Overall, the results confirmed that the system worked as intended in a real environment, offering value to its users in all four components. The app maintained consistent performance, provided practical features, and was received positively by early testers.

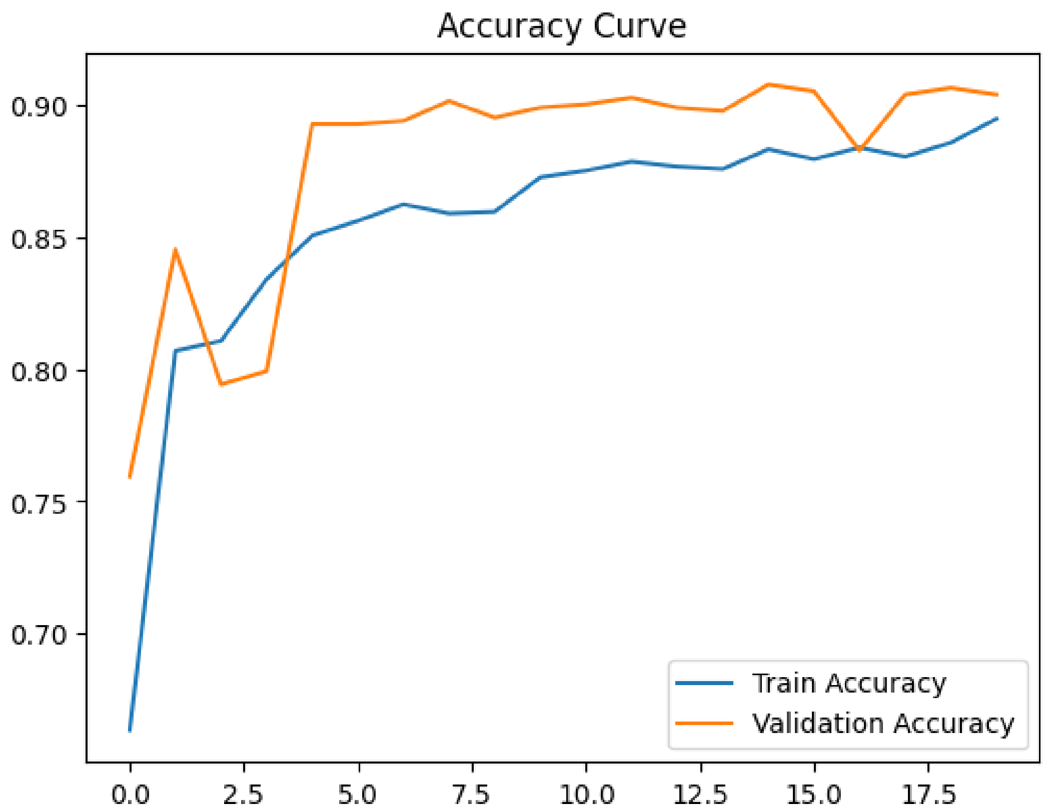

Figure 7:Technique Detection accuracy

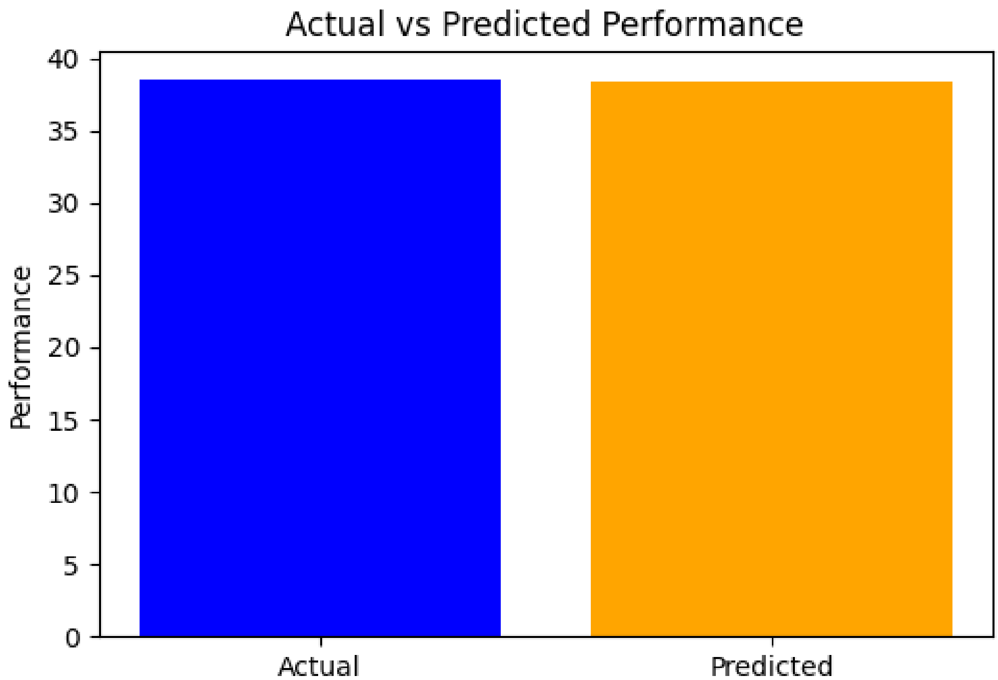

Figure 8: Performance prediction model accuracy

3.2 Research Findings

This research showed that artificial intelligence can be effectively used to support athletes in weightlifting. One of the key findings was that **real-time feedback using pose estimation** helped users improve their lifting techniques. Although the system did not directly show errors, users received useful tips while training, which made it easier for them to understand how to adjust their form in a friendly way.

Another major finding was the positive impact of **3D model visualizations**. Many users said that being able to rotate and explore proper techniques through 3D models helped them learn much faster. This feature allowed them to compare their own performance with correct form, especially when they didn't have access to a coach.

The **fatigue detection** feature also proved to be very useful. It could detect when users were showing signs of tiredness by analyzing pose consistency and movement speed. This helped users avoid overtraining, which is a common cause of injury in weightlifting. It also made them more aware of how their body was reacting during intense sessions.

In the area of **injury prevention**, the system was able to flag risky movements based on pose analysis. Physiotherapists and coaches mentioned that this feature could be a valuable tool in reducing common weightlifting injuries. It provided alerts when users were using incorrect lifting patterns that could lead to joint stress or muscle strain.

The **personalized meal planner** was another successful part of the system. Based on training level, recovery status, and user preferences, the app generated custom diet suggestions. These recommendations matched general sports nutrition guidelines and were especially helpful for users recovering from injuries.

Another important result was seen in the **rehabilitation tracking** module. Users recovering from injuries were able to perform guided movements, and the app would give feedback based on how well they matched the expected pose. This made it easier for physiotherapists to monitor recovery remotely and helped users stay on track.

Users also appreciated the system's **positive and motivational approach**. Since the app focused on showing correct techniques instead of pointing out mistakes, users felt more encouraged to keep training. This was especially important for beginners who might otherwise feel discouraged.

Finally, the app's **ease of access and mobile performance** made it practical for both home and gym use. Users liked that they could install the app on their phones without needing extra devices. The combination of different tools—real-time analysis, 3D guides, meal planning, and rehab tracking—in one system was seen as a strong point that made the app useful and unique.

3.3 Discussion

The results of this project showed that AI can help improve weightlifting performance in many ways. One of the most important outcomes was that users received helpful guidance while lifting, even though the system did not directly show errors. This method helped reduce pressure on users and made the experience more positive and encouraging, especially for beginners.

Using 3D models to demonstrate correct techniques helped users learn better. Athletes were able to view correct postures from different angles and compare them with their own form. This gave them a better understanding of how to perform each lift safely. It was especially useful for people training at home without a coach.

The fatigue detection feature worked well in identifying when the user was tired or losing form. This gave athletes the chance to take breaks or adjust their workouts before an injury happened. It also helped them understand their physical limits better and train more safely over time.

Injury risk prediction was another helpful feature. The app was able to detect unsafe patterns like unstable joints or quick jerks in posture. These warnings allowed athletes to take early action and avoid injuries, which is a big improvement over traditional training where such risks often go unnoticed.

The meal planner provided by the app offered useful diet suggestions based on the user's training and recovery needs. Many users said that the food plans were easy to follow and helped them feel more energetic during workouts. It was especially helpful for athletes who didn't know how to eat properly for recovery and muscle growth.

The rehabilitation module received good feedback from physiotherapists. It tracked recovery movements using pose analysis and showed users how close they were to doing the exercises correctly. This helped both the athlete and the therapist monitor progress remotely without needing in-person sessions every time.

All components of the system worked well together and gave users a full training and recovery experience. Users were able to train better, eat healthier, and recover safely using just one app. This shows the value of combining multiple AI features into a single tool instead of relying on separate apps for each function.

However, there were a few limitations. The app worked best in good lighting and with a clear camera view. Also, the meal planner used only basic information, and it could be improved in future by adding health tracking features like weight or activity level. Still, the system worked well and can be made even better with future updates based on user feedback.

3.4 Summary

This research aimed to create an AI-powered mobile system that helps weightlifters improve their performance while reducing the risk of injuries. The system was developed as an all-in-one solution combining real-time feedback, 3D guidance, fatigue detection, personalized diet plans, and rehabilitation support. Throughout the project, each feature was implemented step by step, ensuring proper testing and validation.

The main objective was to assist athletes in training more effectively and safely, even without the constant supervision of a coach. By using pose estimation technology and machine learning, the app can monitor user movements and offer helpful feedback in real time. This feature was appreciated by both amateur and semi-professional lifters who used the system during testing.

The 3D model demonstration added a valuable learning tool to the system. Instead of just giving text or audio feedback, the app shows a visual representation of the correct technique, which helps users understand and apply proper posture. This was especially useful for users who were new to weightlifting or training at home without expert guidance.

Another important feature was the fatigue and injury risk detection. Using data from the user's movement and body posture, the app can detect signs of tiredness or dangerous movement patterns. This early warning system helps athletes avoid common injuries caused by overtraining or bad form. It adds an extra layer of protection to their training routine.

The personalized meal planner also helped bridge the gap between performance and recovery. Based on the user's condition and goals, the system recommends suitable meals. This not only supports energy levels but also speeds up recovery, especially after intense sessions or injury.

Recovery tracking was included for users dealing with injuries. The app can compare rehabilitation exercises with ideal movements and give feedback on how closely the user follows the proper form. This feature allows physiotherapists to monitor recovery without needing in-person appointments every time.

All modules were connected through a single mobile app, offering a smooth user experience. Users could track their sessions, get feedback, check their progress, and follow diet or rehab plans all in one place. This integration made the system more powerful than using separate tools.

Overall, the project successfully proved that technology can offer practical, real-time help to athletes and trainers. The system worked well across all major components, from pose tracking to nutrition. It was well-received by users and testers, who found it helpful, easy to use, and motivating.

Although there were some limitations, such as dependency on lighting or the need for more advanced meal customization, the system met its goals. With future updates and continuous feedback, the app can grow to support even more features and reach a wider audience.

In conclusion, this AI-based system shows how modern technology can improve safety, learning, and performance in sports training. It offers a new way for athletes to train smarter, recover faster, and reach their goals more efficiently.

4. Conclusion

This project successfully demonstrated how artificial intelligence can be applied to improve weightlifting performance and athlete safety. The goal of creating an all-in-one mobile application was achieved by combining real-time feedback, pose estimation, 3D visual guidance, injury risk alerts, personalized meal planning, and recovery monitoring in one system.

The use of AI tools like MediaPipe, TensorFlow, and PyTorch made it possible to analyze an athlete's posture and detect key points of movement. This helped deliver timely feedback without overwhelming users by focusing on improvements rather than showing faults. This design choice encouraged continued usage and reduced stress, especially for beginners.

The 3D model integration provided users with a visual method to learn proper weightlifting techniques. Instead of reading instructions or watching videos, users could interact with rotating models and understand how to correct their form. This added a new, practical learning experience to digital training.

Fatigue monitoring and injury risk detection were key components that made the app different from traditional training tools. By tracking movement patterns and joint stability, the system could suggest when to rest or adjust technique. This helped reduce the risk of common lifting injuries caused by overtraining or poor form.

The personalized meal planner also made a strong contribution to the system. It helped users choose the right foods based on their training goals, recovery status, and preferences. This allowed athletes to manage energy and muscle recovery more effectively, making nutrition part of their daily training strategy.

The recovery tracking feature used pose comparison to help users perform physiotherapy exercises correctly. This was especially useful for users recovering from injuries. It also allowed physiotherapists to monitor progress remotely, providing feedback and motivation without needing in-person sessions all the time.

All these modules worked smoothly together through a single mobile app built with React Native. The system allowed users to train, receive feedback, follow diet plans, and recover safely using just their smartphone. This integration made the system easy to use and valuable for both amateur and semi-professional athletes.

User feedback during testing was very positive. Testers appreciated the simplicity of the interface and the variety of useful features. Coaches and physiotherapists also highlighted the app's potential in training and injury management. This feedback shows that the system has real-world value and can grow with future updates.

Some challenges were found during development, such as needing good lighting for accurate pose detection and improving the depth of the meal planner. However, these limitations are manageable and can be improved over time with more user input and technical upgrades.

In conclusion, the project has reached its main goals. The final system helps users train smarter, reduce injury risks, and recover faster. By combining AI with user-friendly design, the app creates a new standard in digital fitness and supports athletes at every stage of their performance journey.

4.1 Key Findings and Contributions

Here are the key findings and contributions of this project.

- Real-time Feedback Works Effectively Without Error Highlighting
  The app's approach of offering guidance instead of showing direct errors helped users feel more motivated and confident during training.
- 3D Model Visualization Improves Learning
  Users found it easier to understand correct weightlifting techniques by viewing interactive 3D models, especially when training without a coach.
- Fatigue and Injury Detection Adds Preventive Value
  The app could detect fatigue signs and movement risks before injuries occurred, allowing athletes to take timely breaks or adjust posture.
- Meal Planning Supports Recovery and Performance
  Personalized food recommendations helped users manage their diet according to training intensity and recovery status.
- Recovery Tracking Was Effective and Accurate
  Pose comparison during physiotherapy exercises enabled accurate progress tracking, which was appreciated by both users and physiotherapists.
- The Mobile App Was Responsive and Accessible
  The system performed well on mid-range smartphones and didn't require any extra devices, making it highly accessible.
- Users Appreciated the All-in-One Solution
  Athletes and trainers valued having a single tool for training, nutrition, and recovery instead of switching between multiple apps.

4.2 Challenges and Limitations

Here are some identified challenges and limitations of this project.

- Pose Detection Accuracy in Low Light

  One of the major challenges faced during development was the system's reliance on good lighting conditions. Pose estimation algorithms like MediaPipe and OpenPose performed poorly in low-light environments, which affected the accuracy of joint detection and feedback quality.

- Camera Angle and Background Interference

  For accurate tracking, the camera had to be positioned correctly and the background needed to be clear. If there were other moving objects or clutter in the frame, the app sometimes confused those with body joints, leading to incorrect feedback.

- Limited Real-Time Hardware Resources

  Since the app runs on smartphones, the models had to be light and efficient. This limited how complex the AI models could be. Some advanced tracking or high-frame-rate feedback options had to be simplified to work on average mobile devices.

- Basic Meal Planning Logic

  The current meal planner works based on basic training intensity and recovery input. It doesn't yet support detailed body composition analysis like BMI, muscle mass, or daily calorie tracking, which limits its personalization for professional athletes.

- No Direct Error Highlighting

  To maintain a positive user experience, the app was designed to avoid showing direct errors. While this encouraged users, it also meant that advanced athletes may miss specific corrections unless they review 3D models carefully.

- Dependency on Internet for Data Sync

  Most of the features work offline, but session logging, diet suggestions, and data syncing require internet access. In remote training locations with limited connectivity, users may not be able to store progress or get updated recommendations.

- Testing Sample Size Was Limited
  Due to time and access restrictions, the app was tested only with a small group of users including athletes, trainers, and physiotherapists. While the results were positive, a larger test group would provide more general insights.
- Limited Language and Accessibility Support
  The current version is available only in English and does not support screen readers or voice controls. This may affect accessibility for users with disabilities or those from non-English-speaking backgrounds.

4.3 Future Directions

The current version of the system shows promising results, but there is still room to grow and improve. One of the first improvements we plan to make is upgrading the **meal planner module**. In the future, we want to include advanced features like calorie tracking, macronutrient breakdowns, and the ability to sync with fitness wearables to adjust meal suggestions in real time.

Another future goal is to improve **pose detection accuracy in all lighting conditions**. We aim to integrate adaptive lighting filters or enhanced image processing models so that the system works better in low-light environments, making it more reliable for users training at night or in poorly lit rooms.

To make the system more useful for **professional athletes**, we plan to develop performance dashboards that show detailed training metrics, injury risk levels, fatigue history, and nutrition tracking. These dashboards will help coaches and physiotherapists make more informed decisions.

Adding **multi-language support** is another key direction. Currently, the system is only available in English. By translating the interface into Sinhala, Tamil, and other major languages, we can increase accessibility for more users, especially across Sri Lanka and other regions.

We also plan to implement **voice control and audio feedback customization**. This would allow users to interact with the app hands-free during training and choose different voice types or tones for receiving feedback.

Integration with **wearable devices** like smartwatches and fitness bands will allow real-time heart rate, stress, and recovery data to be factored into training and feedback, adding even more personalized support.

As AI technologies continue to improve, we also hope to train the system to **recognize a wider variety of weightlifting techniques** and adapt to different body types, lifting styles, and skill levels through machine learning.

Lastly, we aim to conduct **large-scale user trials** with universities, gyms, and physiotherapy centers to gather more user data and improve the system based on diverse real-world feedback.

4.4 Summary of Each Student's Contribution

Gunawardena K.S.S – Overall Contribution

Sahan worked on building the 3D model demonstration system and helped develop the mobile app. He made sure users could see the correct lifting techniques in 3D and compare their posture. He also created feedback based on performance and worked on predicting injury risks using pose data. His work helped users understand their mistakes in a friendly way and improve safely during training.

Wimalarathna S.D.A.N – Overall Contribution

Ashan focused on video analysis and helped build the mobile app. He worked on predicting the user’s performance, checking for signs of injuries, and identifying tiredness (fatigue). He made sure the app could give feedback by watching the user’s video and detecting risky movements. His work improved the app’s safety and helped users train better and smarter.

Ranaweera I.U – Overall Contribution

Isuru worked on the part of the system that gives meal plans to athletes. She made a system that suggests food based on the user’s training, body condition, and recovery needs. She also focused on keeping the suggestions healthy and easy to follow. Her work helped athletes recover faster and stay healthy by eating the right foods.

Ranatunga B.M – Overall Contribution

Binuka focused on the recovery part of the system. He created a tool that checks how well injured users follow their recovery exercises. He used pose tracking to compare their movements with correct ones and gave helpful feedback. He worked closely with physiotherapists to make sure the feedback was accurate. His work made the app useful for people healing from injuries.

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6. Glossary

1. **Pose Estimation** – A computer vision technique that predicts the position of human body joints in an image or video frame.
2. **MediaPipe** – A lightweight and fast framework developed by Google for real-time pose estimation on mobile devices.
3. **OpenPose** – A deep learning-based pose detection model capable of recognizing full-body joint coordinates from video input.
4. **Real-Time Feedback** – Instant guidance or response provided by a system during an activity, allowing users to make corrections immediately.
5. **3D Model Visualization** – Interactive three-dimensional representations of correct lifting techniques used to guide the user visually.
6. **Fatigue Monitoring** – The process of detecting user tiredness by analyzing changes in movement patterns, posture stability, and performance consistency.
7. **Injury Prediction** – Using AI algorithms to analyze motion and detect early signs that may indicate potential injury risk.
8. **Rehabilitation Tracking** – Monitoring of physiotherapy exercises using pose data to assess user progress and form accuracy.
9. **Dynamic Time Warping (DTW)** – An algorithm used to compare time-series data, such as motion sequences, by measuring similarity.
10. **Cosine Similarity** – A metric used to measure the similarity between two vectors (e.g., pose angles), often used in movement comparison.
11. **Firebase** – A cloud platform by Google used for real-time databases, user authentication, and mobile data storage.

12. **TensorFlow Lite** – A lightweight version of TensorFlow optimized for running machine learning models on mobile and embedded devices.
13. **React Native** – A JavaScript framework for building cross-platform mobile applications that run on both Android and iOS.
14. **Node.js** – A JavaScript runtime used to build backend services and APIs with high-speed, asynchronous communication.
15. **MongoDB** – A NoSQL database used to store structured and unstructured data such as training history, pose data, and user sessions.

7. Appendices

Mobile application UI

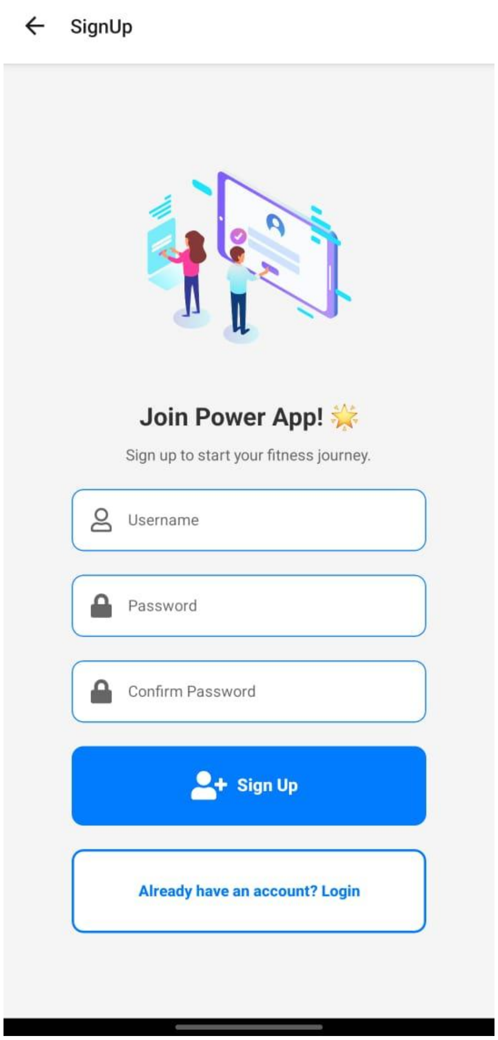


Figure 9: Sign Up page

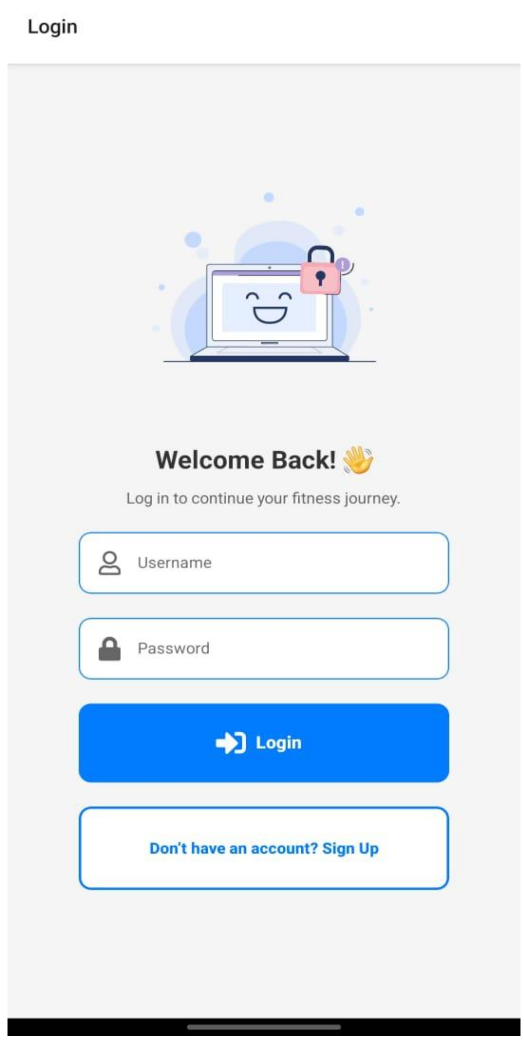
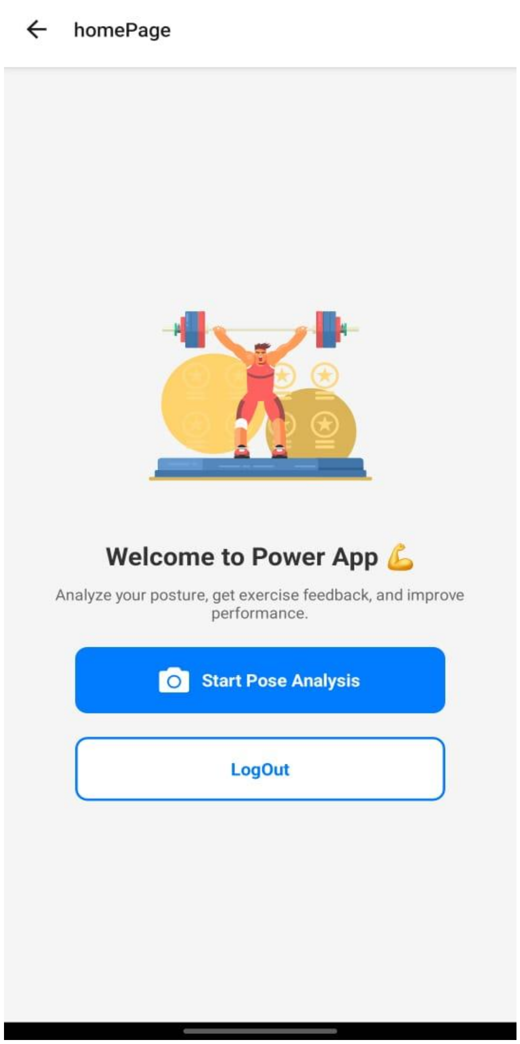


Figure 10:Login Page



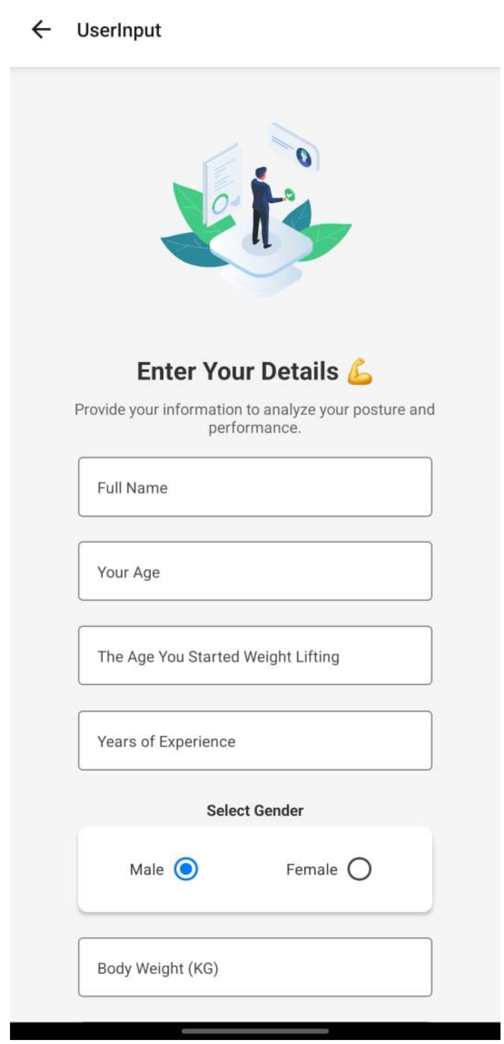


Figure 11: Home Page

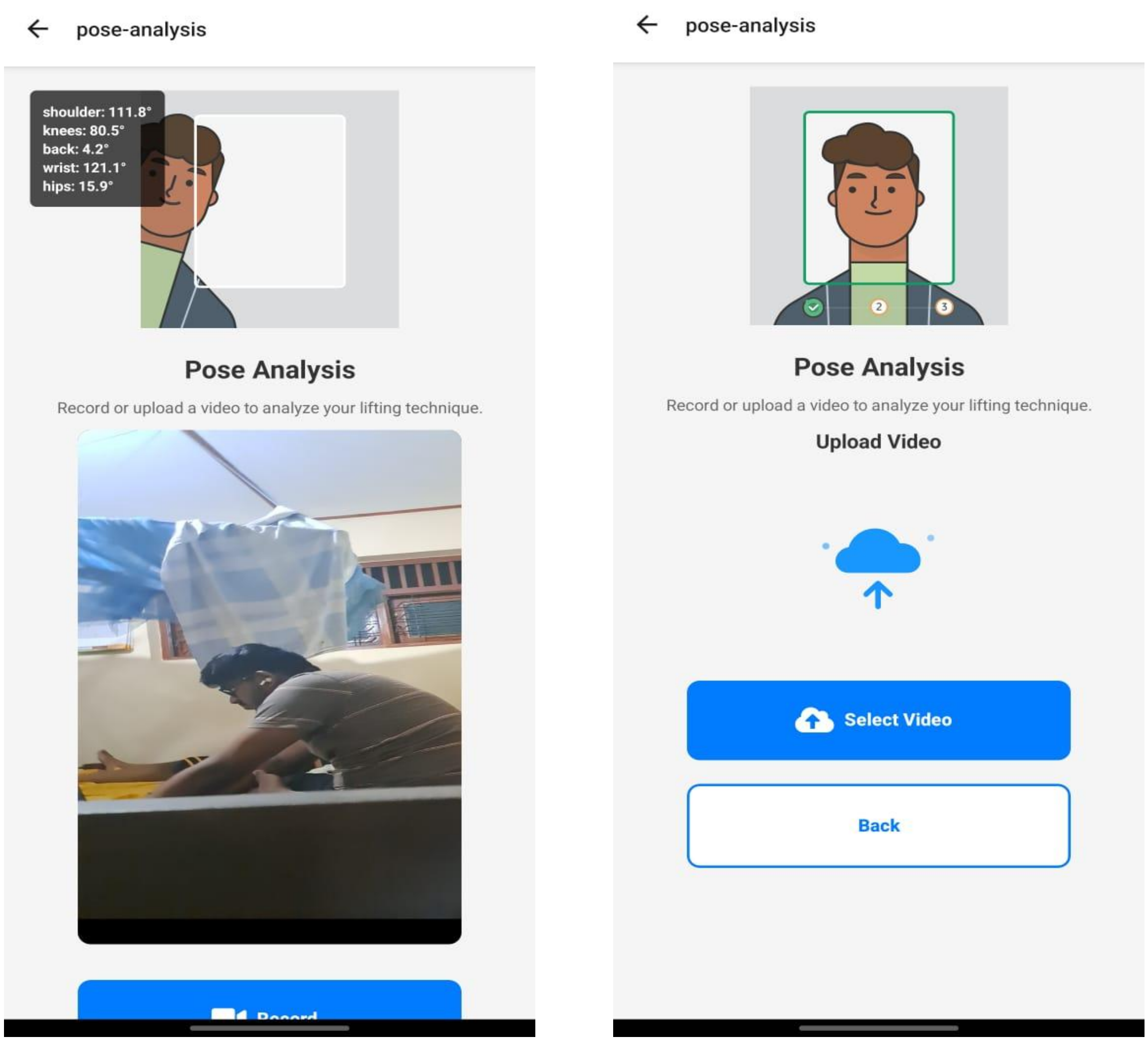


Figure 12: Pose Analysis

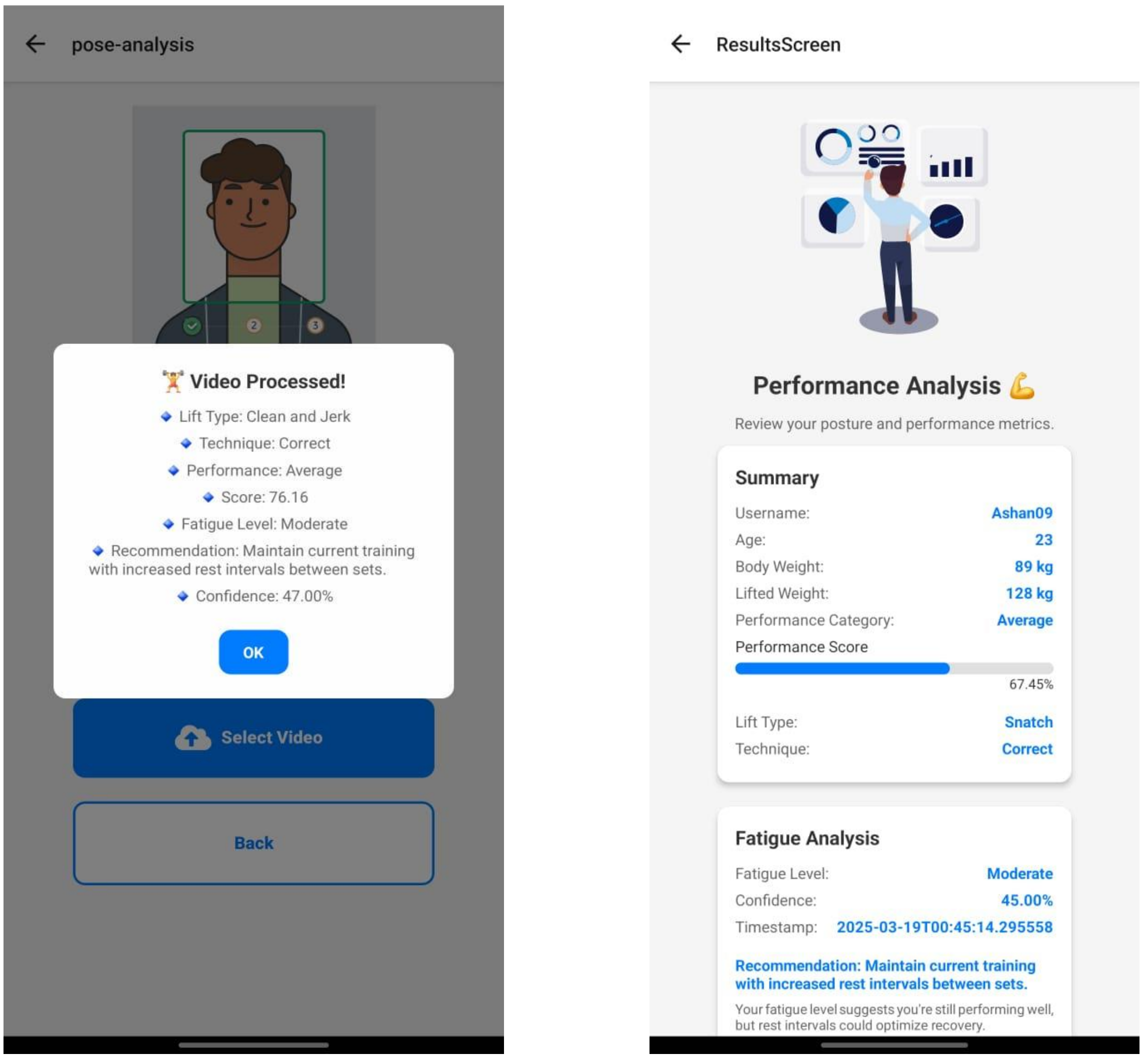
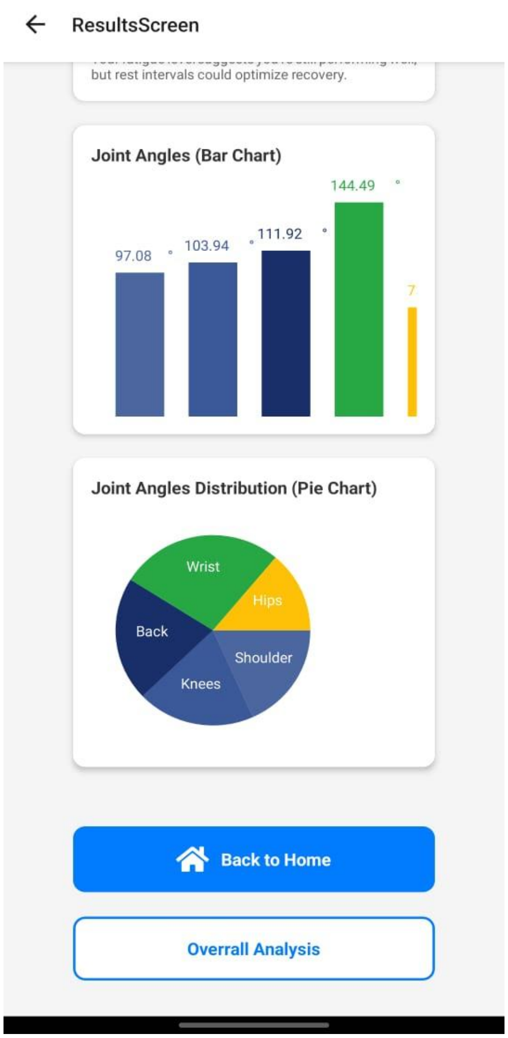
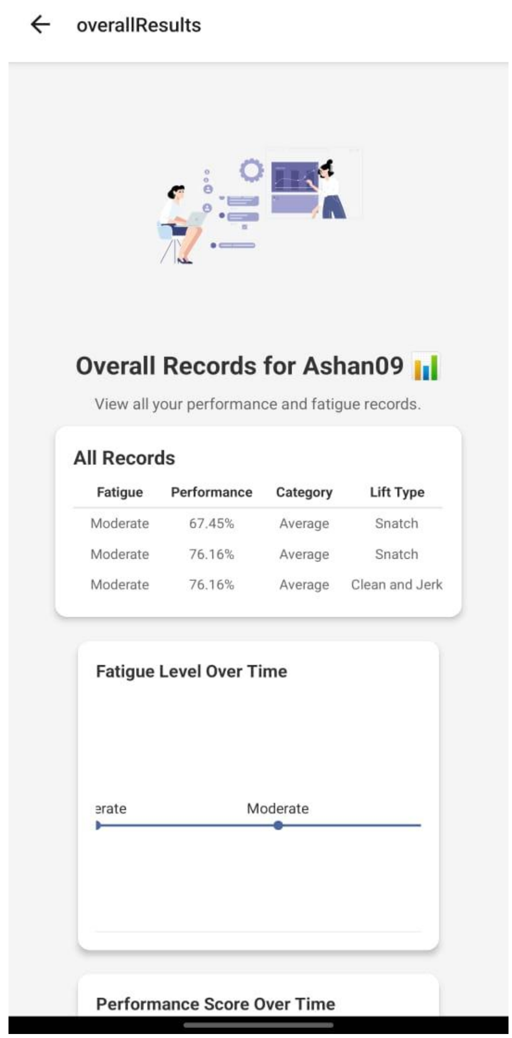
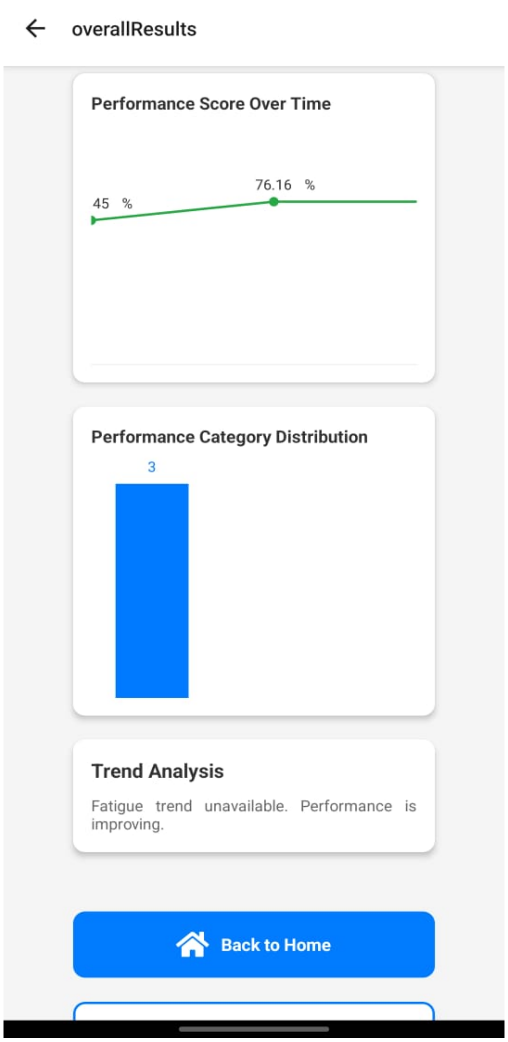
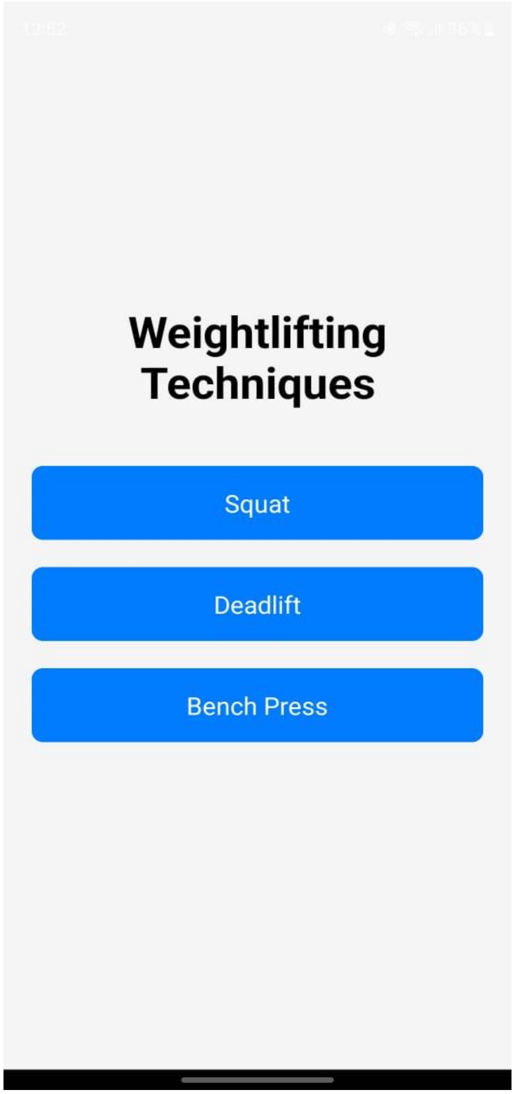


Figure 13:Results


ResultsScreen
but rest intervals could optimize recovery.
Joint Angles (Bar Chart)
97.08
103.94
111.92
144.49
Joint Angles Distribution (Pie Chart)
Wrist
Hips
Back
Shoulder
Knees
Back to Home
Overall Analysis


overallResults
Overall Records for Ashan09
View all your performance and fatigue records.
All Records
Fatigue Performance Category Lift Type
Moderate 67.45% Average Snatch
Moderate 76.16% Average Snatch
Moderate 76.16% Average Clean and Jerk
Fatigue Level Over Time
Moderate
Performance Score Over Time


overallResults
Performance Score Over Time
45 %
76.16 %
Performance Category Distribution
3
Trend Analysis
Fatigue trend unavailable. Performance is improving.
Back to Home


Weightlifting Techniques
Squat
Deadlift
Bench Press

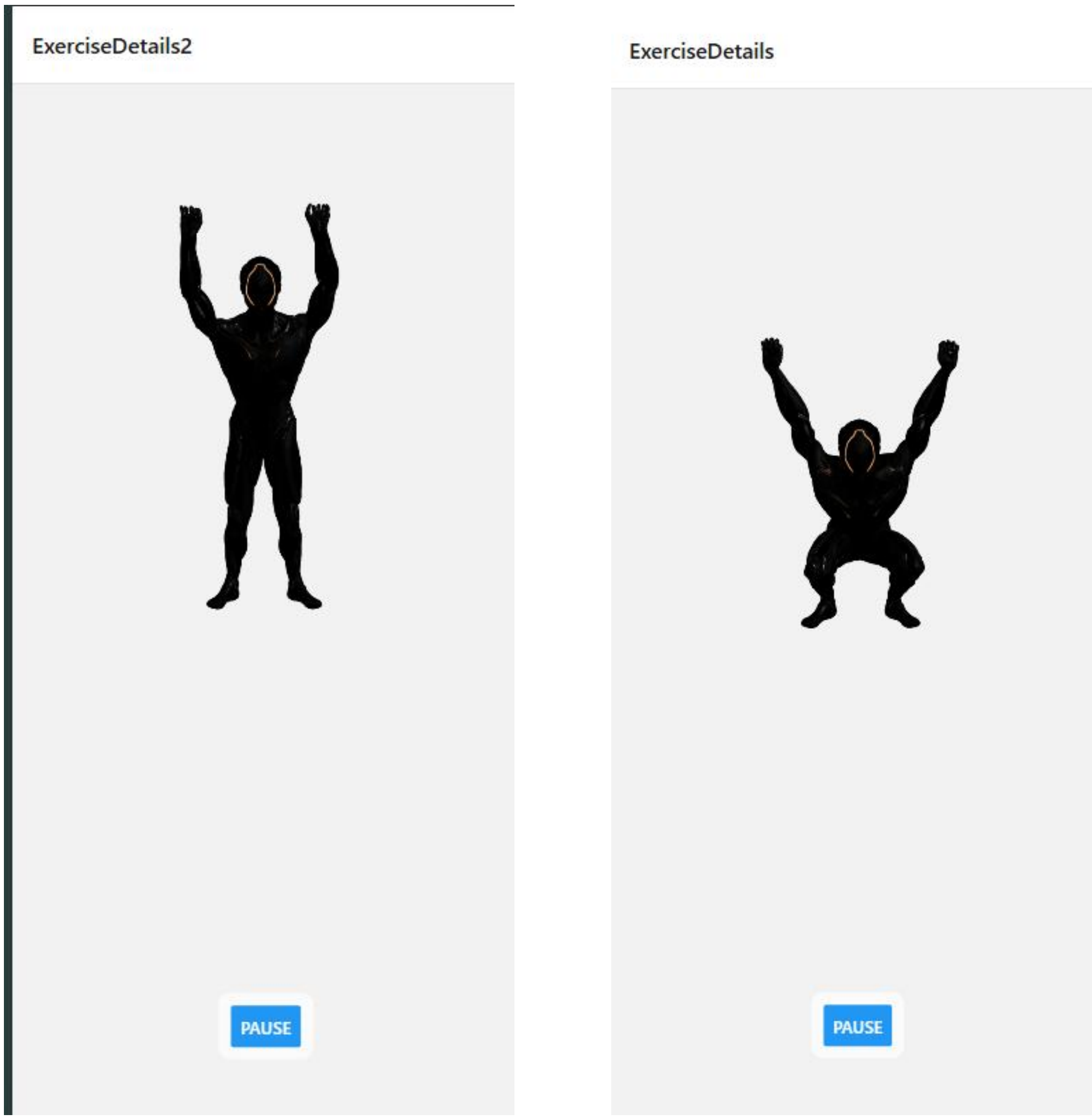


Figure 14:3D models

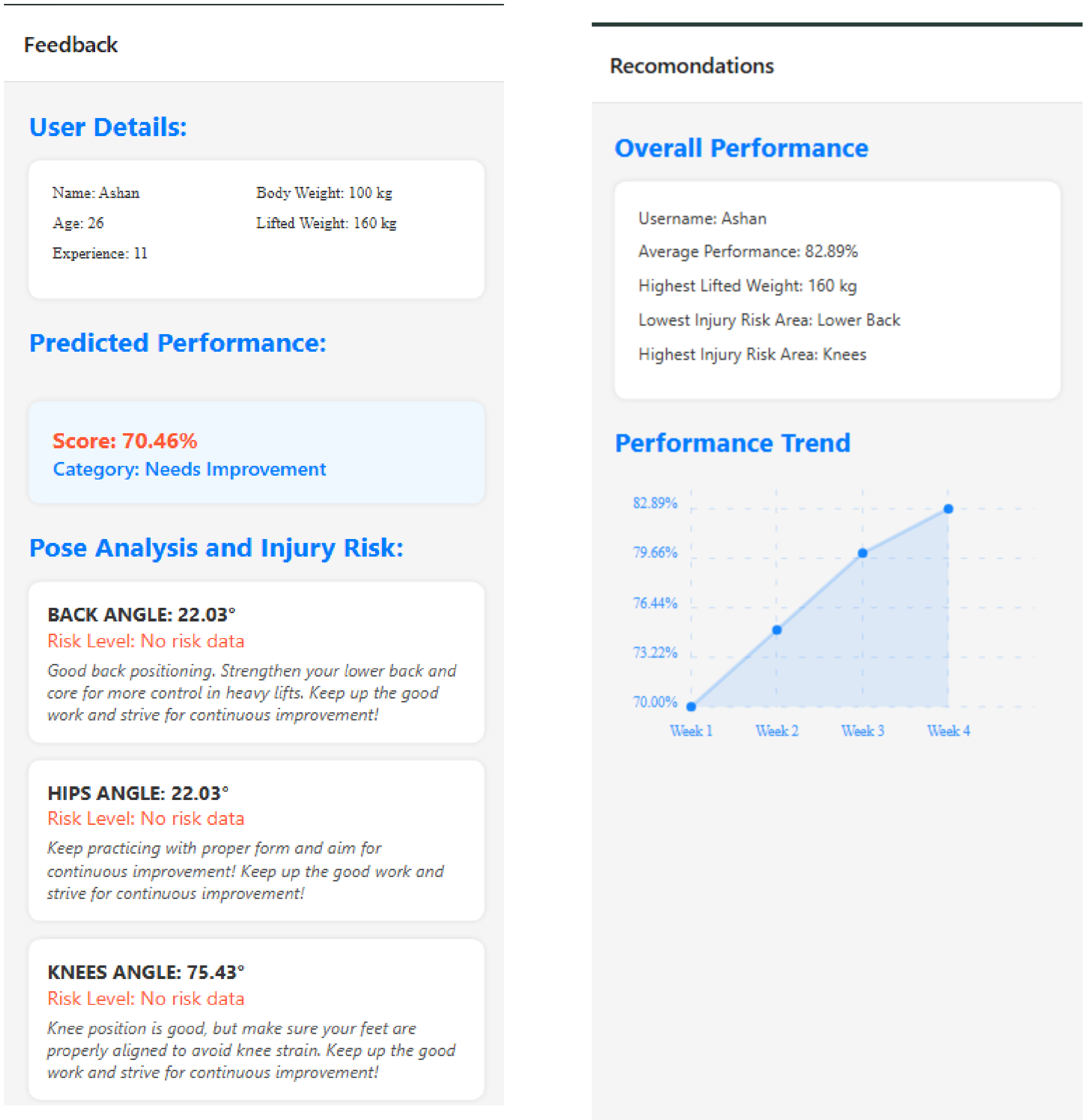


Figure 15: Feedbacks

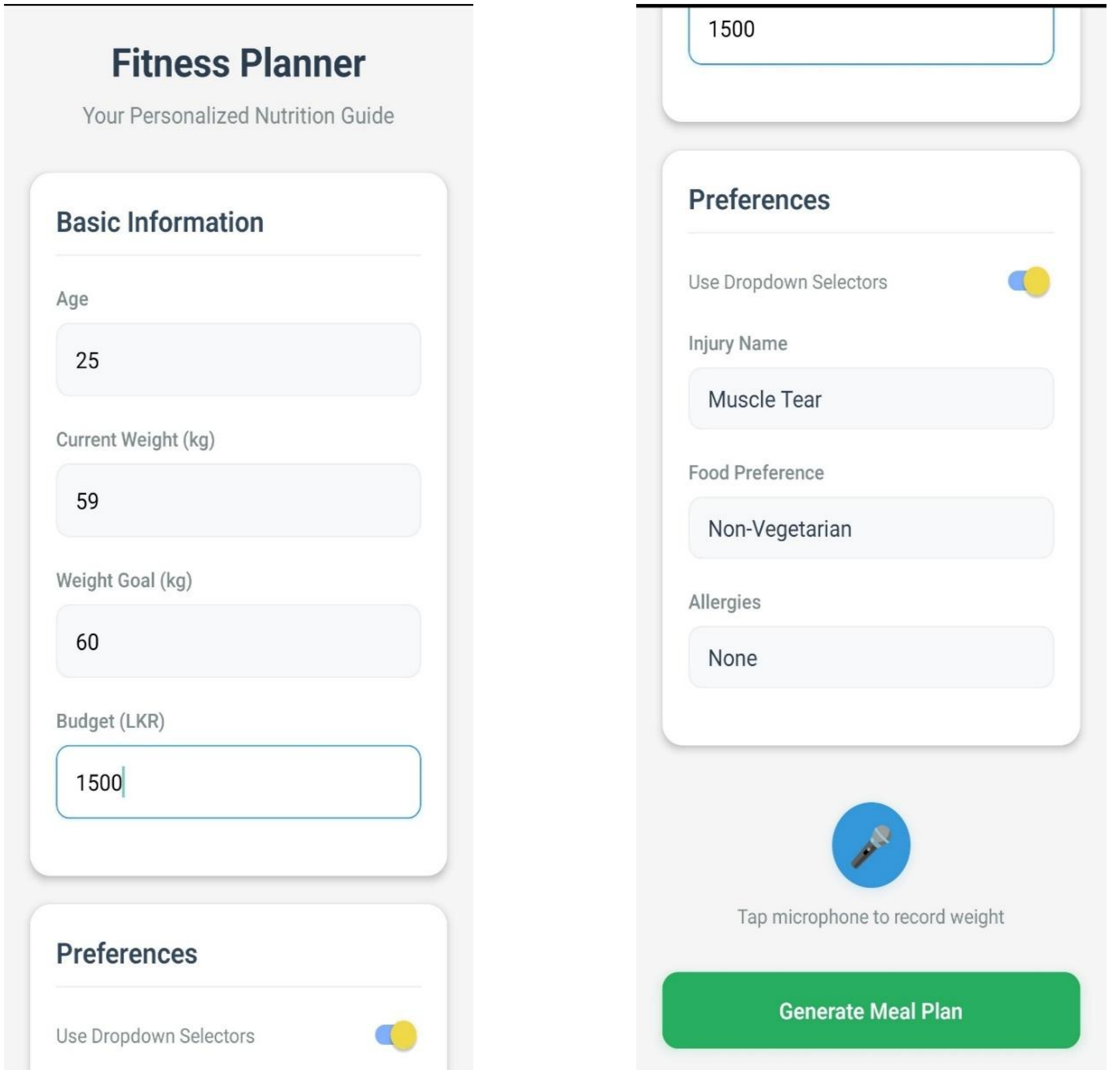
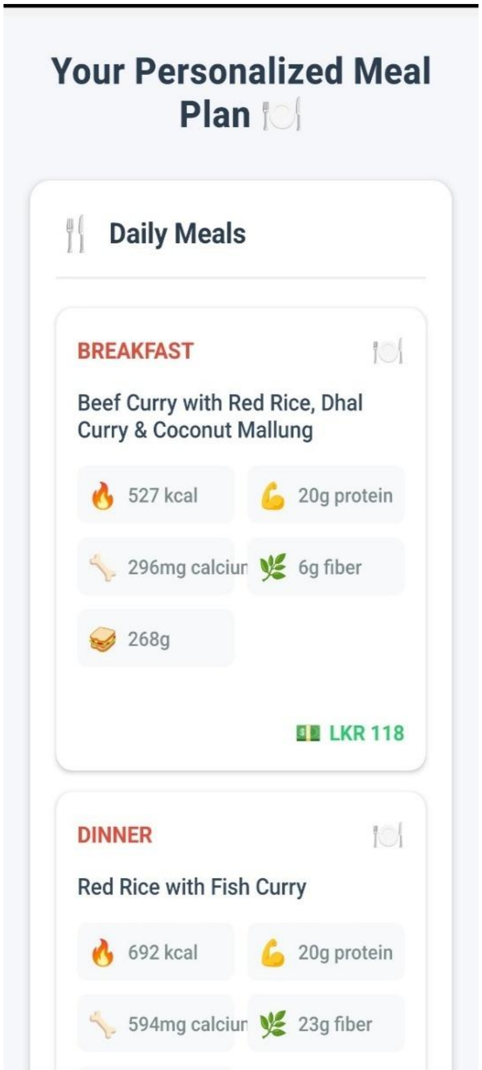
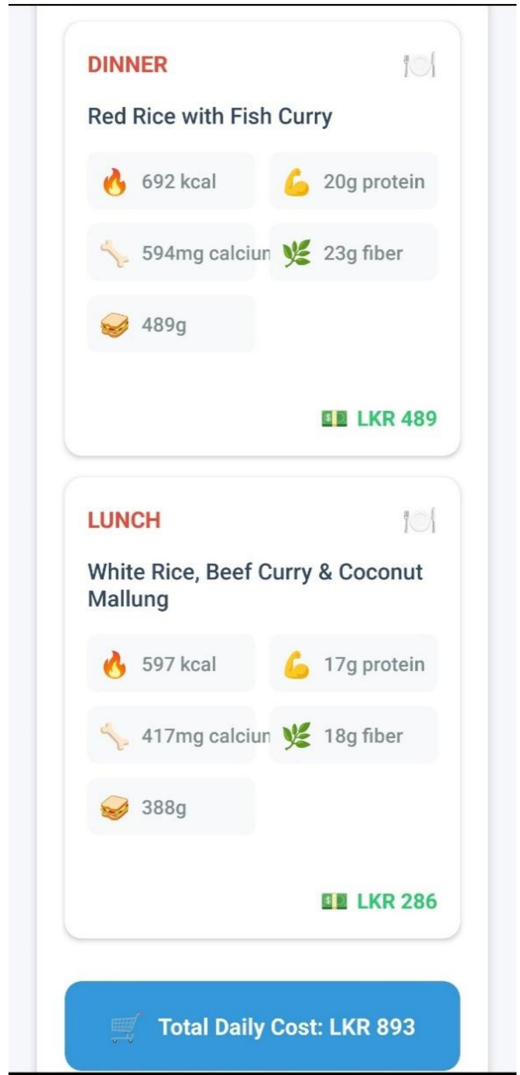


Figure 16: Meal Plans


Your Personalized Meal Plan
Daily Meals
BREAKFAST
Beef Curry with Red Rice, Dhal Curry & Coconut Mallung
527 kcal
20g protein
296mg calcium
6g fiber
268g
LKR 118
DINNER
Red Rice with Fish Curry
692 kcal
20g protein
594mg calcium
23g fiber


DINNER
Red Rice with Fish Curry
692 kcal
20g protein
594mg calcium
23g fiber
489g
LKR 489
LUNCH
White Rice, Beef Curry & Coconut Mallung
597 kcal
17g protein
417mg calcium
18g fiber
388g
LKR 286
Total Daily Cost: LKR 893

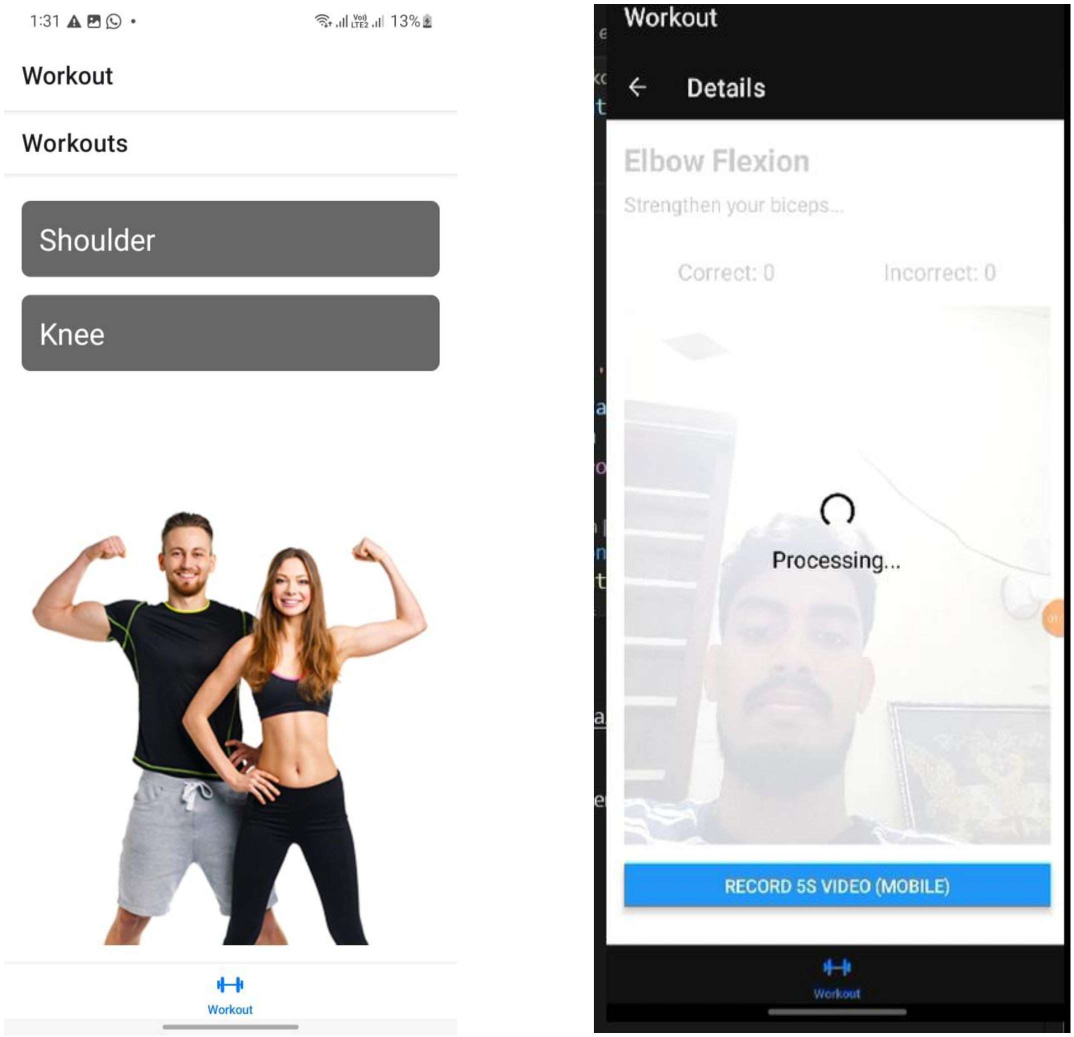


Figure 17: Workouts