LiftRight: Real-Time AI Posture Assessment with Fatigue Pattern Recognition Using Computer Vision

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Crispino, Zyrus Angel B.

Martin, Nicole Christianne F.

Par, Febrilo F.

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CHAPTER 1

INTRODUCTION

This chapter presents the introduction and background of the study. It outlines the research context, objectives, and significance of the study. Additionally, it discusses the conceptual framework, scope and limitations, and definition of terms, providing a comprehensive overview of the research.

1.1 Background of the Study

The concept of fitness has existed for civilizations. Prehistorically, it was once a means of survival for hunter-gatherer societies. One would need to be able to outrun predators, find food, and travel distances to settle. However, with the transition from hunting to agriculture, this reduced the average amount of daily physical activity of the primitive man. It gave them the opportunity to explore the concept of fitness outside the means of survival. Ancient Greek society believed physical fitness embodies discipline and develops the mind. It raises someone's education and socioeconomic status. Even the act of coming together to train the body was a social gathering where the Ancient Greeks would have conversations about art, philosophy, and debate. It would be the emergence of the Industrial Revolution that would greatly influence the modern-day concept of fitness. As a result of the distinct changes in socioeconomic and cultural systems, much of the working class have found themselves leading sedentary lifestyles. It was during this period that many have begun to see physical fitness to keep both the mind and body healthy. (Sevilmis et al., 2023)

Weight-training has long played a major part of physical fitness even during prehistoric times. Ancient Greeks would lift stones and Indians would make use of weighted bats to increase strength and flexibility. Even in the early instances of fitness being attributed to aesthetics, many would resort to lifting older versions of barbells and iron weights to improve the look of their physique.
(Sevilmis et al., 2023).

Weightlifting involves pushing the body to its limits. A key idea in weightlifting is progressive load, which involves progressively increasing the volume, resistance, or intensity of exercises over time to increase endurance, strength, and muscle hypertrophy. Because the body adjusts to stress, making workouts harder guarantees ongoing improvement and avoids plateaus. Although, even when applied effectively, the imminent risk of injury is still present. One of the challenges when progressively overloading is maintaining proper form. Improper form is shown to increase the risk of injury by applying unnecessary strain to uninvolved muscles. Aside from that, overtraining has also been known to contribute to the occurrence of injury. (Bukhary et al., 2023) For athletes, these kinds of injuries end careers. For the casual lifter in full body exercises like squats and bench presses, especially in the absence of a spotter, a moment of weakness could put them in situations between life and death. Understanding these patterns of risk are paramount to preventing injuries, minimizing risk, and maximizing gains while exercising.

There have been countless efforts to utilize technology in the prevention of weightlifting injuries. Shi and Sun (2022) have cited the Chinese National Weightlifting team’s work to reduce the risk of injury and increase athletic performance such as providing their athletes with new gyms and specialized equipment. One study, (Jenkins & Weerasekera, 2022) made use of a low-powered sensor in a wearable device to detect back strain while performing an exercise.

To reduce weightlifting injuries, the researchers have turned to employing techniques in pose estimation. Frameworks in pose correction like that of Thoutam et al. (2022) typically involved experimenting on yoga poses. They relied on techniques in deep learning to identify, correct a specific pose, and provide feedback to the user on their performance.

In applying this framework to sports like weightlifting where deadly injuries can instantaneously happen during continuous movement, users who workout at home or lack the access to a personal trainer now can reduce the risk of injury and lift safely.

The study aims to achieve this goal by developing LiftRight, a cloud-based mobile application that utilizes techniques in deep learning and pose estimation to monitor a person's form and provide comfortable and real-time feedback. By indicating possible areas of risk and pinpointing issues in the user's technique, the application allows the user to improve their form and increase their awareness while training.

1.2 Objectives of the Study

The primary objective of this study is to develop LiftRight, an AI-powered system that provides real-time posture correction for weightlifting exercises. Specifically, the study aims to:

1. Create a dataset to help train the model.

2. Develop and train a pose estimation model using deep learning techniques to accurately detect body keypoints and track movement during weightlifting exercises.

3. Develop a web application that has a real-time feedback system that provides instant visual and textual guidance to users based on detected posture deviations.

4. Incorporate fatigue pattern recognition to adapt feedback based on form degradation caused by physical exertion during weightlifting.

5. Evaluate the system's performance by measuring accuracy, obtaining user feedback and a thorough review from a professional opinion in the exercise domain.

The study benefits from the incorporation of artificial intelligence into our model, which allows us to analyze and provide a proper posture correction application that helps weightlifters with the sense of safety and prevention from injuries or any form of harm. With the utilization of Computer Vision, this study allows real-time feedback from how the users move while training, which allows users to maintain proper form and posture while lifting, know what risks may happen, and incorporate a better lifting regimen.

With this, the study tries to aid weightlifters between their physical capabilities and prevention from injuries. Injuries such as strains, ligament tears, or life-threatening situations are what this study tries to prevent by promoting greater self-awareness for lifters to be able to push beyond their limits without any risk of harm and injury.

The following groups will benefit from this study:

- Weightlifters and Fitness Enthusiasts – The application will allow the users under this group to improve their form during a lift, minimize risks from injuries and harm, and utilize every effective measure during workouts and weightlifting sessions.
- Personal Trainers and Coaches – They can check the system and monitor those who they teach and assist with how their form or posture is during a workout, allowing them to give feedback to their clients, which allows enhanced performance and safety for them.
- Beginners in Weightlifting – Those who are starting a journey in weightlifting will have a grasp on what the proper forms or postures are in real-time, allowing them to improve and determine the correct form and avoid any injuries that they may incur if in the worst case it happens.

- Future Researchers – The study may be able to contribute to further research ideas with relation to AI-powered weightlifting solutions, computer vision, and mobile applications, allowing researchers to ponder upon the study for references and be able to know its impact in the aspect of weightlifters, trainers, and coaches.

1.3.1 Implications of the Study

- Many weightlifting injuries result from improper form and technique.
- This study may promote greater awareness of proper weightlifting form and safety measures.
- The application of AI in weightlifting could lead to more personalized and data-driven training experiences.

1.4 Scope and Limitations

This study aims to develop an AI-powered real-time pose estimation application for weightlifting with the help of computer vision, This application allows weightlifters in aiding them with their posture and improve their form and widen their awareness during training or weightlifting sessions. This study, however, includes these limitations set by the researchers, and these include the following:

- The study will focus on developing the LiftRight cloud-based web application for real-time weightlifting posture correction using AI-powered computer vision techniques.

- The study will be conducted with weightlifters of varying experience levels, primarily targeting beginners and intermediate lifters as the client base.

- Pose estimation will be utilized to track and evaluate posture during weightlifting exercises.

- The system will exclude the use of any additional hardware, such as external sensors, to keep costs low, relying solely on a smartphone camera and cloud processing.

- The study will only include three upper body exercises to be modeled and tested on. These are the shoulder press, bicep curl, and the lateral raise.

- As the system is only intended for pose evaluation of fixed exercises, the system will not include guided warm-up exercises before the user's first session of any given day. There will be, however, a pop-up instead inquiring of the state of the user before their first session of the day, asking if they have or have not warmed up, and informing them of the benefits of doing so, and risks of not doing so.

- Samples for the dataset will only consider well-lit or medium well-lit settings to train the model

1.5 Definition of Terms

Artificial Intelligence (AI) – The ability of machines to simulate human intelligence. Usually used to carry out and perform tasks like computing, recognition, and learning.

Biomechanics – The study of the mechanical aspects of human movement, including how forces interact with the body during physical activity such as weightlifting.

Computer Vision – A field of artificial intelligence that enables computers to interpret and analyze visual data, such as images or video, to understand patterns in human movement.

Cloud-Based Application – A software application that operates using cloud computing resources, allowing users to access features without requiring local processing power.

Cloud Storage Integration - The use of online platforms to store data.

Injury Prevention – Strategies and techniques used to minimize the risk of injury during exercise by maintaining proper form, avoiding overtraining, and using
corrective feedback.

ISO 9241 - A set of international standards focused on the ergonomics of human-system interaction, published by the International Organization for Standardization (ISO).

Latency - the time delay between the input and the output.
Pose Estimation – A computer vision technique that detects and analyzes the positions of key body points (joints) to understand human posture and movement.

Posture Correction – The process of identifying improper body alignment and adjusting improve stability, balance, and safety during exercises.

Progressive Overload – A principle in strength training where the resistance or intensity of exercises is gradually increased to stimulate muscle growth and adaptation.

Real-time Feedback – Instant corrective assistance provided to users based on their detected posture, allowing for immediate adjustments during workouts.

System Usability Scale (SUS) - A standardized 10-item questionnaire used to evaluate the perceived usability of a system.

Usability – The ease of use and accessibility of a system, ensuring that users of all experience levels can interact effectively with the application.

Weightlifting – A form of strength training that involves lifting weights to build muscle strength, endurance, and power. This study focuses on exercises such as squats, deadlifts, and bench press.

CHAPTER 2

REVIEW OF RELATED LITERATURE

This chapter contained the relevant literature and studies that the researchers consider in validating the significance of the study. It also contains information to better comprehend the source and ideology of the research for better understanding.

2.1 The principles of resistance training and it's risks

According to Berry (2025), resistance training is defined as an exercise which involves utilizing working muscles to exert work upon an external force to improve one's strength, performance, and muscle size. In the National Strength and Conditioning Association's basic Strength and Conditioning Manual (Haff, G. G., & Triplett, N. T., 2021), it further expounds upon the definition of strength training by providing some key terms and its principles. The most notable ones being the principle of individuality, specificity, and progressive overload.
Individuality refers to the principle where each person is physically unique and therefore responds differently even when exposed to similar training stimuli. Characteristics like sex, age, genetics, differences in the body like long limbs or wider hips, and previous injuries, can all influence the results of the workout and the individual's optimal training form in each exercise.

The principle of specificity refers to training according to the metabolic demand of a muscle group. This is where we encounter the key components of a training session, namely volume, intensity, and frequency. Volume refers to the amount of work performed. In resistance training specifically, this oftentimes refers to the number of sets and repetitions in an exercise. Intensity refers to the difficulty of the

work performed. As a strength trainer, increasing intensity would mean increasing the weight of your working load. Frequency is the number of training sessions per unit of time, i.e. days, weeks, months. The key to achieving progress in an individual's personal strength goals is the balance of these three components, i.e. when a training session involves high intensity reps, it's best practice to decrease the volume.

Lastly, the principle of progressive overload refers to the practice of gradually increasing the intensity, volume, or difficulty of an exercise to achieve greater muscular strength, size, or endurance. The key point is that the human body is capable of growing accustomed to a specific volume, frequency, or intensity. To further progress, one must train with a load or volume greater than what the individual's body is accustomed to, in slight increments and with adequate rest.
One example in a study by Yang et al (2024) tested for the optimal load increment during warm-ups on college weightlifters. Between 10%, 15%, and self-selected increments, a 10% increment per set improved the snatch performance of the weightlifters, suggesting that a gradual increase is favorable compared to a sizable increase in training load.

Achieving a desired physical outcome involves balancing these aspects according to the nature of an individual's goal. A meta-analysis by Schoenfeld et. al (2018) examines the effect of a high-volume and lower intensity training on the hypertrophy of a group of individuals. While the results indicate that higher volume training increases hypertrophy, it fails to suggest that a higher volume regimen increases strength. Another paper (Schoenfeld et al., 2021) further confirms this by examining the volume-load relationship to three principal outcomes: muscular strength, hypertrophy and endurance. The paper finds that a moderate volume but low intensity workout increases hypertrophy while a low volume and high-intensity training regimen increases strength.

However, as training intensity and volume increase, so does the demand placed on the muscles and nervous system, eventually leading to fatigue. Fatigue is a natural byproduct of progressive overload and is influenced by factors such as training load, rest periods, and individual recovery capacity. When fatigue accumulates, it can compromise movement efficiency, leading to form degradation. This breakdown in technique not only reduces the effectiveness of the exercise but also increases the risk of injury, highlighting the importance of proper load management, rest, and technique reinforcement in resistance training.

2.2 Understanding fatigue in resistance training and the degradation of Form

In both professional and casual settings, injuries are an incidental occurrence. In powerlifting and weightlifting exhibits, common injuries are typically found in the back, shoulders, and knees, with both sexes reported to be at risk for pelvic floor displacement, especially women. (Tung et al., 2024).

A notable paper (Hooper et al, 2012) investigates the link between the effect of fatigue from resistance training on joint biomechanics. The experiment was done with the participants training using a powerlifting regimen known as the (squat, bench, and deadlift). The training sessions were designed to introduce as much fatigue as possible. At the end of the sessions, the researchers observed significant changes in form and technique. The paper emphasized that "every effort should be made to maintain a consistent pattern of motion to load the muscles in a consistent manner and help prevent injury". What they observed is that in the participants' attempt to deload stress from the target muscle, they subconsciously shift the work to an unrelated muscle or group of muscles. As a result, this leads to unnatural contortions and flexions of the muscle group. A level of fatigue is still necessary to stimulate strength, however, after a certain point, any excess volume will lead to overtraining and increase the risk of an injury.

Hegg (2023) explores how social facilitation, particularly through the presence of a spotter, can enhance performance in resistance training. The study examined squat and bench press performances under three conditions: passive spotter (PS), supportive spotter with verbal encouragement (SS), and no spotter (NS). The results showed that the presence of a spotter, especially when providing verbal encouragement, led to significant improvements in squat performance compared to the alone condition. This paper suggests that external support both in the form of protective equipment and fostering a positive environment significantly reduces the exercising party's cognitive load and mental fatigue. This effectively allows them to maintain proper form and boost performance.

Fatigue in resistance training works closely with training methods. Typically, that of training to failure. A paper by Santanielo et al. (2020) analyzes how training to muscle failure affects strength and hypertrophy in trained individuals. To conclude their study, achieving different goals requires different methods. Training to failure allows for greater hypertrophy and strength gains, however, increases the accumulation of fatigue. This can put the trainer in a situation where their form can degrade overtime. Similarly, a meta-analysis by Vieira et al. (2021) assesses the effects of training to failure like in Santanielo et al. (2020), even introducing a new target variable, measuring its effect on power output. Both papers have produced identical results. This emphasizes the need to balance intensity and volume to prevent excessive fatigue while still achieving optimal results. Planning an effective workout method requires a careful approach and consideration of a trainee's goals. It's vital to maintain the delicate balance between volume and intensity to produce long-lasting results without the increasing risk of injury that can come with age or prolonged overtraining.

A paper by Lacerda et al. (2019) leverages volume against intensity as a way to increase muscular size and strength. They argue that the volume of a workout has more influence in promoting muscular growth compared to intensity. The number of repetitions and sets in a workout, with adequate intensity, suggests that it would be in the best interest of an athletes to maximize the load within a given amount of repetitions compared to progressively overloading. This approach minimizes fatigue while maximizing muscular development.

He et al. (2025) employs the use of convolutional neural networks (CNN) to evaluate the biomechanisms in posture-related errors that can lead to injury. Although the human body is resilient, if a set of joints or a muscle group operate in unnatural or sub-optimal conditions for a prolonged period, their physical condition will suffer. Improving posture awareness by providing feedback can reduce strain on working muscle groups and help athletes in practicing proper placement of their extremities to reduce self-inflicted harm.

It is essential to understand the relationship between fatigue and form degradation. Pushing the limits of the human body and mind, despite being an honorable feat, comes with great risk. The papers mentioned above give us insight into how fatigue leads to restricted biomechanical movement patterns that cause poor form. Recent attempts to solve this issue concentrate on incorporating pose estimation algorithms to offer feedback on an athlete's technique. The next section further explores the technologies employed to resolve the issue.

2.3 Pose-estimation as form correction in fitness

Advances in deep learning and artificial intelligence has allowed for real-time video detection to prosper in effectiveness. Pose estimation is a popular method in computer vision that takes the eroded form of an object to identify key joints and make predictions based on their placement within space. By leveraging deep learning-based pose estimation models, researchers are able to discover new information about optimal biomechanics, improving training efficiency, and reducing

harm.

By mapping key skeletal points to a figure, we can assess movement patterns and alignment to gain more information about the human body. Several studies highlight its application in fitness environments. In 2023, Brown et al. was able to detect technique deviations in weightlifting phases like the snatch and clean using a CNN.

Aside from resistance training, pose estimation is widely utilized in training models for other fitness disciplines, such as yoga. Shih et al. (2024) and Thoutam et al. (2022) were able to develop deep learning-based pose correction systems provide feedback and make suggestions about body alignment. These methods can be adapted for fitness respects that involve dynamic movement such as resistance training. Duan et al. (2023) employed single target pose estimation to track players during a basketball game and detect specific actions like if they were running, about to shoot, or dribbling. The data gathered from analyzing the movements of individual players can be utilized to develop strategies based on past matches. Another paper by Choi et al. (2024) utilized a deep-learning pose estimation-based system to make estimations on joint angles during everyday movements. These papers explore the potential of efficient movement tracking and how it can be applied to LiftRight.

A notable aspect of AI-driven form correction is its potential for real-time, personalized feedback, addressing the principle of individuality in training. Body diversity is hardly considered when designing a training regimen for an individual. Factors like limb length and hip width displacement can redefine what "optimal form" can look like per individual. AI-powered models can adapt feedback to the user’s unique biomechanics. Wristwear like that designed by Alves et al. (2023) were able to operate effectively, which can introduce more energy-efficient fitness solutions that can be employed on low-powered hardware like mobile phones.

Huang et al. (2022) demonstrated this by using smartphone-based AI models to recognize fitness activities.

Despite these advancements, recent pose estimation-based fitness correction technologies often fail to explore fatigue as a key parameter in their assessment. A paper by Hooper et al. (2012) poses the existence of a link between fatigue and form degradation. Incorporating fatigue-sensitive mechanisms into AI-based posture correction systems can provide further context in injury prevention by adapting feedback in real time according to the fatigued state of a trainer.

Incorporating predictive fatigue models encourages a comprehensive approach when providing training feedback for safe and effective strength training. This can help lifters avoid movements that put unnecessary strain on a set of joints which can lead to increased risk of injury, providing a more comprehensive training report to the user. This section covers mitigating fatigue in its physical form. The next section covers mental fatigue that can hinder an individual's training performance.

2.4 Cognitive Load

Cognitive load plays a silent but significant role in an individual's physical performance. A study by Staiano et al. (2023) investigates the effects of mental fatigue (MF) during a rigorous training session. The paper has found that increasing cognitive load raises the rating of perceived exertion (RPE) of an individual. Their perception of a physical task appears to be more challenging because of the mental strain. The decrease in motivation can lessen the effectiveness of a training session.

A paper by Ovchinnikova et al. (2023) highlights the link between intense physical activity and improving an individual's level of neuroplasticity. Physical strain affects bioelectric brain activity and can alter cognitive processes such as memory, attention, and decision-making. Managing cognitive load allows us to make informed decisions about adequate amounts of volume and intensity during strength training.

Van Cutsem and Marcora (2021) further examine the effects of mental fatigue in performance in team sports. Team sports like basketball, soccer, and volleyball not only require lasting physical endurance but the ability to maintain camaraderie and make decisions that would benefit the team. The findings suggest that mental fatigue not only impairs physical performance, but also reaction time and decision-making abilities. To combat this, athletes include fatigue conditioning as part of their training to practice maintaining peak performance even in a fatigued state.

These studies make the role of fatigue in physical training abundantly clear. Managing physical and mental fatigue is essential to optimize physical performance, make informed choices about volume and intensity of an exercise, and reduce injury. When fatigue is kept under control, it becomes easier to recover, avoid overtraining, and reduce the risk of injury. Ignoring fatigue can lead to poor form, lack of focus, and a higher chance of getting hurt. Overall, understanding and managing fatigue is a key part of any effective and safe training program.

2.5 Future directions/current direction of the paper

One area for the advancement and further improvement of Machine Learning and Artificial Intelligence is the possibility to aid in the medical field. Particularly in this case, injury and risk prevention ahead of time. As Van Eetvelde et al, (2021) has said before that the growth of Machine Learning is being applied in the field of athletics in the sense that the machine could learn and predict sports injuries as well as prevent them, while seeing patterns that would otherwise be practically invisible to human beings in terms of information parsing. For "LiftRight", the current direction of the paper is the further detect subtle changes in movement patterns, rep speed, comfort, and stress that can possibly be identifiers or parameters in predicting and preventing weightlifting injuries or incidents.

Adding to that, in our current time, "LiftRight" is only a mobile app. However, such gadgets like wearable sensors are very prevalent now. Specifically speaking in the field of sports, Lloyd (2021) has discussed how wearable gadgets with models that track tissue loading in real time could possible change in-field sports biomechanics, in addition to weightlifting. The possibility to add such wearable gadgets and sensors in addition to the mobile app and web client can help the model in further identifying true positives and true negatives, as opposed to simple visual and pose estimation data. Such systems could help monitor heart rate, for one instance, and even blood oxygen, for another, which may be additional parameters that can aid in injury and incident prevention in regard to weightlifting. After all Henriquez et al, (2020) has spoken about how machine learning can be used to predict lower extremity musculoskeletal injury risk in student athletes. Their research can be highly relevant in regard to weightlifting, specifically in weightlifting exercises may use the lower body as well on top of the upper budder. Such weightlifting exercises may include but are not limited to, squats, deadlifts, and lunges.

And speaking of such devices, Kovoor et al. (2024) had said that sensor-enhanced wearables have potential for injury prevention. Their work on such devices and automated analytics for injury prevention in sports does give credence to the idea that combining sensors on top of real-time data analytics specific to a user's activity can give significant insights when it comes to monitoring their normal state and finding anomalies. "LiftRight" and systems similar may benefit from such technologies to track data and parameters otherwise unavailable to the current pose data estimation system. To which the sensor and the model would correspond with each other to better identify anomalies and identify proper risk from the usual norm within a weightlifting session.

Taking all of this into account, "LiftRight" aims to continue to create a real-time pose estimation-based model that will assist weightlifters in performing their exercises safely, as well as preventing injury or incident by identifying improper form via pose estimation data. Comparing the user's current pose data, against the model's ideal pose data for that weightlifting exercise, in addition to identifying patterns in the user's repetition score throughout sets and suggesting appropriate actions. Further development could lead to a more robust system as well as even smoother integration between human and system. And with the help of user and developer feedback, "LiftRight" can continue to improve to the benefit of both.

CHAPTER 3

METHODOLOGY

This chapter will present a discussion of the methodological framework of the study, the process of data gathering, the research design and instruments, the testing methodology, the system components, process and design, selection of samples and ethical considerations to be able to determine proper processes and accurate data gathering and interpretation.

3.1 Methodological Framework

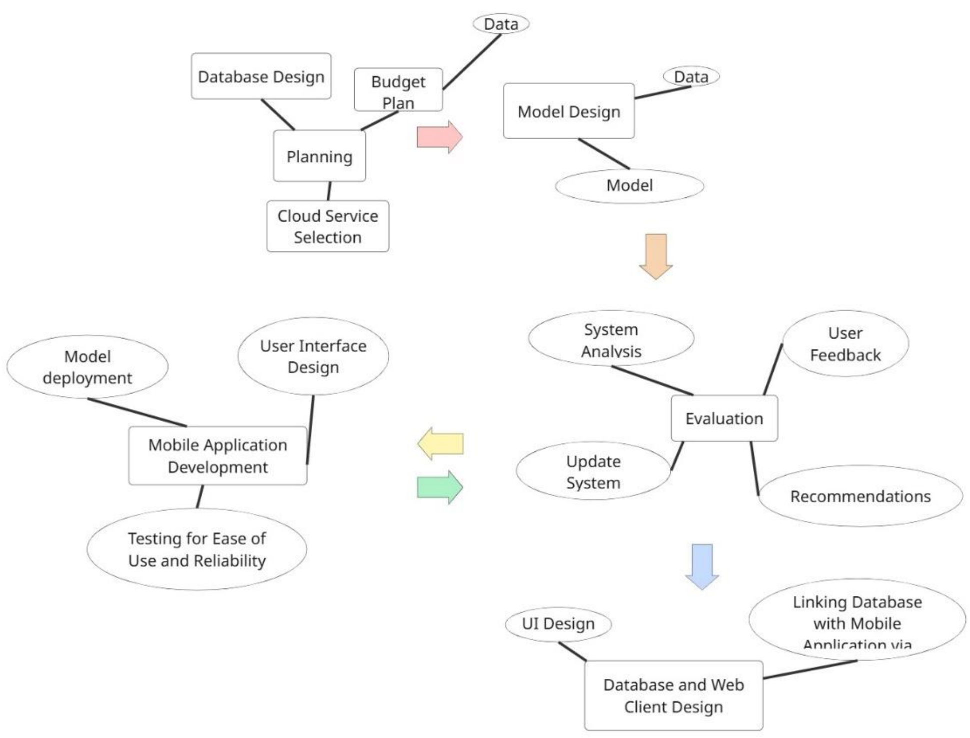

Figure 3.1 : Methodological Framework

Shown in the figure is the framework of the study, the researchers aim to obtain resources necessary for the completion of the study, as well as a budget to fit the outcomes and be able to suffice for the study. Appropriate resources such as a database design for clarity in acquiring data, and cloud services that allow us to run our application smoothly and without the need of physical hardware to function for the entire application.

Next is the model design, which includes obtaining a dataset, training this data and developing this to become the main model for the application. This model will be tested by means of acquiring certain metrics that depict the effectiveness of the model, and whether it can be deployed during the next phase.

Evaluation would help ensure that the model has the right metrics and measures to predict the desired output of pose estimation; this part ensures that the model would run smoothly, and alongside this, would be the development of a web application of which the model will be incorporated onto. The web application is one of the outliers to know the effectiveness of the model as well as the mobility and effectiveness of the application. Recommendations would also be seen here to improve certain lapses during the testing and evaluation, and this will go on until seen necessary to be run.

Finally, the database and web client design will be handled for finalizations of the entire application with regards to its database and the web client that connects the users to their data and such. Mobile users can link their progress with the application using the web client, with a fresh UI client so that users can properly analyze and search their data in the database.

3.2 Data Gathering Procedure

3.2.1 Dataset Collection

The researchers will gather and utilize samples of the exercises to be included in the pose estimation model. 50 entries per exercise will suffice to adequately test a model (Nguyen et al., 2019).

To provide the best possible guidance for the users, experts in fitness such as gym coaches and instructors, will be used to train the model. In selecting experts for the dataset, this ensures that the basis for proper form remains accurate and based in reality. Around 5 distinct participants will be used to collect data for the model. A notable study by Ishii et al. in 2020 demonstrates that it's possible to work with a small dataset to train the model, utilizing only one entry per exercise, expert-labeled inputs, and incorporating a correlation approach to their classification model. In this study, the dataset will focus on the number of individual repetitions for the model to learn from. By providing consistent and accurate representations of proper form, this further supports that few but high-quality samples will benefit the model logistically and functionally. While participants without recent injuries dating to at least one month ago will be given priority. (Jones et al., 2020)

3.3 Research Design

The direction of the research favors a mixed-method design. Specifically, that of the explanatory model.

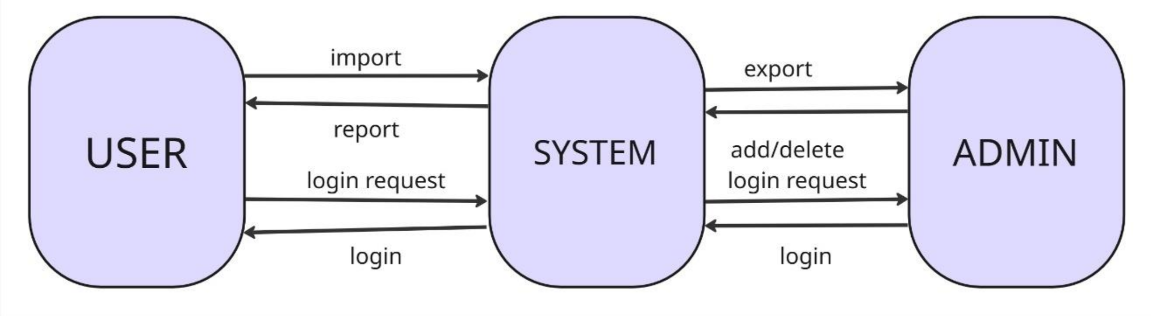

Figure 3.2 : Context Level Diagram

The context level diagram involves the actions of the user, system, and admin. The user can import/export data to the system, the system allows for the generation of a report, and to add/delete data, the admin exports data from the system, and allows to add/delete data.

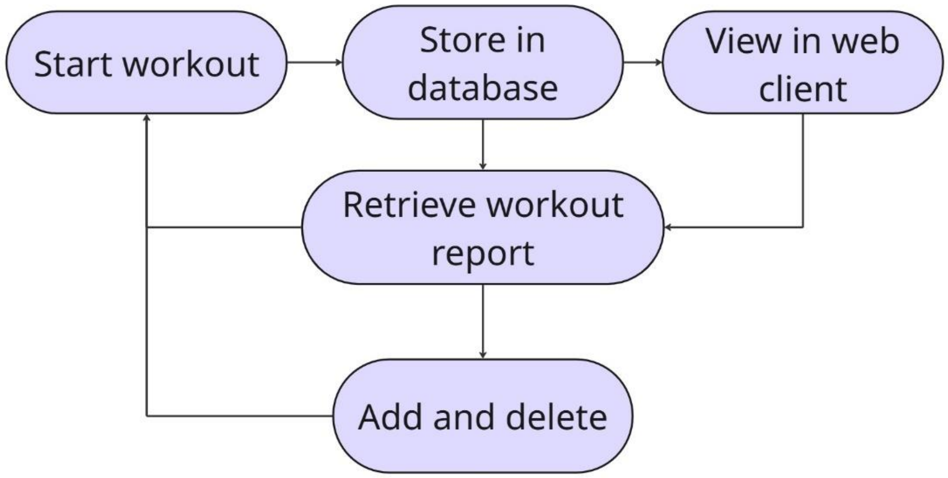

Figure 3.2 : Context Level Diagram Flowchart

(Creswell & Plano Clark, 2007) demonstrates that this design is intended to further interpret the results of a quantitative investigation by providing insight from a qualitative standpoint. The numerical data most likely to be interpreted would include personal information about the participants, the number of correct and incorrect repetitions, the amount of time it takes to complete an exercise, and the volume of a set. Understanding and recognizing patterns among these factors will likely provide further insight to how fatigue can affect different bodies and how the application gives the users supplementary awareness surrounding their fitness goals. The collection of user feedback and professional opinion in the later phases of the study will offer critique on the functionality of the application and how it can be improved.

3.4 Research Instruments

To evaluate the system's usability and effectiveness, the following research instruments will be used:

- System Usability Scale (SUS) - A standardized 10-item questionnaire that the research participants will complete after using the system.
- Open-Ended Questions - To gain insights not covered by structured questions included at the end of surveys for suggestions such as app improvements or issues discovered during use.
- Interviews - An interview with a fitness professional shall be conducted to further validate or improve the practicality and functionality of the mobile app.

3.5 Testing Methodology

3.5.1 Algorithms

The conceptual framework for this study follows the sequence of an input, a process, and an output. Input data consists of the user's pose estimation data while performing an exercise. This data follows these steps:

- Pose Estimation - Extracts key body landmarks using computer vision techniques and libraries
- Pose Correction Feedback - Analyzes user form and pose data, compares to expected ideal data from a trained model, and provides auditory and visual feedback.
- Fatigue Recognition – Identifies error patterns within a user's length of a

given exercise over time and suggests extended periods of rest, or a lesser number of sets.

The system will then output real-time feedback, progress tracking, and a session report, to which a summary will be provided in the mobile app, while a full one will be available in the user's web client.

3.5.2 Performance Evaluation Metrics

To evaluate system performance, the following criteria will be used:

1. Accuracy- Compare against expert annotated data using performance metrics such as precision, recall, F1 scores, and keypoint detection.

2. Usability- The usability of the software will be graded according to IS0 9241-11 based criteria which includes effectiveness (if a user is able to complete a given task), efficiency (the amount of time it takes to complete a task), and user satisfaction. The practicality of the system will be measured using the System Usability Scale (SUS).

3. Latency- Measuring the time between user input to system output.

4. Effectiveness- The effectiveness of the system will take into consideration of both user and expert feedback.

3.6 System Process and Design

3.6.1 Block Diagram

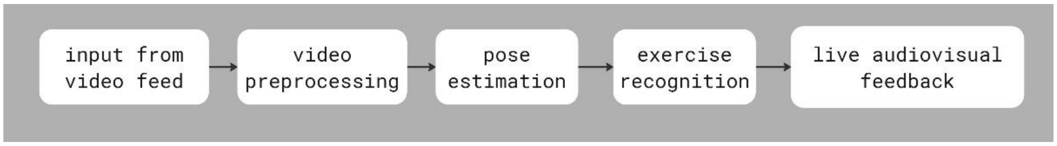

Figure 3.3 : Block Diagram

The system first captures video feed from the end user. The video feed is preprocessed to be able to initiate pose estimation from the system, as well as

this, the exercise being done by the user is recognized. Finally, audio-visual feedback will be demonstrated to show the user their results and be able to identify their pose, if there are errors in their pose, or analyze their pose based on the exercise the user is doing.

The system will be hosted as client-based to make it faster and more private for the user. Since it runs on the user's own device, it doesn't need to send video to a server, which helps keep personal data safe. It also means the feedback can happen right away, even without a strong internet connection.

3.6.2 System Flowchart

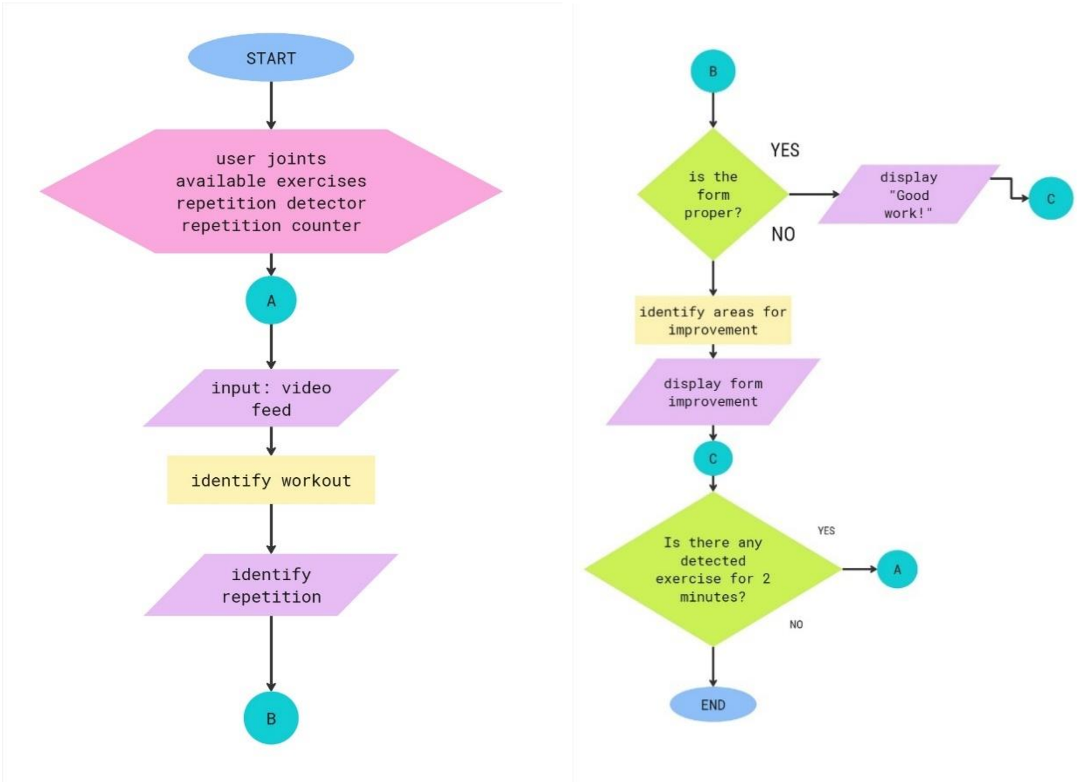

Figure 3.4 : Proposed System Flowchart

This flowchart explains how the exercise tracking system is supposed to function. First, the system takes the video input from the user and tries to recognize the exercise by looking at their joints. Then, it counts how many times the exercise is repeated. After that, it checks if the user is doing the movement correctly. If the form is good, it shows a message like "Good work!" to encourage the user. But if the form is wrong, the system will try to find mistakes and tell the user how to fix them. Also, if the system does not see any exercise happening for two whole minutes, it will stop because maybe the user is not exercising anymore. This is how the system is designed to work.

3.6.3 Architecture

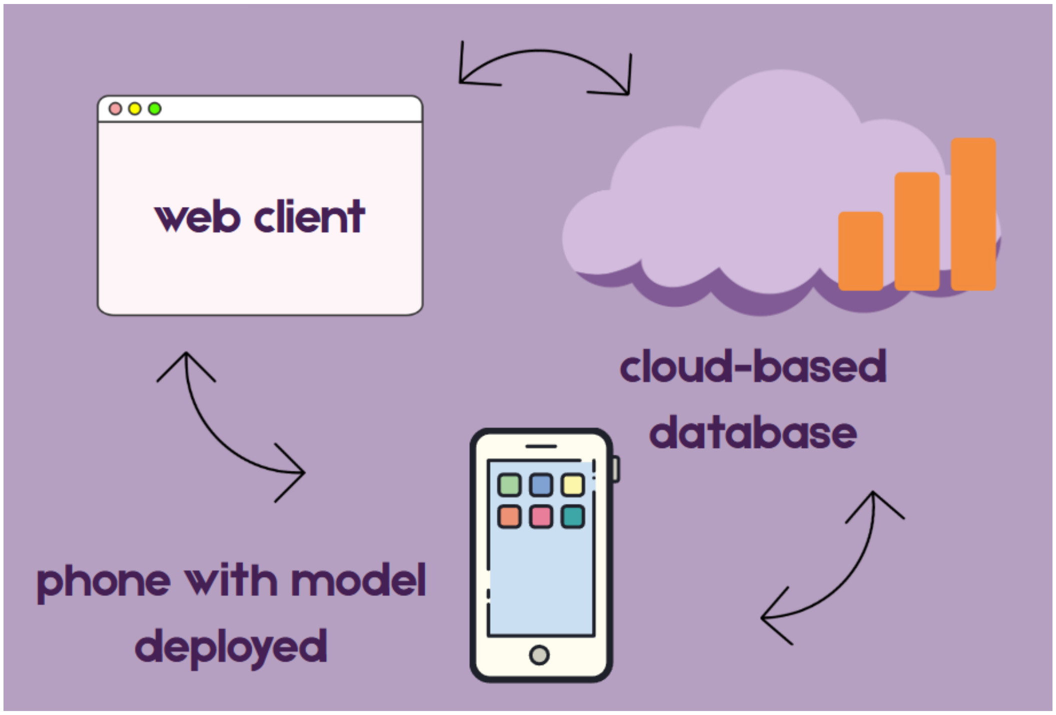

Figure 3.5: System Architecture

This figure shows the architecture of the system, which goes through the following: a web client, a cloud-based database, and a phone with the model deployed. The architecture simplifies the overall structure of the system, which allows for seamless access through all contributors inside the architecture.

3.6.4 User Onboarding Process

Users are urged to input relevant personal data including but not limited to; height, age, gender, weight, and prior experience with weightlifting, which will be utilized to better categorize feedback data and provide user context.

3.6.5 Warm-up Warning Prompt

Before starting an exercise session, there will be a display of a pop-up message prompting the user to confirm if they have performed adequate warming-up. This reminder will be used to reduce the risk of injury by encouraging users to prepare their muscles properly before weightlifting only if that is the user's first exercise of the day. The system will not include guided warm-up exercises, however.

3.6.6 Fatigue Pattern Recognition

The system will utilize Fatigue Pattern Recognition, which will be defined by the user's decline in performance in repetitions per sets. Despite the human body's resilience, a muscle group or a set of joints will deteriorate if they function under abnormal or suboptimal conditions for an extended length of time (He et al. 2025). Athletes would benefit more from maximizing the load within a specific number of repetitions than from gradually overloading, according to the number of repetitions and sets in a session with appropriate intensity (Lacerda et al. 2019).

3.7 System Components

The system will include the following architecture:

1. A camera to track and detect movement from the end user
2. Pose estimation and validation software to process pose data.
3. A Web Application through which will allow the user to view their past session data and reports.
4. A cloud-based database where all user data will be stored with.Role Based Access Control wherein the following roles will be included:

- User – performs exercises and receives feedback.
- Coach – views reports from assigned users and provides additional comments.
- Admin – manages accounts, uploads new exercise models, and oversees system integrity.

3.8 System Design

3.8.1 Software Process

The software will detect the weightlifting process of the end user; it tracks how many repetitions the user has lifted and will correct their form if necessary. A sound or a warning inside the application or system will detect the error and remind the user that their form has irregularities, which then the software corrects for the user. All the information, such as reps and errors, will be stored inside the database, and the application also tracks this data.

3.8.2 Proposed Database Design

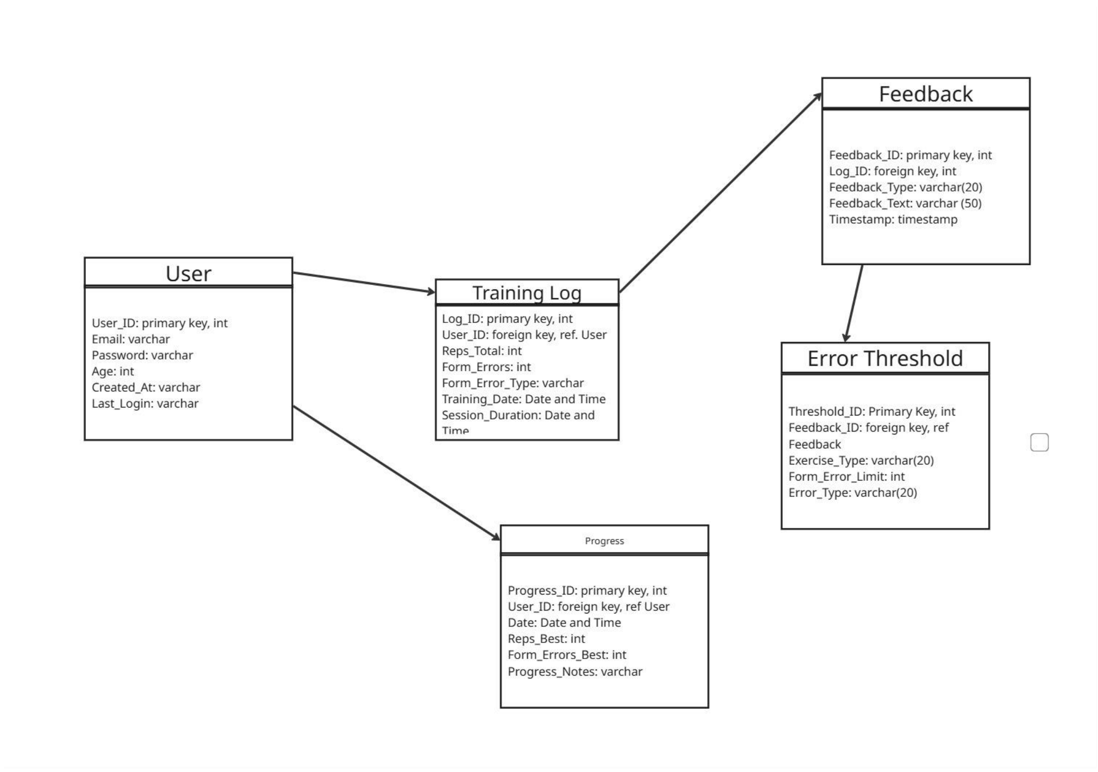

Figure 3.4 : Proposed Database Design

The database design may include the following tables:

1. User Table - This table stores personal and account information for each user.
    a. User_ID: Unique identifier for each user.
    b. Name: Name of the user
    c. Email: The user's email address
    d. Password: The user's hashed password
    e. Age: Age of the user
    f. Created_At: Timestamp for when the user account was created
    g. Last_Login: Timestamp for when the user's last login

2. Training Log Table - logs each user's weightlifting session, including performance metrics.
    a. Log_ID: Unique identifier for each training log entry.
    b. User_ID: Foreign Key linking to the User table.
    c. Reps_Total: Total number of repetitions performed during the session.
    d. Form_Errors: Number of errors detected in form during the session.

3. Feedback Table - stores the feedback provided to the user after each training session, including real-time corrections and suggestions.
    a. Feedback_ID: Unique identifier for each feedback entry.
    b. Log_ID: Foreign Key linking to the Training Log table.
    c. Feedback_Type: Type of feedback.
    d. Feedback_Text: Detailed feedback or explanation for the

correction.

e. Timestamp: Timestamp for when the feedback was generated.

4. Progress Table - tracks user progress over time, including improvements in form and performance.
    a. Progress_ID: Unique identifier for each progress record.
    b. User_ID: Foreign Key linking to the User table.
    c. Date: Date of progress update.
    d. Reps_Best: Best repetition count achieved.
    e. Form_Errors_Best: Minimum number of form errors recorded.
    f. Progress_Notes: Additional notes on the user's progress.

5. Error Threshold Table - tracks the thresholds of form errors that would trigger alerts or feedback and serves as a reference table for exercise-specific feedback parameters.
    a. Threshold_ID: Unique identifier for each error threshold.
    b. Feedback_ID: Foreign key linking to feedback table
    c. Exercise_Type: Type of weightlifting exercise.
    d. Form_Error_Limit: The maximum number of errors allowed before feedback is triggered.
    e. Error_Type: Type of error.

3.8.3 Proposed User Interface

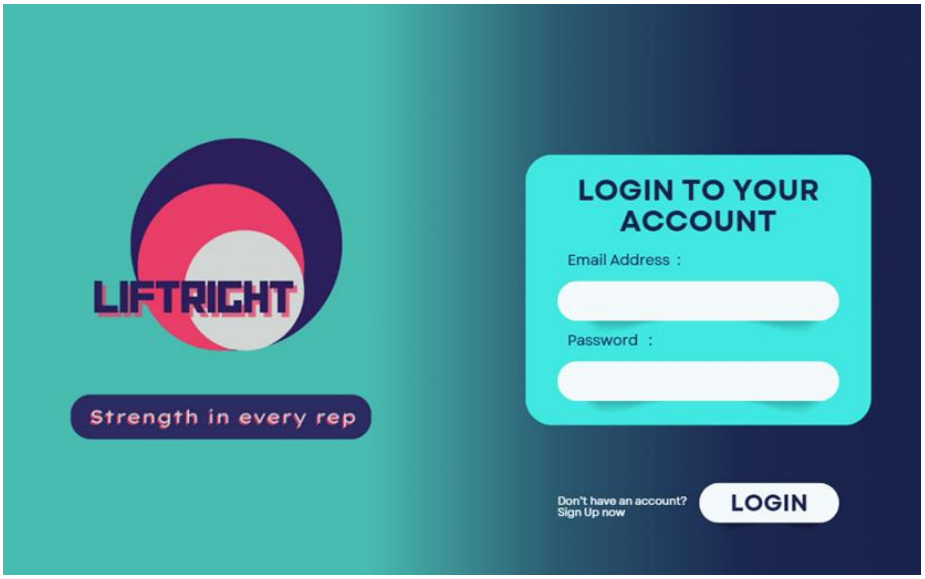

Figure 3.5 : Loading screen

This figure shows a simple login screen, which requires the user's registered email address and password before login. This screen usually comes first upon accessing the website.

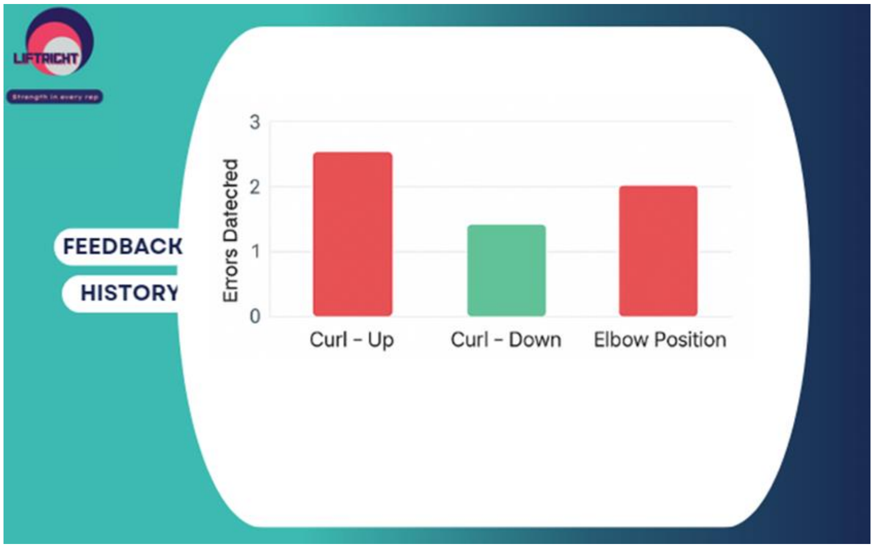

Figure 3.6 : Feedback History

This figure shows a sample report of the number of errors detected in an exercise repetition. These figures are represented in a bar graph to accurately display exercise performance.

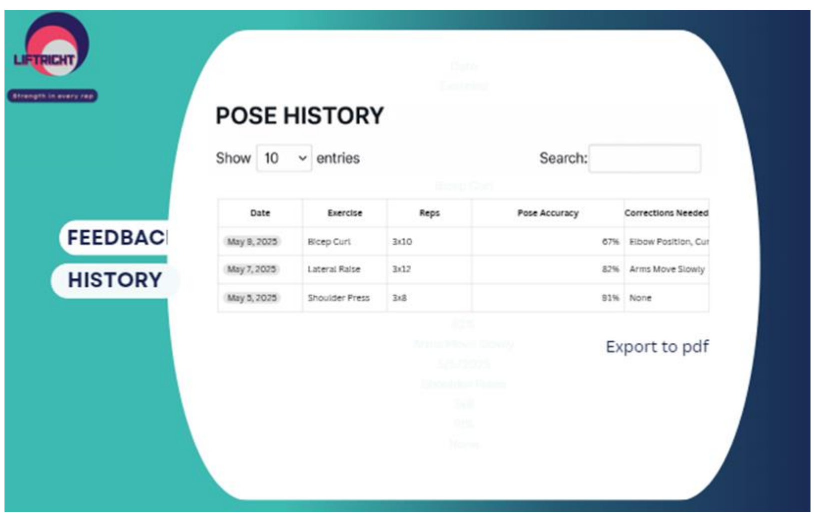

Figure 3.7 : Exercise Report

The figure above shows the report generated which can be exported via pdf. It details the amount exercise, number of reps, and the percentage of good reps per exercise.

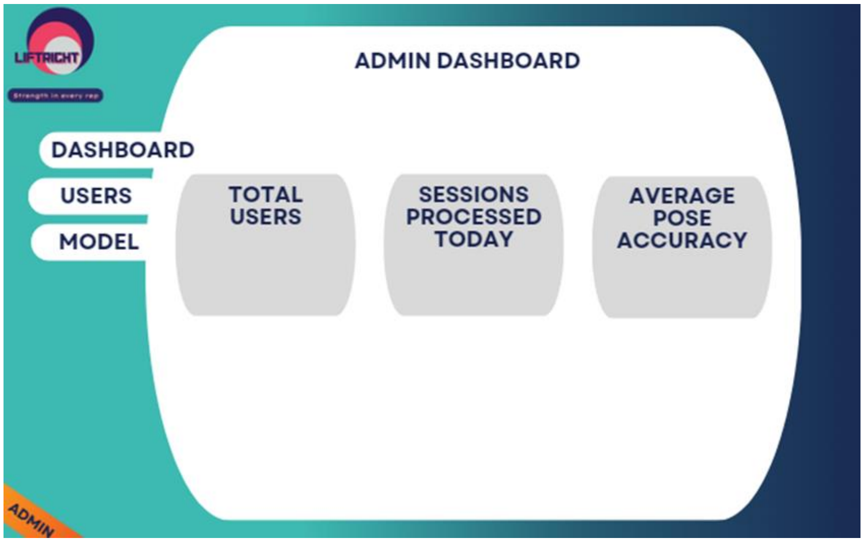

Figure 3.8 : Admin Dashboard

The figure above details the UI for the admin dashboard. It includes data such as total users, sessions processed today, and the average pose accuracy of each report.

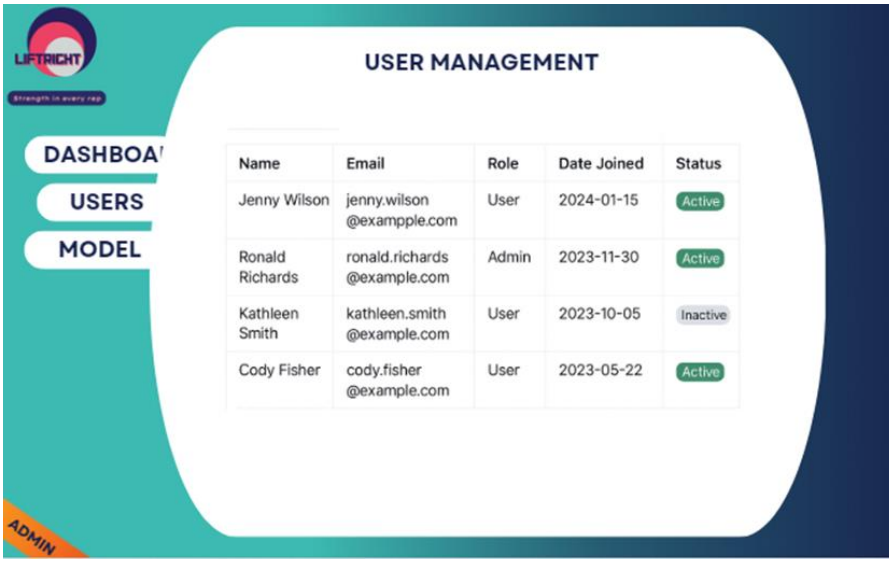

Figure 3.9: User Dashboard

The figure above shows the proposed user dashboard. What's shown here is the list of users, their roles, and whether they're actively using the app.

3.9 Selection of Samples

As the dataset has specific requirements to garner data, the researchers plan to use non-probability sampling methods such as purposive sampling/criterion sampling. Due to the requirements, it purely resembles purposive sampling that gathers data using specific requirements from the participants that fits the study's purpose. Purposive sampling, in the researchers' terms, can also be called criterion sampling since certain criteria should be met to be included in the study, criteria such as low light/low contrast video samples, an age requirement of 18-50, and so on shows the required criterion for the study.

3.10 Ethical Considerations

All participants shall be informed and be asked for their consent before participation in the research, in accordance with ethical standards. Specifically:

- Informed Consent: Participants shall be briefed on the objective of the research. As well as given information on how their data will be used should they continue.
- Data Privacy: Personal information will be stored securely in compliance with data protection laws.
- Participant Health: Participants must meet health requirements. Ensuring that they are fit for the study.
- Purposive sampling.

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Appendices

Appendix A

Budget Plan

Name	Cost
Colab Pro	P2767.8 per month
Printing Supplies	P1200
Gym Membership	P840 (P70 daily pass * 9 visits per month)

Table A. 1 : Budget Plan

Appendix B

Gantt Chart

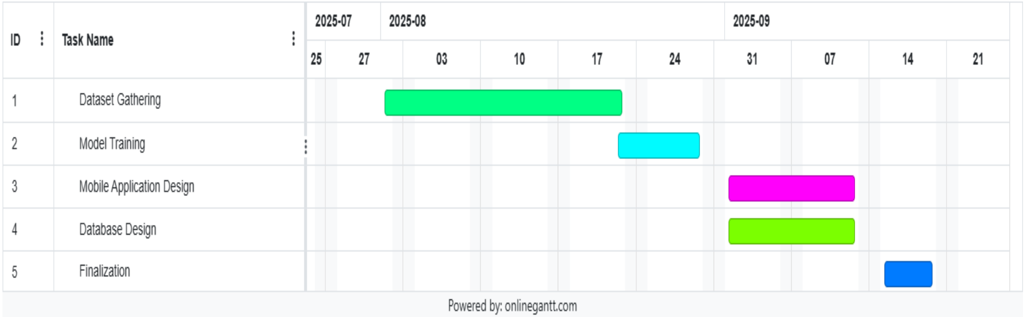

Table B. 1 : Budget Plan