Real-Time Biomechanical Squat and Deadlift Posture Analysis Using Google Machine Learning Kit

AI-Powered Fitness Coach

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***Abstract*—This project presents the development of a mobile application for real-time posture analysis during squat and deadlift exercises, using Google Machine Learning (ML) Kit pose detection. Proper exercise form is critical in preventing injuries, underscoring the need for systems that provide immediate feedback, an aspect often missing in existing fitness applications. This study addresses that gap by designing an app that not only guides users through motion analysis but also incorporates a safety mechanism to detect sudden falls. The system employs algorithms to process landmarks, calculate joint angles, count repetitions, and trigger emergency alerts. Two groups of bodybuilders confirmed the usability and accuracy in real-time biomechanical squat and deadlift posture analysis. These findings contribute to the field of AI-driven fitness by introducing a non-wearable, mobile-based solution for guided strength training. In addition, it offers societal benefits as an AI-powered fitness coach that aims to promote public health.**

Keywords*—Pose detection; squat and deadlift; Google ML Kit; fitness; posture analysis; emergency; public health

I. INTRODUCTION

The evolution of technology within the fitness industry has significantly advanced training methods and monitoring capabilities for athletes, particularly in strength training disciplines such as bodybuilding and powerlifting. However, experts such as coach / trainer are required to provide real-time feedback during the training to ensure the accuracy and efficiency of training [1,2]. This is an issue for those who cannot afford a high-paying coach or lack of sufficient coach for everyone. Furthermore, common injuries in strength training, which often result from improper form, continue to be a major concern [3,4]. These injuries not only hinder progress but can also lead to long-term health issues, significantly impacting an athlete's training and competitive performance.

Current fitness applications predominantly emphasise quantitative metrics such as calories burnt, distance covered, or heart rate variability. While these data points are valuable, they fail to capture the qualitative dimensions of strength training exercises, such as joint angles during a squat or spinal alignment during a deadlift. These qualitative aspects are critical to ensure proper form and minimizing the risk of injury. Consequently, there is a compelling need for more specialised technology that provides real-time, context-aware feedback on exercise form and technique.

This project presents a novel mobile application that utilises real-time motion capture technology to improve exercise performance and safety in strength training. By integrating Google's ML Kit pose detection for accurate skeletal tracking, the application delivers immediate, actionable feedback to users during their workouts. This capability not only supports injury prevention but also improves training efficiency by ensuring correct biomechanics are maintained throughout each exercise. The innovative design and user-centric interface address a significant weakness in existing fitness solutions, which often neglect real-time biomechanical evaluation. By bridging this gap, the proposed system empowers users to train more effectively, safely and autonomously.

This paper is constructed in five sections. Section II summarises the existing research studies and market products of fitness assistance and highlights the research gap. Section III presents the proposed architecture of the system with associating algorithms. Section IV records the performance of the proposed AI-powered fitness coach using an experiment carried out among bodybuilders. Finally, Sections V and VI discuss and compare this research with previous research and market products, highlight the limitations of the research and future works.

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This article processing costs are supported by INTI International University and Asia Pacific University, Malaysia.

II. Literature Review

This review of the literature systematically examines key areas relevant to the development of a real-time posture analysis application tailored for squat and deadlift exercises. It begins with an overview of motion capture technologies, including both optical and non-optical systems, and traces their evolution with the integration of artificial intelligence - highlighting the enhanced analytical capabilities brought about by these advancements. The review then focusses on Google's ML Kit for pose detection, highlighting its role in enabling real-time feedback mechanisms that are critical for immediate posture correction in exercise applications.

A detailed exploration of existing applications that employ Google's ML Kit illustrates its practical implementation and growing adoption in domains such as fitness, yoga, and posture correction. Furthermore, the review delves into the biomechanics of squats and deadlifts, discussing correct form, joint alignment, and load management, thus emphasising the importance of precise execution to prevent injury and optimise performance.

The analysis also evaluates current fitness applications, identifying their core functionalities and limitations compared to the proposed system. In particular, the proposed application differentiates itself by offering advanced analytics, AI-driven real-time posture feedback, and built-in emergency response mechanisms. Each component of the review is structured according to the PRISMA methodology, ensuring a comprehensive, systematic, and evidence-based foundation that supports the rationale and design of the proposed solution.

A. Background of Motion Capture Technology

Motion capture (MoCap) refers to the digital tracking and recording of movement patterns of objects or living beings within a defined space, using a variety of technologies and methodologies [5]. It is widely used in domains such as the military, entertainment, sports, medicine, and the validation of computer vision and robotic systems [6]. Broadly, motion capture systems are classified into two categories: optical and non-optical.

Optical systems typically use cameras in conjunction with reflective markers or light-emitting diodes (LEDs) to capture motion as shown in Fig. 1 [7]. These systems are renowned for their high precision and are widely used in industries such as film production, video game development, and sports performance analytics [8,9]. On the contrary, non-optical systems—such as inertial measurement units (IMUs)—employ embedded sensors to track motion independently of camera setups, offering enhanced mobility and adaptability across diverse environments [10]. Fig. 2 is an example of non-optical system [11]. Despite their differing methodologies, both types can deliver high levels of accuracy and precision in motion tracking.

Recent advances have seen the integration of artificial intelligence (AI) with optical motion capture technologies, significantly enhancing their analytical and functional capabilities. AI-driven models enable more advanced data interpretation and facilitate real-time feedback mechanisms, which are crucial for dynamic applications [12]. This fusion of AI and motion capture not only improved the efficiency and reliability of motion analysis but has also broadened its applicability to fields such as medical diagnostics, personalised fitness training, and rehabilitation, where accurate real-time movement assessment is essential.

Fig. 1. Optical system [7].

Fig. 2. Non-optical system (Inertial system) [11].

B. Recent AI Motion Capture Technology

Recent advances in AI-powered motion capture technologies have significantly improved the precision, accessibility, and adaptability of these systems in various environments. Current innovations primarily aim to improve the speed and accuracy of pose estimation through deep learning models, while expanding the application beyond its traditional domains. One notable milestone in this evolution is the introduction of Deep3DPose, a pioneering model that applies deep learning to human pose estimation. Using cascaded deep neural networks, Deep3DPose directly infers human poses from images and introduces a multitask framework capable of concurrently predicting multiple outputs, thereby enabling accurate 3D pose estimation and full-body reconstruction in real time [13]. Fig. 3 shows an example of AI motion capture technology introduced in the Brau et al. (2016) research.

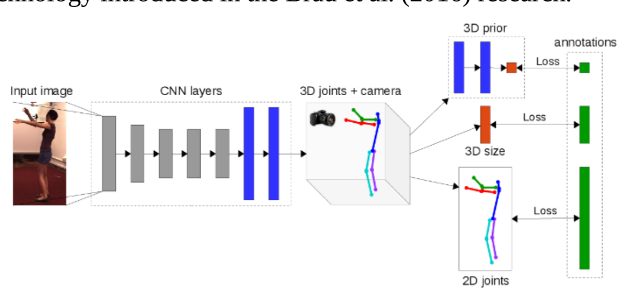


Fig. 3. AI motion capture technology captures human pose and convert it into 3D joints [14].

Subsequent research has introduced numerous algorithms aimed at addressing the limitations of conventional motion capture systems. These include enhanced marker-based approaches [15], hybrid architectures such as Convolutional

Neural Networks (CNNs) combined with Long Short-Term Memory (LSTM) models [16], and frameworks grounded in Human-Centred Artificial Intelligence (HAI) that prioritize interpretability and user-specific customisation [17]. Collectively, these developments signify a paradigm shift towards more intelligent, robust, and user-centric motion capture technologies, with implications for fields such as rehabilitation, sports science, ergonomics, and interactive systems.

C. Google's ML Kit for Pose Detection

Within the domain of AI-driven motion capture technologies, Google's ML Kit for pose detection emerges as a crucial tool, enabling the efficient development of mobile applications capable of real-time human pose estimation. The ML Kit provides a flexible and accessible framework for embedding machine learning functionalities directly into mobile applications on both the Android and iOS platforms. It includes a comprehensive set of APIs that support the detection and tracking of human body joints from static images and live video streams [18].

The pose detection API in the ML Kit is engineered to recognize 33 anatomical landmarks in the human body, including major joints such as shoulders, elbows, wrists, hips, knees, and ankles, as illustrated in Fig. 4 [19]. This level of granularity enables the development of fitness and wellness applications capable of assessing user posture and movement patterns. In particular, it supports real-time form analysis and corrective feedback for strength training exercises such as squats and deadlifts, delivering functionality comparable to that of more complex and computationally intensive motion capture systems, but with significantly lower resource demands and greater accessibility.

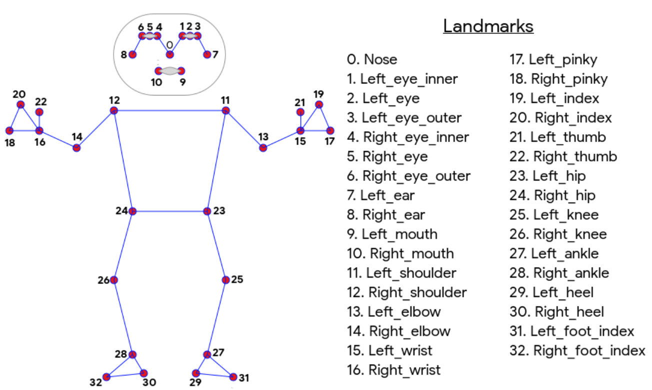


Fig. 4. 33 landmarks of a human pose [19].

A distinguishing feature of Google's ML Kit is its dual-mode operational capability. It supports both a high-accuracy mode, which utilises cloud-based processing and requires an active internet connection, and a real-time mode that functions entirely offline to ensure minimal latency. This flexibility is particularly advantageous for applications in real-time sports analytics, fitness coaching, and augmented reality, where immediate and continuous feedback based on user movement is critical. By accommodating both high-performance and resource-constrained environments, ML Kit broadens its applicability across a wide range of mobile use cases. Fig. 5 shows an example of application using Google's ML Kit landmarks no. 11-18. Sample angles calculations are shown Fig. 6.

Landmark	Type	Position	InFrameLikelihood
11	LEFT_SHOULDER	(734.9671, 550.7924, -118.11934)	0.9999038
12	RIGHT_SHOULDER	(391.27032, 583.2485, -321.15836)	0.9999894
13	LEFT_ELBOW	(903.83704, 754.676, -219.67009)	0.9836427
14	RIGHT_ELBOW	(322.18152, 842.5973, -179.28519)	0.99970156
15	LEFT_WRIST	(1073.8956, 654.9725, -820.93463)	0.9737737
16	RIGHT_WRIST	(218.27956, 1015.70435, -683.6567)	0.995568
17	LEFT_PINKY	(1146.1635, 609.6432, -956.9976)	0.95273364
18	RIGHT_PINKY	(176.17755, 1065.838, -776.5006)	0.9785348

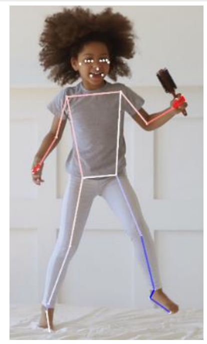


Fig. 5. Example of Google's ML Kit for pose estimation [19].

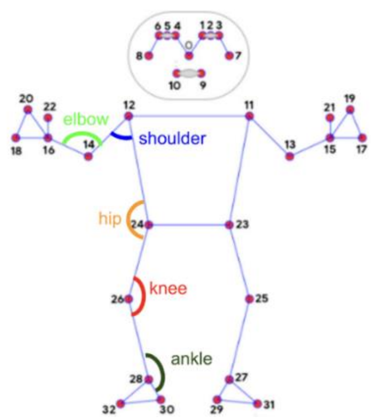


Fig. 6. Calculate the angle between landmarks [19].

D. Applications Using Google's ML Kit for Pose Detection

Google's ML Kit Pose Detection API has seen widespread adoption in mobile application development in both academic research and industry practice. Numerous projects, from student-level prototypes to fully deployed applications, have demonstrated their effectiveness in tracking human posture and interpreting movement in domains such as fitness, yoga, and dance. These implementations underscore the practicality of the ML Kit as a lightweight, on-device solution for real-time pose analysis, even on resource-constrained devices.

A notable academic implementation is the undergraduate thesis by Nguyen (2024), which investigated the integration of ML Kit Pose Detection into Android applications [20]. The project resulted in two mobile applications: one designed for detecting static body poses from images and another for real-time yoga pose recognition using a custom-trained classifier. Using the detection of the landmarks of the pose of the ML Kit, the system successfully identified common yoga postures - including tree pose, downward dog, and plank - demonstrating the API's potential of the API to support mobile health and wellness applications through computer vision–driven feedback.

Another example is RepDetect, a real-time fitness assistant developed by students at Metropolia University of Applied Sciences. This Android-based application uses the ML Kit to monitor exercises such as push-ups, sit-ups, and lunges by evaluating the consistency of the pose and counting repetitions [35]. The app uses pose confidence scores to assess form accuracy, providing users with real-time feedback and exercise statistics. This project exemplifies how small development teams can leverage the ML Kit and Kotlin to create fully functional, AI-driven workout tracking solutions.

In industry settings, the ML Kit has also been incorporated into commercial applications. Groovetime, a dance-based mobile app, utilises pose estimation to help users learn choreographed routines by comparing user movements against predefined dance sequences. It offers real-time feedback on movement accuracy, acting as a virtual dance coach [21]. Similarly, NeckFit uses the ML Kit to analyse upper-body posture and suggest corrective exercises aimed at alleviating neck strain and improving spinal alignment. Designed for daily use, NeckFit targets users seeking ergonomic improvements and posture correction [22].

Together, these examples reflect the growing utility and adaptability of ML Kit Pose Detection in diverse application areas, reaffirming its value as a robust, accessible tool for real-time, mobile-based human pose analysis.

E. Squat

Squat is a fundamental compound exercise that engages multiple muscle groups in the body, including the quadriceps, hamstrings, glutes, lower back, and core. The movement involves lowering the body into a squatting position by flexing the knees and hips while maintaining a neutral spine, followed by returning to a standing position. Known for its effectiveness in enhancing lower body strength, flexibility, and balance, the squat is, however, frequently performed incorrectly in gym settings. Improper execution can result in a variety of injuries, such as lower back pain, muscle strains or tears, knee sprains, and tendinopathy, an overuse injury commonly associated with repetitive movements [1].

Fig. 7 demonstrates proper squat execution: place the barbell on the trapezius muscle and hold it in a comfortable hand position. The feet should be slightly wider than shoulder-width apart with toes pointing outward, ideally not exceeding 10 degrees [23]. As you descend into the squat, ensure that your trunk remains parallel to your tibia to maintain balance and alignment. The depth of the squat and the angle of knee flexion should correspond to the specific type of squat being performed: mini squats typically range between 140° and 150°, semi-squats between 120° and 140°, half-squats between 80° and 110°, and deep squats go below 80° [24]. Precise joint angles are crucial to prevent injuries and optimise the exercise's effectiveness: hip joints should ideally be angled at approximately 58.0°±9.8°, ankle joints at about 81.0°±7.3°, and the torso at roughly 38.2°±5.8° [25, 26]. These biomechanical considerations help to perform squats correctly and safely, reducing the risk of injuries while improving training outcomes.

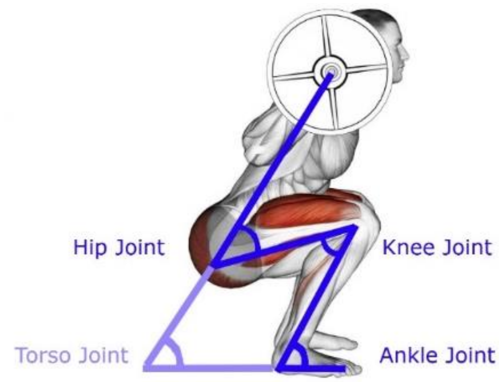


Fig. 7. Proper squat pose.

According to Strength Level (2024), the selection of appropriate dumbbell weights for squats is influenced by three primary factors: strength level, body weight, and age [27]. As illustrated in Fig. 8, the advised weight varies significantly between different strength levels. For example, a beginner who weighs 60 kg is typically advised to use lighter weights, which are 45 kg (0.75x body weight), to promote correct form and ensure safety. Additional guidance is provided in Fig. 9 and Fig. 10, which delineate the recommended weights according to body weight and age, respectively, helping to tailor the exercise to the individual's physical condition and reducing the risk of injury.

Strength Level	Bodyweight Ratio
Beginner	0.75x
Novice	1.25x
Intermediate	1.50x
Advanced	2.25x
Elite	2.75x

Fig. 8. Advice weight for dumbbell for different strength level for squats [27].

Bodyweight	Beginner	Novice	Intermediate	Advanced	Elite
50	33	52	76	104	136
55	40	60	86	116	149
60	47	68	95	127	161
65	53	76	104	137	173
70	59	83	113	147	184
75	66	91	122	157	195
80	72	98	130	166	205
85	78	105	138	175	215
90	83	112	146	184	225
95	89	118	153	192	234
100	95	125	160	201	243
105	100	131	168	209	252
110	106	137	174	216	260
115	111	143	181	224	269
120	116	149	188	231	277
125	121	155	194	238	284
130	126	160	201	245	292
135	131	166	207	252	299
140	136	171	213	259	307

Fig. 9. Advice weight (kg) for dumbbell according to different body weight (kg) and strength level for squats [27].

Age	Beginner	Novice	Intermediate	Advanced	Elite
15	55	80	111	147	187
20	62	91	127	168	214
25	64	93	130	173	219
30	64	93	130	173	219
35	64	93	130	173	219
40	64	93	130	173	219
45	61	89	123	164	208
50	57	83	116	154	195
55	53	77	107	142	180
60	48	70	98	130	165
65	44	63	88	117	149
70	39	57	79	105	134
75	35	51	71	94	119
80	31	46	63	84	107
85	28	41	57	75	96
90	25	37	51	68	86

Fig. 10. Advice weight (kg) for dumbbell according to different age and strength level for squats [27].

F. *Deadlift*

The deadlift is a fundamental weight training exercise that engages multiple muscle groups, making it one of the most effective compound movements to build overall strength. Primarily, deadlift targets the glutes, hamstrings, lower back, and core, while also activating the forearms and traps [28]. The exercise involves lifting a loaded barbell from the ground to the level of the hips, followed by a controlled lowering of the weight back to the floor. Recognised for its ability to enhance muscular strength and hypertrophy, the deadlift is also valued for improving grip strength and overall body stability.

Fig. 11 shows several variations of the deadlift, including the conventional deadlift, sumo deadlift, straight-leg deadlift, and Romanian deadlift (RDL) [29]. However, improper technique during deadlifting can result in excessive compressive and shear forces on the lumbosacral spine, potentially leading to disc herniation or other spinal injuries [30].

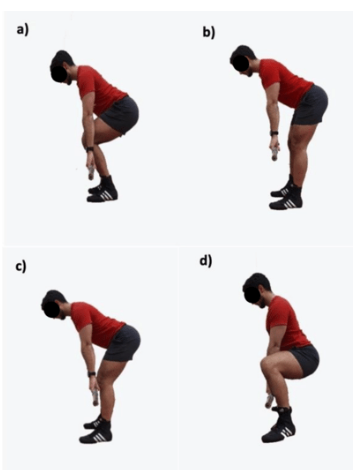


Fig. 11. a) Conventional deadlift, b) Straight-leg deadlift, c) Romanian deadlift, d) Sumo deadlift [29].

Proper execution of deadlifts varies according to the specific style being performed, with each variation emphasising distinct stances and grip positions. The conventional deadlift, as outlined by Escamilla et al. (2002), involves a stance narrower than shoulder width, with the feet positioned close to the centre of the bar and the hands gripping the bar just outside the legs [31]. Straight-leg deadlift is similar to the Romanian deadlift, but differs by maintaining fully extended knees and ensuring that the bar does not come into contact with the legs. On the contrary, the Romanian deadlift retains the stance width of the conventional deadlift but limits knee flexion to no more than 15 degrees, ensuring that the barbell stays in contact with the legs throughout the movement [32]. Lastly, the sumo deadlift features a significantly wider stance, exceeding shoulder width, which facilitates the participation of different muscle groups [31].

In terms of determining the appropriate weight for the deadlift, the guidelines provided by Strength Level Limited (2024) emphasise the importance of adjusting weight based on an individual's strength level, body weight, and age. As illustrated in Fig. 12, there is considerable variation in recommended deadlift weights in different strength categories. For example, a beginner weighing 60 kg is typically advised to lift a weight equal to your body weight (60 kg) to ensure proper form and reduce the risk of injury. Additional recommendations are provided in Fig. 13 and 14, offering customised weight guidelines based on body weight and age, respectively. These individualised suggestions enable users to adjust their training to their physical abilities, thereby promoting safety and reducing the likelihood of injury.

Strength Level	Bodyweight Ratio
Beginner	1.00x
Novice	1.50x
Intermediate	2.00x
Advanced	2.50x
Elite	3.00x

Fig. 12. Advice weight for dumbbell for different strength level for deadlift [27].

Bodyweight	Beginner	Novice	Intermediate	Advanced	Elite
50	44	65	93	125	160
55	51	74	103	137	174
60	58	83	114	149	187
65	66	92	124	160	200
70	73	100	133	171	212
75	79	108	142	182	224
80	86	116	151	192	235
85	93	123	160	201	245
90	99	131	168	211	256
95	105	138	176	220	266
100	111	145	184	228	275
105	117	151	192	237	284
110	123	158	199	245	293
115	129	164	206	253	302
120	134	171	213	261	311
125	140	177	220	268	319
130	145	183	227	276	327
135	150	188	233	283	335
140	155	194	240	290	342

Fig. 13. Advice weight (kg) for dumbbell according to different body weight (kg) and strength level for deadlift [27].

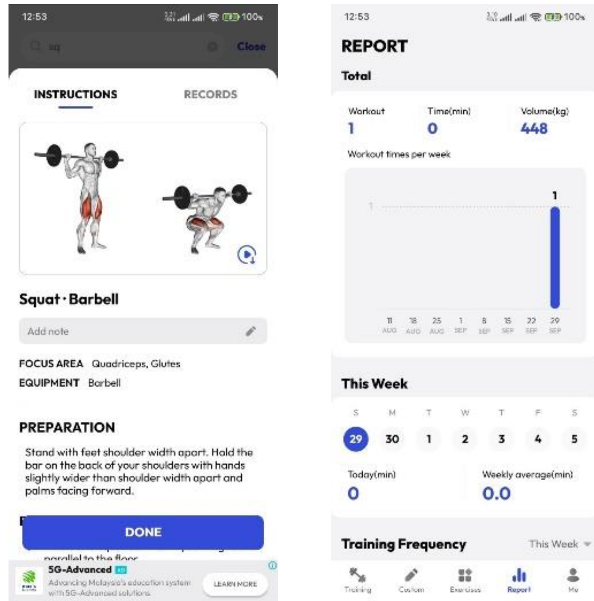
Age	Beginner	Novice	Intermediate	Advanced	Elite
15	67	95	130	170	213
20	76	109	148	194	244
25	78	112	152	200	250
30	78	112	152	200	250
35	78	112	152	200	250
40	78	112	152	200	250
45	74	106	145	189	238
50	70	99	136	178	223
55	65	92	125	164	206
60	59	84	115	150	188
65	53	76	103	135	170
70	48	68	93	122	153
75	43	61	83	109	136
80	38	54	74	97	122
85	34	49	67	87	109
90	31	44	60	79	99

Fig. 14. Advice weight (kg) for dumbbell according to different age and strength level for deadlift [27].

G. Existing Product

1) Gym workout tracker: Gym Log: This fitness app, developed by Leap Fitness Group, has amassed more than 5 million downloads and boasts a perfect 5.0/5.0 rating from 92.8k reviewers on the Google Play Store [33]. Launched on December 8, 2021, the app is designed to serve beginners and experienced bodybuilders by offering customisable workout routines that align with individual goals and available gym equipment. It functions as a comprehensive fitness tool, providing access to a robust database of more than 500 exercises, each accompanied by detailed visual and written instructions (Fig. 15). In addition to facilitating workout planning and tracking, the app replaces traditional pen-and-paper methods by allowing users to log workouts digitally. It also tracks progress through intuitive statistics and charts, offering users a detailed overview of their performance. Features such as adjustable rest timers, unlimited routine edits, and the ability to create personalised workout routines ensure a highly flexible and enriched training experience. By combining these functions, the app helps users optimize their workouts, improve training efficiency, and maintain motivation, all without the expense of a personal trainer.

(a) Gym log app



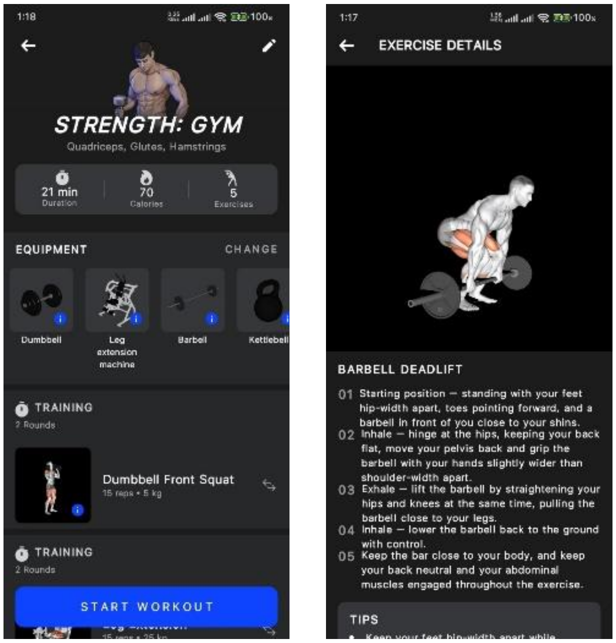
(b) Guidance page (c) Report page

Fig. 15. Gym Log mobile apps [33].

2) Muscle booster – Plan workouts: With more than 10 million downloads and a rating of 4.8/5.0 from users on the Google Play Store, Muscle Booster is a highly rated fitness app developed by Welltech Apps Limited on November 27, 2019 [34]. This dynamic and comprehensive fitness assistant is designed to cater to both men and women, offering customisable workout plans tailored to individual fitness goals, equipment availability, and personal constraints.

Muscle Booster is versatile enough to be used both at home and in the gym, featuring a vast library of over 1,000 workouts. It also includes interactive challenges and provides detailed guidance through a workout player that offers audio tips and timed instructions. Whether users are looking to gain muscle, lose weight, or focus on recovery, the app allows them to set specific objectives, target muscle zones, and receive personalised recommendations. It also incorporates mini milestones to track progress, helping users stay motivated throughout their fitness journey. As a result, Muscle Booster serves as an all-encompassing platform to improve physical fitness and facilitating health transformations efficiently (Fig. 16).

(a) Icon of the muscle booster – Plan workouts



(b) Gym planner (c) Guidance page

Fig. 16. Muscle booster mobile apps [34].

H. *Summarise of Existing Product*

In summary, while apps like Gym Workout Tracker: Gym Log and Muscle Booster – Plan Workouts primarily focus on providing extensive exercise libraries and detailed instructional content, this project distinguishes itself by incorporating advanced real-time posture analysis. This feature is particularly valuable as it not only guides users through exercises but also offers instant feedback on their form, thereby improving both safety and effectiveness.

TABLE I. COMPARISON OF EXISTING PRODUCT WITH THIS PROJECT

Criteria	***Gym Workout Tracker***	***Muscle Booster***	***This project***
Registration	✓	✓	✓
Login	✓	✓	✓
Profile	✓	✓	✓
Custom workout	✓	✓	✓
Workout planner	✓	✓	✓
Weight tracker	✓	✓	✓
Workout weight recommender			✓
AI Real-time posture analysis with feedback			✓
Advanced analytics			✓
Emergency mechanism			✓

This project further differentiates itself through the integration of more sophisticated technology, specifically Google's ML Kit for pose detection, something existing apps do not utilize to the same extent. This technology enhances the accuracy of posture and form analysis, representing a significant advancement in the app's capabilities. Additionally, the emergency mechanism is a unique safety feature designed to detect potential distress or unsafe conditions during workouts, triggering a prompt response. This feature is especially noteworthy in the fitness app market, where similar safety features are typically reserved for expensive high-tech fitness devices, such as smartwatches. Table I summarises the comparison of this project with existing products found in the market focusing on features comparison.

III. MATERIAL AND METHOD

A. *System Architecture Design*

This section presents the overall system architecture design that includes 1) real time input, 2) pose analysis, and 3) real time pose adjustment. For real time input, the Google machine learning kit is used to detect and extract key joint landmarks from the user's body. These coordinates are used in later calculations for the classification of angles, positions, and postures. Pose analysis is carried out using angles between joints calculation and detects incorrect reps (posture validation). If there are emergencies, such as injuries or falls, an AI-powered fitness coach will alert surrounding users to help in the emergency. In the event of incorrect posture, the system will alert the user, too. A workout plan is incorporated into this system to monitor the duration of each workout. The details of each component will be further explained using workflow, and algorithm will be illustrated using pseudocode in the following subsections (Fig. 17).

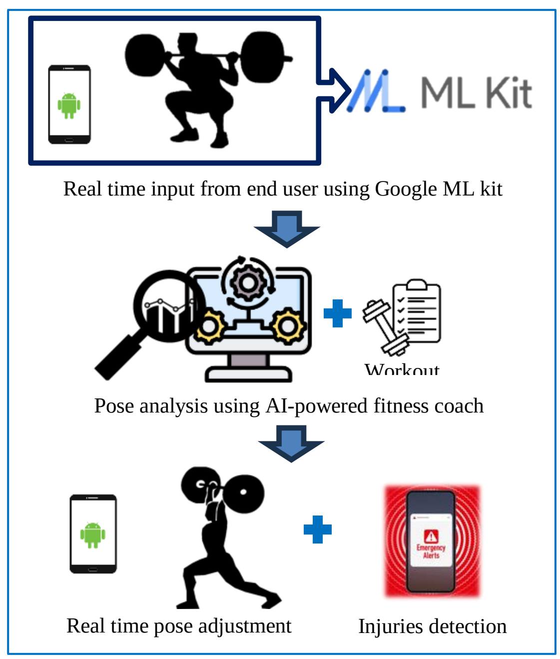


Fig. 17. AI-powered fitness coach system architecture design.

B. *System Components Workflow Design*

This section presents three flowcharts designed to support real-time biomechanical posture analysis for squats and deadlifts. The first flow chart (Fig. 18) outlines the process of capturing a user's workout plan based on their profile, followed by the generation of personalised exercise recommendations. The process begins when the user navigates to the workout planner page. The system retrieves and displays all existing workout plans from the database. At this point, the user can choose to create a new plan, modify an existing one, or delete a plan. When creating a new workout plan, the system displays a recommended weight based on the user profile. The user then inputs key details of the working of the exercises, including selected sets, weights, and repetitions. Before finalising the plan, a confirmation prompt ensures that the user reviews the input. Once confirmed, the workout plan is stored in the database, and a success dialogue notifies the user of the successful creation.

The modification process mirrors the creation workflow. After selecting a plan to modify, the system again displays recommended weights. Users can update the exercise details and confirm the changes. Upon validation, the updated plan is saved in the database and a confirmation dialog is displayed. For deletion, the user is asked to confirm the action to prevent accidental loss. If confirmed, the selected workout plan is removed from the database and a success dialog provides final confirmation.

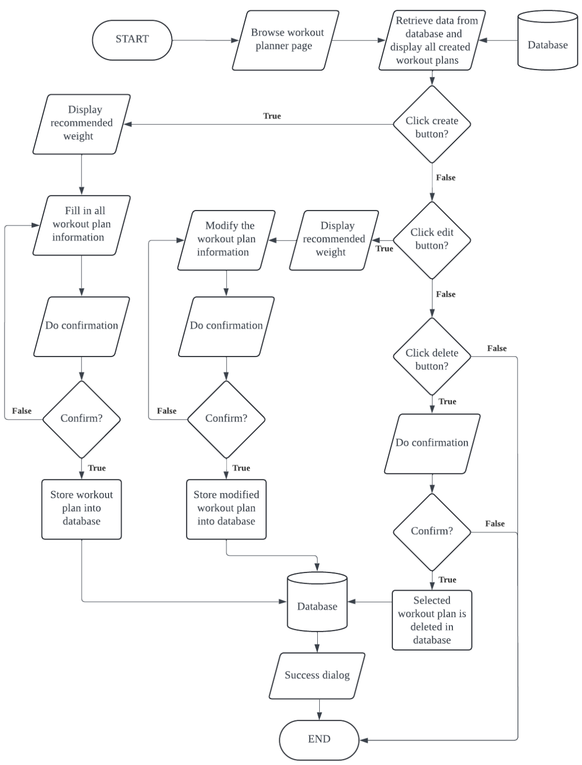


Fig. 18. Flow chart for the exercise planner module.

Fig. 19 illustrates the flow chart for the motion capture module. The process begins when a user accesses the workout planner page and selects a workout plan. The application then displays relevant instructions and tips based on the selected workout, including information on necessary equipment and targeted muscle groups. If the user chooses to calculate the appropriate barbell weight, they can utilise the built-in plate calculator by entering the desired total weight and selecting the available weight plates. The application then generates the optimal plate configuration for the workout. Once the user starts the workout, the application becomes a real-time monitoring interface that captures and analyses the user's movements. Using motion capture technology, the system provides immediate feedback on exercise form, helping the user make real-time adjustments to maintain proper posture and technique.

During the workout session, users can add additional sets if needed. The system also includes an embedded emergency detection mechanism that continuously monitors for abnormal activity, such as sudden falls. If an emergency is detected, the application triggers an audible alarm, notifies the designated emergency contact, and offers the user the option to stop the alert. Upon completion of all sets or if the user chooses to end the workout, the system stores the entire session's data, including performance metrics and form analysis, into the database. Finally, a congratulatory screen is displayed to acknowledge the effort before redirecting them back to the workout planner page for future session planning or review.

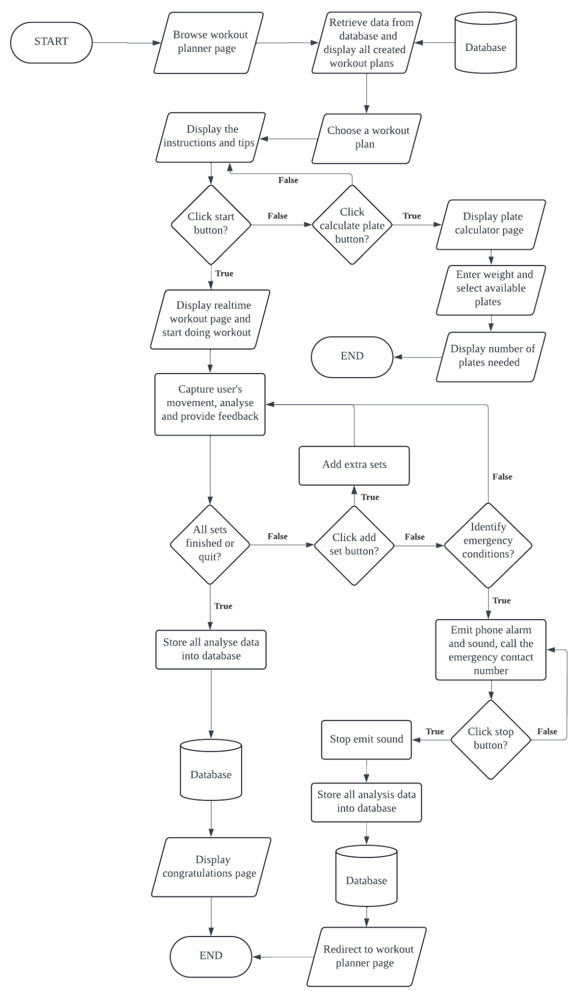


Fig. 19. Flowchart for motion capture module.

Fig. 20 delineates the process by which users interact with their exercise and body weight data within the fitness application. The process begins when a user accesses the report page, prompting the app to retrieve and display several types of data: an overall summary of the frequency and volume, detailed logs of individual workout sessions, and trends in the progression of body weight. Users are presented with a weekly overview of all recorded workouts. For a more granular view, they can select the “View All” option, which opens a calendar interface that allows users to filter historical data by specific dates. Upon selecting a date, the application displays only the corresponding workout sessions, allowing users to examine detailed performance metrics, including repetitions, joint angles, and explosive power.

Alternatively, if the user chooses to log their current body weight rather than review historical data, the system prompts them to input the new weight value. These data are then securely stored in the database, contributing to long-term tracking and analysis of physical progress.

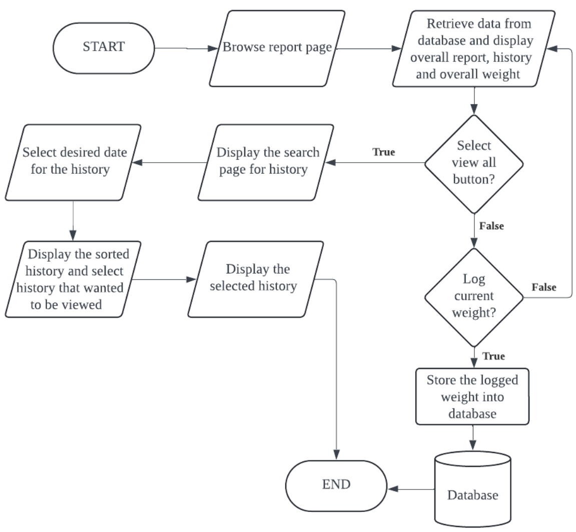


Fig. 20. flow chart for report module.

C. Algorithm Design

The algorithmic framework of this project is based on Google’s ML Kit Pose Detection, a machine learning-based tool capable of identifying up to 33 anatomical landmarks in the human body. These landmarks encompass key joints and reference points, including the nose, eyes, shoulders, elbows, wrists, hips, knees, and ankles. By processing image or video input in real time, the pose detection model generates accurate spatial coordinates for each landmark, enabling detailed analysis of the user's posture and body orientation. This capability forms the basis for providing real-time feedback on exercise form and alignment.

This project uses a targeted subset of these anatomical landmarks to implement core motion capture functionalities, specifically tailored for the biomechanical analysis of squats and deadlifts. The subsequent sections detail the custom algorithms developed to process these landmarks, encompassing joint coordinate extraction, full-body visibility, joint angle calculation, repetition counting, posture error detection, and emergency fall detection. Each algorithmic component plays a critical role in enabling precise form evaluation, improving user safety, and delivering meaningful, real-time feedback during strength training exercises.

1) Extracting joint coordinates: The initial phase of the algorithm involves detecting and extracting key joint landmarks from the user’s body using the Google ML Kit pose detection framework. Although the pose detection model identifies up to 33 anatomical landmarks, this system focusses on a critical subset, specifically shoulders, elbows, hips, knees, and ankles, which are most relevant for analyzing squat and deadlift movements. The landmarks index used in this project is: landmark 0 (for detecting whole body within the frame or not and sudden fall); landmarks 11, 12, 13, 14, 23, 24, 25, 26, 27, 28, 31, 32 (Fig. 4). The extracted coordinates serve as the foundation for subsequent calculations, including joint angle computation, positional tracking, and posture classification. Additionally, the algorithm incorporates a visibility check to ensure that all required joints are detectable in the frame, thus validating full-body visibility before proceeding with further analysis. Fig. 21 illustrates the pseudocode implemented for joint coordinate extraction.

```
FOR each frame:
  pose = runPoseDetection(frame)
  IF pose is null THEN
    SKIP frame
  END IF

  EXTRACT key joint coordinates:
    leftShoulder = pose[LEFT_SHOULDER]
    rightShoulder = pose[RIGHT_SHOULDER]
    leftHip = pose[LEFT_HIP]
    rightHip = pose[RIGHT_HIP]
    leftKnee = pose[LEFT_KNEE]
    rightKnee = pose[RIGHT_KNEE]
    etc.

  IF any key joint is null THEN
    DISPLAY "User not fully in frame"
    CONTINUE
  END IF
```

Fig. 21. Pseudocode used to extract joint coordinates.

2) Detect full body within camera frame: To ensure accurate detection and tracking, the system verifies the visibility of all critical joints. If one or more of these essential landmarks are not detected in each frame, the algorithm assumes that the user is not fully within the camera's view. In such cases, the system bypasses further analysis for that frame to avoid inaccurate posture evaluation and maintain the reliability of the feedback mechanisms (Fig. 22).

```
CHECK full-body detection:
  REQUIRED_JOINTS = [NOSE, LEFT_HIP, RIGHT_HIP,
LEFT_ANKLE, RIGHT_ANKLE]
  FOR joint IN REQUIRED_JOINTS:
    IF joint is missing or confidence < threshold:
      DISPLAY "Please align yourself in the frame"
      RETURN
```

Fig. 22. Pseudocode to detect and ensure user’s body is within the frame.

3) Calculate angles between joints: Using the extracted coordinates, the system calculates joint angles, specifically at the knees and hips, to evaluate movement phases and assess posture. These angles are computed using a standard geometric method involving three points, where the joint of interest (e.g.

the hip) is positioned between two adjacent landmarks (e.g. the shoulder and the knee). By continuously analysing these angle values, the system can determine the depth of a squat, detect misalignments, and identify potential deviations from proper form (Fig. 23).

```
FUNCTION calculateAngle(A, B, C):
  angle = arccos( (AB² + BC² - AC²) / (2 * AB * BC) )
  RETURN angle

hipAngle = calculateAngle(shoulder, hip, knee)
kneeAngle = calculateAngle(hip, knee, ankle)
```

Fig. 23. Pseudocode designed to calculate the angles between joints.

4) Count repetitions (squat/deadlift): The repetition counting logic is based on tracking the sequential movement patterns of key joints, particularly the hips and knees, over time, as shown in Fig. 24. For squats, the system continuously monitors changes in hip and knee joint angles to identify the different phases of the exercise. Repetition is initiated when both the hip and knee angles decrease beyond a predefined threshold, indicating that the user is descending into the squat. The repetition concludes when these angles increase as the user returns to a standing position. To ensure accuracy, repetition is counted only when this full motion cycle is completed and specific posture conditions are met, such as appropriate squat depth and joint alignment.

```
INITIALIZE:
  phase = "Standing"
  successfulRepCount = 0
  failedRepCount = 0

ON EACH FRAME:
  UPDATE kneeAngle, hipAngle, handHeight
  UPDATE timestamp for motion duration

  // Squat Detection Logic
  IF motionType == "SQUAT":
    IF kneeAngle < 100 AND hipAngle < 100:
      IF phase == "Standing":
        phase = "Squatting"

    ELSE IF kneeAngle > 150 AND hipAngle > 150:
      IF phase == "Squatting":
        IF postureIsValid():
          successfulRepCount += 1
        ELSE:
          failedRepCount += 1
        END IF
        phase = "Standing"

  // Deadlift Detection Logic
  IF motionType == "DEADLIFT":
    IF handHeight below knee:
      IF phase == "Standing":
        phase = "Lowering"

    ELSE IF handHeight above hip:
      IF phase == "Lowering":
        IF postureIsValid():
          successfulRepCount += 1
        ELSE:
          failedRepCount += 1
        END IF
        phase = "Standing"
```

Fig. 24. Pseudocode used in this project to count repetitions.

For deadlifts, the system uses the relative position of the hands in relation to the hips and knees to identify the lifting and lowering phases. Repetition is detected when the hands descend below the level of the knees and then ascend back above the hips in a controlled, continuous motion. This movement must also meet predefined posture conditions, such as proper spinal alignment and full extension to the top—for a repetition to be considered valid. The use of relative joint positioning ensures that only complete and correctly executed repetitions are counted.

5) Detect incorrect reps (posture validation): The app continuously tracks key joint landmarks (such as the hips, knees, shoulders, and hands) across frames during a squat or deadlift. To validate the posture for each repetition, the system compares the relative positions of corresponding joints (e.g. left and right shoulders, hips, elbows, and hands) to ensure that the user is performing the movement in a controlled and balanced manner. For instance, if the hands are misaligned or one shoulder is significantly lower than the other, the system flags these discrepancies as errors. Error flags are assigned to each joint segment and, if any of these flags are activated, the repetition is deemed invalid. When an error is detected, the app displays a relevant error message on the screen (e.g. "Hands are not parallel") and excludes the repetition from the count (Fig. 25).

```
Initialize errorFlags = {
  handPosition: false,
  shoulder: false,
  hip: false,
  feet: false,
  elbowAngle: false
}

FOR each frame during motion capture:
  IF absolute(leftHand.y - rightHand.y) > hand_threshold:
    errorFlags.handPosition = true
    Show error message: "Hands are not parallel"

  IF absolute(leftShoulder.y - rightShoulder.y) > shoulder_threshold:
    errorFlags.shoulder = true
    Show error message: "Shoulders not aligned"

  IF absolute(leftHip.y - rightHip.y) > hip_threshold:
    errorFlags.hip = true
    Show error message: "Hips not aligned"

  IF absolute(leftFoot.y - rightFoot.y) > feet_threshold:
    errorFlags.feet = true
    Show error message: "Feet not aligned"

  IF elbow angle not within correct range (deadlift only):
    errorFlags.elbowAngle = true
    Show error message: "Elbow angle incorrect"

AT end of repetition:
  IF any errorFlags is true:
    Mark rep as incorrect
    Increase failed rep counter
  ELSE:
    Count rep as successful
```

Fig. 25. Pseucode used in this project to detect errors.

6) Emergency mechanism detection: The emergency mechanism within the motion capture system is designed to detect sudden falls or unsafe postural deviations by analysing real-time body landmark data, as shown in Fig. 26. Specifically, the system calculates the trunk angle by measuring the slope between the midpoint of the user's shoulders and ankles. If this angle exceeds a predefined threshold (typically greater than 60 degrees) and experiences a rapid change between consecutive frames (e.g. more than a 25-degree shift), the system flags the event as a potential fall. To reduce the likelihood of false alarms, the angle difference is smoothed using exponential filtering, and a cooling counter is employed to debounce temporary fluctuations, ensuring that only genuine postural changes trigger an alert.

```
function detectEmergency(pose):
        if key landmarks (nose, shoulders, hips, ankles) are missing:
           return false

        upperMid = midpoint(leftShoulder, rightShoulder)
        lowerMid = midpoint(leftAnkle, rightAnkle)
        bodyAngle = angleBetween(upperMid, lowerMid)

        if lastAngle == 0:
           set lastAngle = bodyAngle
           return false

        angleChange = abs(bodyAngle - lastAngle)
        set lastAngle = bodyAngle

        if bodyAngle > 60 and angleChange > 25:
           increment dropFrameCount
           set emergency = true
           return true
        else:
           decrement dropFrameCount
           return false
```

Fig. 26. Pseudocode used to detect emergencies / injuries.

IV. Result

This section presents the results of the User Acceptance Testing (UAT) and accuracy evaluation conducted on the mobile applications Real-time Biomechanical Squat and Deadlift Posture Analysis, based on data collected from two distinct user groups.

A. Usability Test

The usability test (UT) was conducted with six experienced bodybuilders to assess the usability based on real-world user interactions (Fig. 27). Participants completed a full cycle of tasks, including account registration, profile setup, workout planning, motion capture, emergency alert testing, and performance reporting. The demographic profiles of the participants are summarised in Table II.

TABLE II. UAT Participants' Demographics

#	Age	Gender	Years of Bodybuilding	Beginner/ intermediate/ advance level	Occupation
1	22	Male	1	Beginner	Undergraduate
2	22	Male	1	Beginner	Undergraduate
3	22	Male	0.5	Beginner	Undergraduate
4	22	Male	0.5	Beginner	Undergraduate
5	22	Male	0.5	Beginner	Undergraduate
6	22	Male	3	Intermediate	Undergraduate

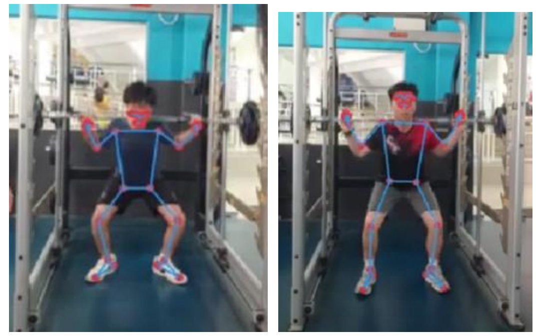


Fig. 27. Screenshots of usability test.

Feedback was collected through a structured questionnaire administered through Google Forms, consisting of 11 items rated on a 5-point Likert scale, alongside open-ended response sections (Fig. 28). In general, the usability of the application received positive evaluations. Specifically, 83.3% of the participants rated the user interface as easy to navigate (a score of 4), while 16.7% awarded it the highest score of 5. The workout planning feature was particularly well received, with 83.3% of users assigning it a score of 5, citing its simplicity and clarity.

UAT1. The app interface is easy to navigate. [Strongly disagree(1) – Strongly agree(5)]
UAT2. The workout planner is simple to use and understand. [Strongly disagree(1) – Strongly agree(5)]
UAT3. The motion capture detected my posture correctly. [Strongly disagree(1) – Strongly agree(5)]
UAT4. The real-time feedback during my squat/deadlift was clear and useful. [Strongly disagree(1) – Strongly agree(5)]
UAT5. The sound alert and emergency contact feature make me feel safer while working out. [Strongly disagree(1) – Strongly agree(5)]
UAT6. The graphs and analytics helped me understand my workout patterns. [Strongly disagree(1) – Strongly agree(5)]
UAT7. The weight log is useful to track my fitness progress over time. [Strongly disagree(1) – Strongly agree(5)]
UAT8. What did you like the most about the app? [Open-ended question]
UAT9. What part of the app did you find confusing or difficult to use? [Open-ended question]
UAT10. Do you have any suggestions for improvement? [Open-ended question]

Fig. 28. Questionnaires used in UAT.

On the contrary, the posture detection module –powered by Google's ML Kit –received moderate feedback. The majority of the participants (66.7%) rated their performance as average (score of 3), while the remaining 33.3% assigned it a slightly higher rating of 4 (Table III). These results indicate that, although the posture detection functionality is operational, its accuracy requires further optimisation to meet user expectations.

TABLE III. Responses of Participants in UAT1-7

UAT Questionnaire	Rating-Percentage in %	Average ratings
UAT1	4-83.3%; 5-16.7%	4.17
UAT2	4-16.7%; 5-83.3%	4.83
UAT3	3-66.7%; 4-33.3%	3.33
UAT4	3-33.3%; 4-33.3%; 5-33.3%	4.00
UAT5	4-50%; 5-50%	4.83
UAT6	3-16.7%; 4-50%; 5-33.3%	3.33
UAT7	3-16.7%; 33.3%; 5-50%	4

Similarly, user responses to the real-time exercise feedback feature were evenly distributed between ratings of 3, 4, and 5 (each representing 33.3%), reflecting a varied user experience. This inconsistency may stem from external factors, such as suboptimal camera angles or insufficient lighting conditions during motion capture, which can impact the effectiveness of real-time feedback.

In particular, all participants agreed that the application effectively helped them assess the correctness of their exercise form. Specifically, 50% rated this feature a 4, while the remaining 50% awarded it a 5, indicating strong user confidence in the form recognition capability. The emergency alert system, which integrates a loud alarm and automated contact notification, also received favourable reviews, with 83.3% of users assigning it a rating of 4 or 5.

Additional features, such as analytics and weight tracking, were similarly well received. The weight logging functionality was rated 4 or higher by 83.3% of participants, and an equal percentage reported that the data visualisation through workout charts enhanced their understanding of training patterns. Average UAT1-UAT7 ratings.

Open feedback offered additional information on both the strengths and potential areas for improvement within the application (see Table IV). The participants highlighted several appreciated features, including real-time posture correction, personalised weight recommendations, the integrated emergency alert system, and the intuitive reporting interface.

TABLE IV. PARTICIPANTS' RESPONSES FOR UAT8-10

UAT8: What did you like the most about the app? 1. The real-time feedback during squats was very helpful — it felt like having a trainer watching me. 2. I liked the emergency feature. It gave me peace of mind knowing it would alert someone if I needed help. 3. The design is clean and it was easy to log my weight and see the progress in the report. 4. I liked how it gives personalized workout recommendations based on fitness level. 5. It's cool how the camera can detect my posture and give feedback instantly. 6. Everything is in one place — workout planner, progress, and form correction.
UAT9: What part of the app did you find confusing or difficult to use? 1. The workout planner interface was a bit overwhelming at first. 2. I wasn't sure how to trigger the motion capture — had to press a few buttons to figure it out. 3. The emergency contact setup took me a while to find in the profile section. 4. The report charts were a bit small on my phone screen. 5. Sometimes I wasn't sure if the camera was properly detecting me or not. 6. Forgot password process was a bit long, especially the OTP step.
UAT10: Do you have any suggestions for improvement? 1. Maybe add a short tutorial for new users when they first open the app. 2. Consider adding labels or tooltips for each button to explain their function. 3. Maybe group the profile and emergency settings under a clearer menu. 4. Allow the charts to be expanded or rotated for better visibility. 5. Maybe show an indicator or guide when the app is actively tracking your movement. 6. Maybe allow the app to resend OTP without waiting too long.

However, users also provided constructive suggestions to improve the overall experience. These included enabling faster OTP (One-Time Password) resends, improving the organisation of profile and emergency settings, expanding report charts for better readability, and incorporating brief tutorials or tooltip explanations to support first-time users. Additionally, some participants recommended the inclusion of a visual indicator to confirm when motion tracking is actively engaged.

In summary, all participants successfully completed the assigned tasks and provided valuable constructive feedback. The application was deemed functionally complete, user-friendly and effective in achieving its intended purpose, thus affirming alignment with the original design objectives. While the overall user experience was positive, incorporating minor usability improvements based on user feedback could further refine the system and strengthen its readiness for a wider deployment.

B. *Motion Capture Accuracy Assessment*

To evaluate the accuracy of motion capture functionality within the Pose Perfect application, a focused assessment was conducted involving three students from the Faculty of Sport Science at Tunku Abdul Rahman University of Management and Technology (see Table V). Each participant had more than three years of practical experience with squat and deadlift exercises. They were invited to independently explore the application and provide feedback through a structured Google Form questionnaire, which evaluated the key posture-related features in terms of precision, responsiveness, and reliability. The details of the questionnaire items are presented in Fig. 29.

TABLE V. ACCURACY ASSESSMENT PARTICIPANTS' DEMOGRAPHIC

#	Age	Gender	Years of Bodybuilding	Beginner/ intermediate/ advance level	Occupation
1	22	Male	3	Intermediate	Undergraduate
2	22	Male	4	Intermediate	Undergraduate
3	22	Male	4	Intermediate	Undergraduate

ACC1. How accurately does the app detect your squat posture in real time? **[Not accurate (1) – Very accurate (5)]**
ACC2. How accurately does the app detect your deadlift posture in real time? **[Not accurate (1) – Very accurate (5)]**
ACC3. Does the app correctly identify incorrect posture during squats (e.g., unbalanced hands, knees not aligned)? **[Never (1) – Always (5)]**
ACC4. Does the app correctly identify incorrect posture during deadlifts (e.g., unbalanced hands, hands not straight)? **[Never (1) – Always (5)]]**
ACC5. How consistent is the real-time feedback timing? **[Very inconsistent (1) – Very consistent (5)]**
ACC6. Have you tested the emergency mechanism (e.g., simulating a fall or sudden collapse)? **[No/Yes]**
ACC7. If yes, how accurately did the app detect the emergency condition? **[Not at all (1) – Very accurately (5)]**
ACC8. Was the emergency alert (alarm + options) triggered at the correct moment during the fall simulation? **[No/Yes]**
ACC9. Would you recommend this app to users at the following fitness levels? **Beginner (No/Yes)**
ACC10 Would you recommend this app to users at the following fitness levels? **Intermediate (No/Yes)**
ACC11 Would you recommend this app to users at the following fitness levels? **Advanced (No/Yes)**
ACC12. Please rate the overall usefulness of the motion capture feature in assisting with safe and effective training: **[Very poor (1) – Excellent (5)]**

Fig. 29. Questionnaire items used in the accuracy test.

The results of the accuracy evaluation indicated that the application generally performed well in detecting squat posture in real time, and most participants rating its accuracy between moderate and high (Table VI). On the contrary, the detection of deadlift posture received slightly lower scores, with participant responses distributed more evenly within the moderate accuracy range. Regarding incorrect posture identification, participants acknowledged that the application could detect noticeable deviations; however, they also noted a need for improvement in recognising more subtle form discrepancies. The feedback on the responsiveness of the system's real-time guidance mechanism was largely positive, with the consistency and timing of feedback highlighted as a particular strength. All respondents agreed that this application is suitable for the beginner level but not for advanced level. Only one respondent would recommend this application to intermediate level users.

TABLE VI. RESPONDANTS' RATING ON ACCURACY

Accuracy (ACC) Questionnaire	Rating-Percentage in %	Average ratings
ACC1	2-33.3%; 4-66.7%	3.33
ACC2	2-33.3%; 3-33.3%; 4-33.3%	3.00
ACC3	3-66.7%; 4-33.3%	3.33
ACC4	3-66.7%; 4-33.3%	3.33
ACC5	4-66.7%; 5-33.3%	3.00
ACC6	YES-100%	-
ACC7	1-33.3%; 2-33.3%; 3-33.3%	3.33
ACC8	YES-66.7%; NO-33.3%	-
ACC9	YES-100%	-
ACC10	YES-33.3%; NO-66.7%	-
ACC11	NO-100%	-
ACC12	2-33.3%; 3-33.3%; 4-33.3%	3

In terms of safety features, all participants were able to successfully simulate emergency scenarios, such as a sudden fall, and confirmed that the emergency mechanism was activated as intended. However, the accuracy of detection varied, with most responses indicating only partial success. This suggests that, while the system is generally responsive under standard emergency conditions, its ability to recognise more nuanced or subtle incidents could be further optimised.

When evaluating the usefulness across different user experience, participants recommended it primarily for beginners, noting that its current functionality may be too limited for more advanced athletes. In general, the motion capture component was rated moderately effective in supporting safe and efficient training practices.

These findings underscore both the potential and limitations of the application. Although it offers a valuable foundation for form monitoring and injury prevention—particularly for novice users—enhancements in detection precision and feature adaptability could significantly broaden its applicability and effectiveness across a wider spectrum of users.

V. DISCUSSION

The project successfully achieved its defined objectives and was completed within the planned scope. The first objective, to examine existing applications in the market, was addressed through a comprehensive literature review and product comparison. This analysis identified key gaps, particularly in the areas of real-time feedback and user safety features, providing a strong rationale for the development of the proposed system.

The second objective, to implement real-time motion capture and feedback, was realised through Google's ML Kit for pose detection. This enabled the system to analyse users' body posture during squat and deadlift exercises and provide immediate visual cues to assist with the corrective action in real time. The third objective, to provide detailed performance analysis, was met by incorporating features to track and reporting exercise metrics, including repetition counts, posture accuracy, and weight logs. These insights allow users to monitor their progress over time and support ongoing self-improvement.

All major components outlined in the scope of the project were implemented, including user registration and registration, profile and settings management, workout planning, motion capture, emergency response functionality, and performance reporting. The system was extensively tested at multiple levels, and user acceptance feedback confirmed that the application met its core functional and usability requirements.

Among the key strengths is the effective implementation of real-time posture feedback using Google's ML Kit, which allows immediate and actionable guidance, particularly beneficial for user training without supervision. The emergency alert mechanism represents another significant achievement, enhancing user safety by detecting abrupt or unsafe motion (e.g. falls), triggering an alarm, and facilitating quick access to emergency contacts. Furthermore, by using Google's pre-trained ML Kit rather than developing a custom model, the project significantly reduced implementation complexity while maintaining satisfactory performance. Basic security measures, including password hashing and session management, were also implemented to ensure user data protection.

As compared to existing studies, Nguyen (2024) research detects static body pose from image and real-time yoga pose recognition. RepDetect [35] on the other hand, monitors exercises such as push-ups, sit-ups, etc. Groovetime and NeckFit provide real-time coaching in dance and body posture [21, 22]. However, gym workout is not included in the research. Existing market products such as Gym Log and Muscle Booster Plan Workouts mainly focus on providing exercises and digital planner without real time coaching.

Despite these achievements, several limitations were identified. The application was developed and tested exclusively on Android, limiting its accessibility across platforms. Additionally, the accuracy of the motion capture functionality is sensitive to environmental conditions such as lighting and camera angle, due to its reliance on visual input. Future improvements could involve the integration of device sensors or depth-sensing technologies to improve detection reliability. The current posture analysis is also based on fixed-angle rules, without adaptation to individual user variability or training history. Furthermore, time constraints limit the implementation of additional features such as workout reminders, voice guidance, and cloud-based data storage.

VI. Conclusion

The proposed system offers a creative and innovative solution to a real and often under-addressed challenge in the fitness technology domain: ensuring proper exercise form and workout safety during strength training without the need for direct supervision. Although many existing fitness applications prioritise features such as workout libraries, activity tracking, and goal setting, this project distinguishes itself by integrating real-time motion capture and posture analysis through Google's ML Kit. By focussing specifically on squats and deadlifts, two high-risk compound movements, the application provides users with immediate visual feedback, allowing them to correct their form in real time and reduce the risk of injury.

One of the most novel contributions is the built-in emergency mechanism, which identifies abnormal movement patterns, such as a fall or dangerous posture, and responds by triggering an audible alarm and initiating contact with a predefined emergency number. This safety feature addresses critical oversight in most fitness applications and adds considerable value for users who train independently, particularly at home or unsupervised gym settings.

In addition to its safety features, the system offers comprehensive tracking of exercise performance, including repetition counts, posture feedback, and progress monitoring through visual logs and charts. These elements enable users to take greater control of their fitness journey, allowing more informed self-assessment and long-term improvement.

The necessity of such a system is underscored by the fact that improper form, particularly during exercises such as squats and deadlifts, can result in serious injury, especially for beginners or users without professional supervision. By providing visual guidance during exercise execution, the application promotes safer training practices and supports proper biomechanics. Additionally, its mobile-based implementation enhances accessibility and convenience, eliminating the need for costly motion capture hardware or personal trainers.

From a marketability perspective, the application demonstrates strong potential. Its focused functionality, user-friendly design, and emphasis on safety align well with the growing demand for intelligent fitness tools. Positioned as a niche solution for strength training, it fills a gap in the current fitness app landscape by combining real-time posture correction with emergency safety features, two elements rarely found together in existing solutions.

A. Limitations and Future Improvements

Although the project successfully met its primary objectives, several limitations were identified during the development and testing phases.

A significant constraint is the current compatibility with only Android devices. This platform-specific implementation limits accessibility for iOS users and, therefore, reduces the potential reach of the application. Broadening the support of the platform is essential to maximize user adoption and market presence.

Another key limitation lies in the motion detection architecture, which relies solely on 2D pose estimation via a single camera angle. This configuration restricts accurate posture recognition to frontal views. If the user is positioned at an angle or partially outside of the frame, the accuracy of detection can be considerably degraded. Furthermore, the pose estimation model used in the application is optimised for larger joints and body segments and is less effective at detecting fine-grained joint movements. This limitation reduces the precision and depth of feedback, which is particularly important for advanced users or nuanced form corrections.

Functionality is further limited by the current scope of exercise support, which includes only squats and deadlifts. While these are foundational compound movements, the lack of support for additional exercises may hinder adoption by users with more diverse training programmes. Expanding the range of supported movements would make the system more versatile and appeal to a wider user base.

Language support presents another accessibility barrier. At present, the application is available only in English, which may exclude non-English speaking users and limit the app's appeal in international markets. Introducing multilingual support would improve usability and broaden the application's global relevance of the application.

Additionally, hardware limitations inherent to mobile devices present challenges to consistent performance. Real-time pose estimation requires continuous processing of video streams and joint calculations, which can strain lower-end devices. Users with limited processing power, low memory, or lower resolution cameras may experience reduced accuracy, frame rate drops, or latency, all of which impact the reliability of the posture feedback system. In high-precision use cases, desktop or high-performance environments may be more appropriate.

To address these limitations, several enhancements are recommended for future development. Expanding cross-platform compatibility to include iOS and desktop environments will enable greater accessibility. Improvements in the pose detection mechanism, such as incorporating multi-angle views or 3D tracking, would allow for more accurate recognition regardless of user orientation. Increasing the number of detectable joints and expanding the exercise library would enrich the system's functionality. Integrating multilingual support into the user interface will improve accessibility for a global audience. Finally, optimising the application for lower-end devices or offering a higher-performance version for PCs would improve consistency and detection reliability across different hardware configurations.

B. Issues and Solutions

One of the main technical challenges encountered during this project was the implementation of Google's ML Kit for pose detection in the context of real-time motion analysis for squats and deadlifts. As this was the first experience working with pose estimation technology, a substantial amount of time was invested in understanding how the model detects body landmarks and how the resulting coordinate data could be interpreted to assess posture. Beyond identifying joints, the system needed to logically evaluate whether a user was completing full repetitions, maintaining correct form, and avoiding potentially dangerous movements. This required designing algorithms capable of calculating joint angles, tracking movement trajectories, and establishing thresholds to distinguish between proper and improper forms. Iterative design and testing of logic flows were necessary to ensure a reliable and consistent posture analysis mechanism.

Device performance presented another significant challenge during motion capture. The real-time detection process required continuous video processing and data analysis, which placed a heavy computational load on mobile devices. This led to overheating and accelerating battery depletion, particularly during extended exercise sessions. To address this issue, a rest mode feature was implemented. When a user completes a set, the system automatically pauses camera usage and suspends pose detection to allow the device to cool down. The user could resume the session manually using a "Continue" button. This approach helped mitigate device stress while maintaining session continuity.

In addition to technical hurdles, the project was also the first experience using the Flutter framework and the Dart programming language. Initially, the lack of familiarity with these tools introduced a steep learning curve, particularly in understanding the Flutter widget-based structure and state management principles. Early development progress was slower than expected due to this unfamiliarity and the increased difficulty of debugging. However, these challenges were progressively overcome through dedicated self-study, including tutorials, official documentation, and community forums, which eventually led to greater fluency and development efficiency.

Despite these obstacles, the challenges encountered throughout the project ultimately served as valuable learning experiences. The development process improved technical competencies in Flutter development, real-time motion detection, and logical algorithm design. As importantly, it fostered growth in project management, problem solving, and self-directed learning. Key takeaways included the ability to deconstruct complex problems into manageable units, adapt designs to accommodate real-world constraints, and implement continuous testing and refinement strategies to achieve reliable results. This is crucial as more advanced AI features could be integrated into the AI-powered fitness coach, such as cardiac detection to prevent fatal death and promote a more sustainable fitness programme to the society [36].

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