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Implication and Evaluation of Cardiopulmonary Resuscitation Assistant

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A dissertation submitted in partial fulfilment
of the requirements for the degree of
MSc Computer Science Intelligent System

Declaration

I hereby declare that this dissertation is entirely my own work and that it has not been submitted as an exercise for a degree at this or any other university.

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Abstract

This research evaluates the efficacy of the Cardiopulmonary Resuscitation (CPR) Assistant, a tool leveraging computer vision to offer real-time feedback to perfect ones chest compression rate and chest compression fraction during CPR training. Current CPR training methodologies often necessitate the use of costly equipment and experienced trainers, posing challenges, especially in financially constrained environments. The study aims to address these limitations by providing an affordable and intuitive solution that ensures quality training. In our study, a cohort of participants engaged with the application, and the results showcased a marked improvement in their CPR performance. The findings underscore the potential of the CPR Assistant as a viable alternative to conventional training methods, especially in regions striving for cost-effective means to elevate CPR awareness and proficiency.

Acknowledgements

I would like to thank my supervisor, Dr. Kenneth Dawson-Howe, for his consistent guidance and constructive critiques throughout this project. My sincere thanks go to the National Ambulance Service North Leinster Area for facilitating my connection with the First Responder's organization. I'm especially grateful to Simon Taylor from the Blessington Community First Responder Unit for enlightening me on the workings of the first responder organization. I would also like to thank my friends for their support throughout the project, especially those who volunteered to test my application.

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1 Introduction

1.1 Goal

The primary goal of this study is to develop a CPR (Cardiopulmonary resuscitation) assistant that is production-ready, tailored for community use. By ensuring its readiness for real-world deployment, the study aims to evaluate the usability and efficiency of the application in training users. Through this evaluation, the study seeks to uncover the practical applications of the system and identify its potential limitations in real-world training scenarios.

1.2 Motivation

The motivation behind this study stems from a series of enlightening interactions and observations. During a discussion with the team coordinator and trainer of the Blessington Community First Responder Unit, it was revealed that recent advancements in their training methods had incorporated the use of a CPR dummy equipped with IoT devices. These sophisticated dummies, designed to provide live feedback and generate reports on both chest compression rate and chest compression depth, represent the pinnacle of current CPR training technology. However, while their efficacy is undeniable, their widespread adoption faces significant challenges.

These units are organized and deployed by the National Ambulance Service, which has only recently started to mandate their use in regions like Dublin. The slow pace of this rollout is attributed to the high costs associated with these state-of-the-art dummies. For volunteer organizations like the Blessington Community First Responder Unit, securing funding for such expensive equipment is a daunting task. Their reliance on voluntary contributions and the inherent financial constraints mean that, at the time of our interaction, they possessed only one such device and faced challenges in procuring more.

Furthermore, the training of first responders or newcomers to the unit presents its own set of challenges. The ideal trainers are experienced first responders, individuals who have not only demonstrated excellence in emergency scenarios but also possess a wealth of experience, numerous certifications, and a commitment to dedicating additional hours to their roles as first responders. However, as the team coordinator highlighted, the voluntary nature of these positions, combined with the demands of their personal primary employment, makes it challenging to find individuals willing to take on the added responsibilities of a trainer.

The 2020 annual report from the Out-of-Hospital Cardiac Arrest Register (OHCAR) in

Ireland highlighted the proactive nature of Irish citizens in attempting bystander CPR, with a remarkable 84% of cardiac arrests in 2020 seeing resuscitation attempts by bystanders [6]. Such high rates of bystander intervention underscore the potential impact of widespread CPR awareness and training. However, this is not the case globally. In many countries, especially those with lower economic resources, the prevalence of CPR training among the general public is significantly lower, from 61 studies spanning 29 countries [7]. The global prevalence of CPR training among laypeople varies significantly, ranging from 3% to 79%. The median rate of those trained stands at 40%. When broken down by income levels of countries, high-income nations report a median training rate of 50%, while upper middle-income and lower middle-income countries report medians of 23% and 17%, respectively.

Furthermore, a study from the UK revealed that 30% of adults would not perform CPR if they witnessed a cardiac arrest, indicating a significant knowledge gap that puts lives at risk [8]. This gap is even more pronounced in low-income, Black, and Hispanic neighborhoods, where individuals are less likely to receive bystander CPR compared to their counterparts in high-income white neighborhoods [9]. Such disparities emphasize the need for targeted interventions to raise awareness and improve access to training in these communities.

Moreover, the study from Takatsuki, Osaka, Japan, in 2008, provided evidence that individuals with prior CPR training were 3.40 times more likely to perform bystander CPR compared to those without such training [10]. This finding underscores the importance of CPR training in influencing bystander behaviour during emergencies. However, the same study also highlighted that the difference in neurologically favourable one-month survival between trained (3.3%) and untrained groups (1.7%) was not statistically significant enough, suggesting that while training increases the likelihood of intervention, the quality and effectiveness of the CPR performed are also crucial factors.

In light of these findings, there is a pressing need for tools and interventions that not only raise awareness and provide training but also ensure the quality and effectiveness of the CPR administered. This is especially true for low and middle-income countries, where barriers such as lack of awareness, limited funding, and restricted access to training are more pronounced [7].

This landscape paints a clear picture, while advancements in CPR training technology are promising, they are not universally accessible. Many communities worldwide lack the financial resources to procure advanced training equipment. Moreover, the scarcity of qualified trainers further exacerbates the challenge of delivering high-quality CPR training.

It is against this backdrop that our study's primary motivations emerge. Our foremost goal is to ensure the global availability of our CPR assistant system, making it accessible to communities irrespective of their financial capabilities. Equally crucial is our aim to diminish, if not entirely eliminate, the dependency on experienced trainers. By addressing these two pivotal challenges, we aspire to revolutionize the domain of CPR training, making it more inclusive, effective, and universally accessible.

1.3 Overview

This research delves into the critical role of Cardiopulmonary Resuscitation in medical emergencies, highlighting essential performance metrics and distinguishing between Compression-Only CPR and Traditional CPR. By reviewing prior work, we understand the evolution of CPR training, especially the integration of augmented reality, accelerometers and computer vision techniques. On the development side of the system, the study is anchored on the MERN stack, with MongoDB adeptly managing the data, and the workflow is designed to streamline user and trainer interactions.

Over a structured five-day evaluation, the application's efficacy in enhancing CPR performance is assessed, taking into account participant demographics and their prior experiences. Insights drawn from visual data representation are paired with results from hypothesis testing to provide a comprehensive understanding. As the research concludes, it not only encapsulates key findings but also acknowledges limitations, setting the stage for future exploration in the realm of CPR training.

2 Background

2.1 Introduction CPR

Cardiopulmonary resuscitation is a lifesaving technique, vital in emergency situations such as cardiac arrest, where an individual's breathing or heartbeats have stopped. It is a combination of chest compressions and rescue breaths that help maintain the flow of oxygenated blood to the brain until the return of spontaneous circulation (ROSC) or medical help arrives [11].

Research has consistently indicated that immediate initiation of CPR can drastically improve survival rates. According to the American Heart Association (AHA), CPR, particularly if performed immediately, can double or even triple a cardiac arrest victim's chance of survival [12].

2.2 CPR Performance Metrics

To optimize the effectiveness of CPR, it is crucial to adhere to the recommended performance metrics, including compression rate, compression fraction, compression depth and proper form.

2.2.1 Rate

The chest compression rate (CCR), which refers to the speed at which compressions are administered, plays a pivotal role in effective CPR. The AHA recommends a compression rate of 100-120 compressions per minute [13].

The ability to maintain this rate can vary significantly among individuals and is contingent on factors such as physical strength and endurance. In practice, consistently achieving the recommended compression rate can be quite challenging, especially over extended periods of time, as the exertion can lead to rescuer fatigue [14]. This can subsequently decrease the quality of compressions, making it less likely for the victim to recover.

To mitigate the challenges of rescuer fatigue, first responder protocols often emphasize the importance of teamwork during life-saving interventions. Typically, first responders are dispatched in pairs, allowing for periodic rotation between individuals administering CPR. By doing so, it ensures that each rescuer can maintain the optimal compression rate without succumbing to excessive fatigue. As one rescuer performs compressions, the other can recuperate, preparing to take over when needed.

2.2.2 Fraction

Compression fraction, also known as chest compression fraction (CCF), is the proportion of time in which chest compressions are performed during a cardiac arrest scenario. The total time for calculating CCF includes the time allocated to compressions and the breaths provided. A higher CCF is generally associated with increased survival rates. The AHA recommends a CCF of at least 60% upto 80% [15].

$$CCF = \frac{T_{\text{compressions}}}{T_{\text{total}}} \times 100 \tag{2.1}$$

2.2.3 Depth

Chest compression depth (CCD) refers to how far the chest should be compressed with each compression. A CCD of at least 2 inches (5 cm) but not greater than 2.4 inches (6 cm) for adults is recommended. For infants and children, the advised CCD is about 1.5 inches (4 cm) and at least one-third the depth of the chest, respectively [15]. While compressions at this depth enhance the likelihood of successful resuscitation, they also raise the risk of causing chest fractures, particularly in adults [16]. However, these potential injuries are typically non-life-threatening and treatable. Also, the benefit of achieving adequate pressure improves the chances of survival and considerably outweighs the risk of such injuries.

2.2.4 Form

For adult victims, the rescuer should interlock their fingers and place the heel of their bottom hand on the centre of the victim's chest (Fig:2.1), which is the lower half of the sternum [15]. In the case of infants or small children, due to their smaller body size, the rescuer should use only two fingers (index and middle fingers) for infants or one hand for small children to deliver chest compressions. The fingers or hand should be placed just below the nipple line [12].

It's equally important for rescuers to maintain a proper posture while performing CPR to ensure effectiveness and minimize fatigue. The rescuer should kneel beside the victim, keeping their shoulders aligned vertically above their hands to use body weight to assist in delivering the CPR [15].

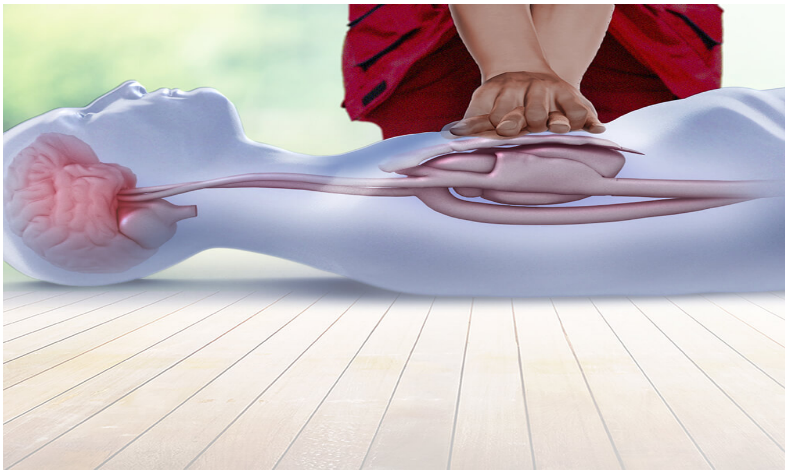


Figure 2.1: Illustration Showing the Correct Alignment of Hands on the Chest [1].

2.3 Types of CPR

2.3.1 Compression-Only CPR

Compression-only CPR (CC-CPR), as the name suggests, involves chest compressions without rescue breaths. It's recommended for untrained bystanders or those uncomfortable with performing mouth-to-mouth resuscitation. It involves performing continuous chest compressions at a rate of approximately 100 to 120 compressions per minute. This technique is centred around the understanding that oxygen remains in the body for several minutes after the heart stops. Thus, it is crucial to pump that oxygen-rich blood throughout the body by continuously performing CPR [13].

2.3.2 Traditional CPR

Traditional CPR (WB-CPR) combines chest compressions with rescue breaths, typically in a ratio of 30 compressions to 2 breaths, while maintaining optimal CCF [17]. When performing breaths, it is advised to pinch the victim's nose and observe the chest fully rise to ensure adequate ventilation. This form of CPR is often recommended in cases where the victim is a child, an infant, a drowning victim, or an individual who collapsed due to respiratory issues.

There are cases when the victim suffers Asphyxial cardiac arrest, when the heart ceases to function because of oxygen deficiency, commonly resulting from incidents like choking or submersion underwater. In such circumstances, performing mouth-to-mouth rescue breathing becomes crucial. This intervention specifically targets the root cause, which is a shortfall in ventilation or oxygen delivery [18].

2.4 Prior Work

In the annals of medical advancements, the development and proliferation of devices designed to provide feedback during CPR represent a significant stride forward. By offering real-time data and auditory or visual cues, these devices assist the rescuer in adhering to recommended guidelines, thereby enhancing the likelihood of successful resuscitation and patient survival.

2.4.1 Augmented Reality

In recent advancements, Augmented Reality (AR) has emerged as a promising tool for CPR training. The study conducted at the University of Pennsylvania introduced an AR CPR system named CPReality, designed to offer an immersive multi-sensory CPR training experience [19]. This system integrates a CPR recording manikin with a head-mounted AR device, specifically the Microsoft Hololens. As participants perform hands-only CPR on the manikin, the system projects an AR holographic image of the circulatory system, providing real-time visual feedback on blood flow based on the quality of chest compressions being performed. If the compression rate deviates from the recommended range, auditory feedback in the form of a heartbeat metronome is provided to guide the user.

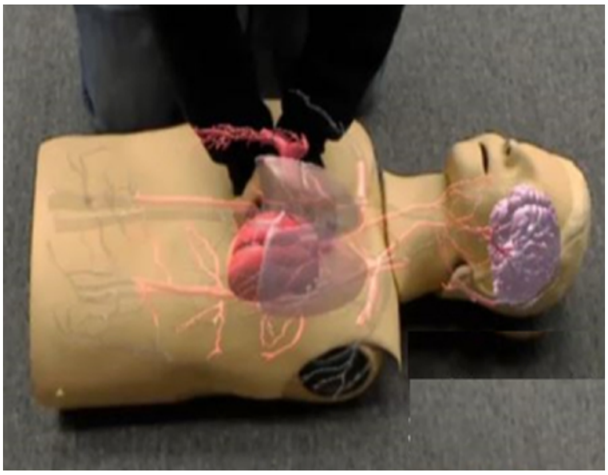


Figure 2.2: Visualization of the AR system during CPR training [2].

The results highlighted the system's potential, with a mean chest compression rate of 126 $\pm$ 12.9 cpm and a median depth of 53 mm. Furthermore, the AR experience was positively received by most participants, who found the audio-visual feedback from the interactive circulatory system both educational and instrumental in guiding effective compression delivery.

The AR approach offers several advantages over traditional methods. It combines both feedback and simulation training into a single immersive experience, potentially enhancing users' attitudes towards CPR training. However, the study highlighted the need for participants to adjust to the AR environment, and the potential underestimation of CPR quality due to unfamiliarity with the AR interface. Additionally, while the system's capabilities are undeniably impressive, it comes with a heftier price tag, which might pose a barrier for widespread adoption. Nevertheless, the initial results are promising, suggesting that AR could play a pivotal role in the future of CPR training.

2.4.2 Accelerometer

In a study by Amemiya et al., the methodology incorporated the use of the accelerometer within smartphones and studied under two distinctive holding conditions [3]. Firstly, the "hand-phone-stack" condition positioned the smartphone directly atop a mannequin's chest. Secondly, the "armband" condition involved strapping the smartphone, encased in a sports armband, to the back of the user's hand (Fig:2.3).

The application was designed to deliver auditory, and visual feedback corresponding to the quality of chest compressions, aiming to guide and improve CPR performance. The system's accuracy was evaluated by a participant executing chest compressions on a training mannequin, while a separate motion capture system simultaneously recorded the reference position data.

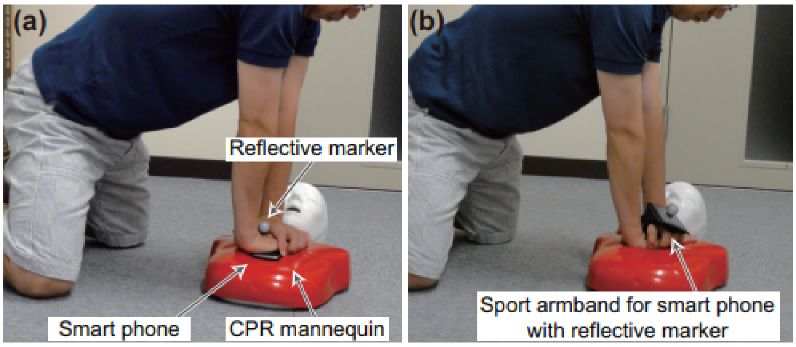


Figure 2.3: Smartphone placement demo [3]. (a) hand-phone-stack (b) armband condition

The results showed a root mean square error (RMSE) of 5.27 beats per minute (bpm) for the hand-phone-stack condition, and 4.19 bpm for the armband condition, when estimating compression rate.

While these results show promising potential, the study did identify some sources of inaccuracies. Also, certain technical constraints emerged due to the inability to control specific hardware keys on the smartphone. Limitations in the Android API potentially caused both. In addition to these technical limitations, the system does not account for the 'rescue breaths' typically administered during traditional CPR, thus narrowing its application scope.

2.4.3 Computer Vision

In the study by J. Alcaras [4], a method that uses live video for evaluating CCR and CCF during CPR was presented. The approach implemented a computer vision technique, specifically leveraging Gunnar Farneback's algorithm for dense optical flow, in a unique and practical setting.

In this approach, the positioning facilitated the capture of a comprehensive bottom-up view of the CPR process, as demonstrated in Fig:2.4. Importantly, the study was designed in such a way that only a well-positioned smartphone was required, thus eliminating the need for additional equipment. This feature made the approach particularly advantageous due to its cost-effectiveness and ease of setup.

Figure 2.4: Placement of smartphone to provide bottom-up perspective [4].

Farneback's dense optical flow algorithm was utilized to calculate the optical flow for all pixels between consecutive frames. In other words, the algorithm was able to compute the displacement of each pixel from one frame to the next. This pixel displacement data was then employed to identify both chest compressions and artificial ventilation within the CPR process, allowing for real-time feedback on CCR.

The evaluation of the algorithm's performance revealed promising results, with detection rates of 88% for chest compressions and 69% for artificial ventilation across both ideal and nonideal testing environments. These findings imply that the system could be effectively utilized in training scenarios to improve the quality and effectiveness of CPR. While the results were promising, further system refinement is needed to optimize its performance and reliability.

In the work by Corkery et al., [5] a method where the device's camera is prompted upwards and situated close to the CPR dummy, with the dummy positioned between the smartphone and the rescuer (Fig:2.5), is evaluated. The exact optimal distance is not rigidly specified due to the variance in the field of view between different smartphone cameras. The crucial requirement is that both the rescuer and the dummy should be within the smartphone camera's field of view, occupying a significant portion of the frame to ensure sufficient data capture.

Figure 2.5: View from the smartphone showing the peak (left) and dip (right) during compression [5].

The recognition algorithm developed for this project identifies compressions and breaths based on the detected movement throughout the scene. By analysing the shifts in pixel intensities between frames, the algorithm determines movement patterns that correlate with chest compressions and artificial ventilation, identical to the technique which was later used in J. Alcaras's system. Dense optical flow is an effective solution because it doesn't rely on edge detection or pre-training, which can be sensitive to noise and variations in light conditions.

Evaluation of the algorithm's performance was conducted using pre-recorded videos of CPR procedures. The results underscored the algorithm's exceptional performance in recognising chest compressions and artificial ventilation. With a recognition accuracy exceeding 99% for compressions and 96% for breaths across 11 test videos, these results provide a compelling argument for the effectiveness of the proposed system.

2.5 Analysis

Based on these previous works, it can be concluded that Corkery's method—leveraging computer vision to evaluate CPR delivery with the camera prompted up—presents the most optimal solution for our use case. It maximizes the use of commonly available technology, i.e., smartphones, and provides high detection accuracy with minimal setup, making it an accessible and reliable tool for CPR training and performance evaluation.

This technique will be adopted for this study as better implementation and refinement could potentially enhance this method's real-world applicability and contribute significantly to the efficacy of CPR delivery and training. Additionally, it's imperative to conduct rigorous testing to ascertain its impact. Only through comprehensive evaluation can we determine if this method can serve as a viable replacement for the existing systems or if it offers any tangible advantages.

3 Implementation

3.1 Architecture

The application was built using the MERN stack architecture, which is an acronym for MongoDB, Express.js, React.js, and Node.js, following a structure as illustrated in Fig:3.1. Each of these technologies was chosen to achieve specific functional and performance goals, as detailed below.

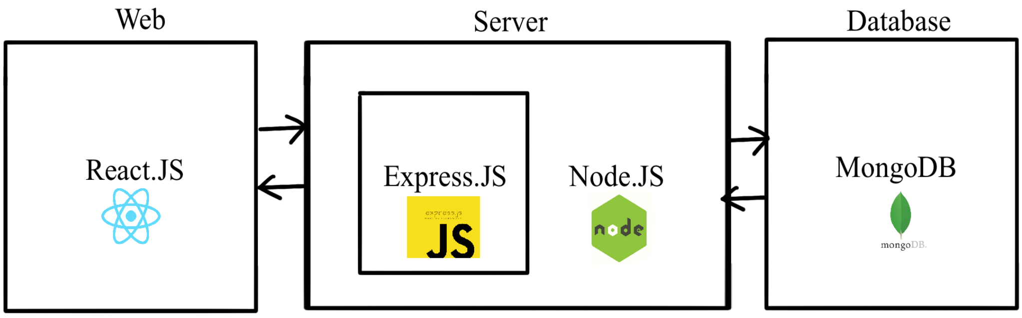


Figure 3.1: MERN Stack Application Architecture

MongoDB: This is a document-oriented database program used to manage the data layer of the application. The decision to use MongoDB was influenced by its inherent flexibility and scalability, allowing for easy modifications and improvements as the project scaled.

Express.js and Node.js: Express.js is a minimal and flexible Node.js web application framework that provides a robust set of features for web and mobile applications. Meanwhile, Node.js, a versatile JavaScript runtime environment, ensures consistent and efficient execution of server-side operations. This formed the back end of the application, handling all the server-side operations.

React.js: The system's front end was built using React.js, a well-regarded JavaScript library for constructing user interfaces. React's component-based architecture only updates the components of the UI that change over time, instead of reloading the entire page, which provides a seamless user experience and better performance.

A significant decision in the development process was the choice of React.js for the front-end development. The choice was made as a departure from the traditional approach of building native applications for specific operating systems. Unlike native apps, a React.js application can run on any system that has an internet connection and a camera, thereby broadening the potential user base. It also facilitates cross-platform compatibility with minimal effort, which means the application can run on various operating systems, be it Android, iOS, Windows, or others. Another key benefit is that the data generated can be viewed using the user's PC or desktop as well, thereby enhancing availability and convenience for users.

3.2 Database

In our application's database, we establish three main entities: Users, Trainers, and CPR/Game Details, as illustrated in Fig:3.2. Users and Trainers are interrelated, as one Trainer can be associated with multiple Users. Every User has two components of their data: CPR Details and Game Details.

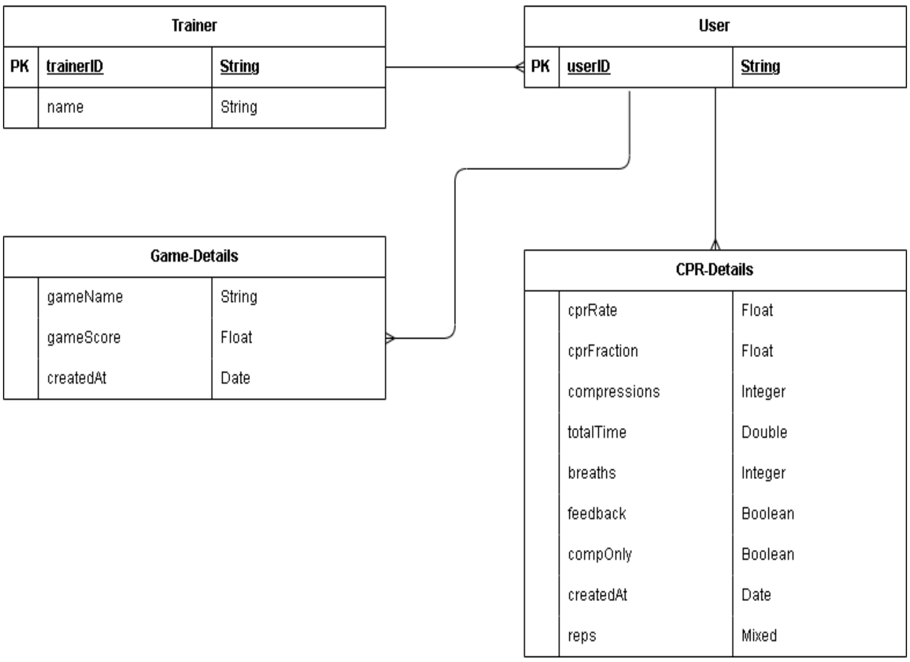


Figure 3.2: Entity-Relationship Diagram of the CPR Assistant Application.

CPR Details encompass a range of performance measures, including the rate and fraction of CPR, compression depth, if the feedback was utilized or not etc. In addition, there's an element called 'reps', which is essentially a chronologically ordered array of events taking place during a CPR session. Each event is either a chest compression, a beginning or ending rescue breath, represented by their respective timestamps.

Game Details include the name of the game and the score obtained, alongside the time when the game was played. This structure allows us to store and retrieve information effectively, paving the way for insightful performance analysis.

3.3 Workflow

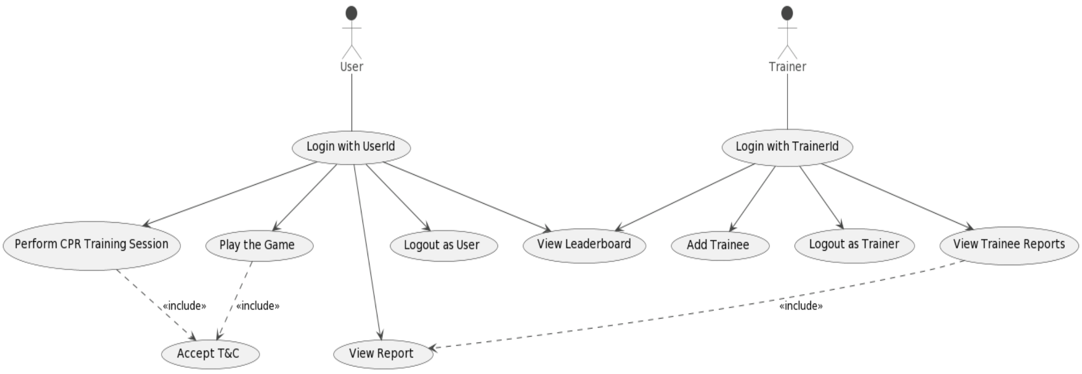


Figure 3.3: UML Use Case Diagram of the CPR Assistant Application.

The workflow of the application is characterized by two primary roles: the User and the Trainer. Each role interacts with the system through a specific set of functionalities, as presented in Fig:3.3 and expanded below:

3.3.1 User Interactions

The User's journey begins with logging in through their unique UserID (Fig:3.4.b). Upon successful authentication, a summary of their latest training and game sessions are presented to the user and multiple options.

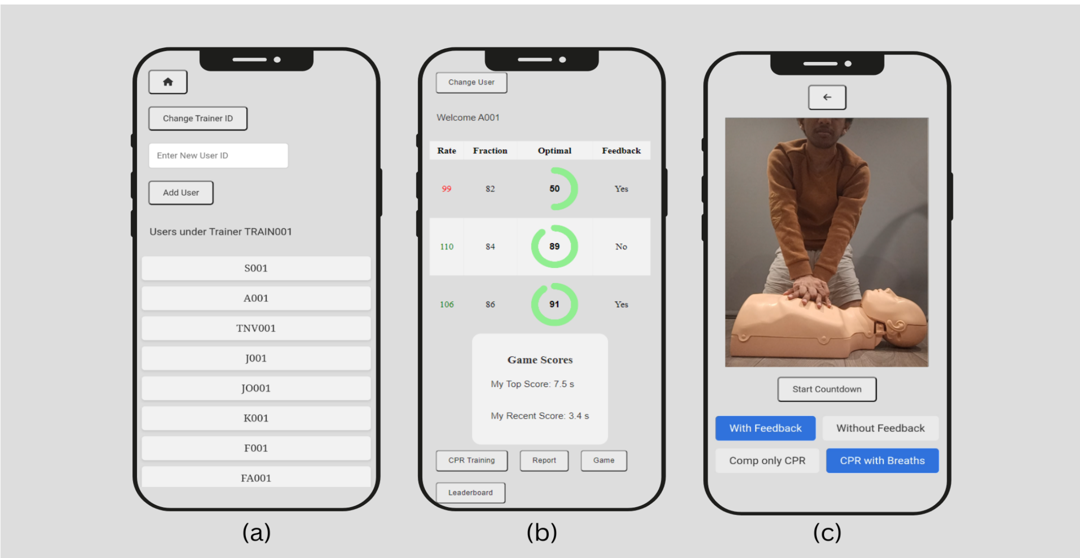


Figure 3.4: Interface of (a) Trainer Homepage (b) User Homepage (c) Training Settings

Perform CPR Training Session: The User can engage in a CPR training session, which necessitates the acceptance of the application's terms and conditions (T&C). This prerequisite ensures that the user is aware of the fact that the application does not store any forms of multimedia while participating in the training and that only their performance data will be shared with their trainer.

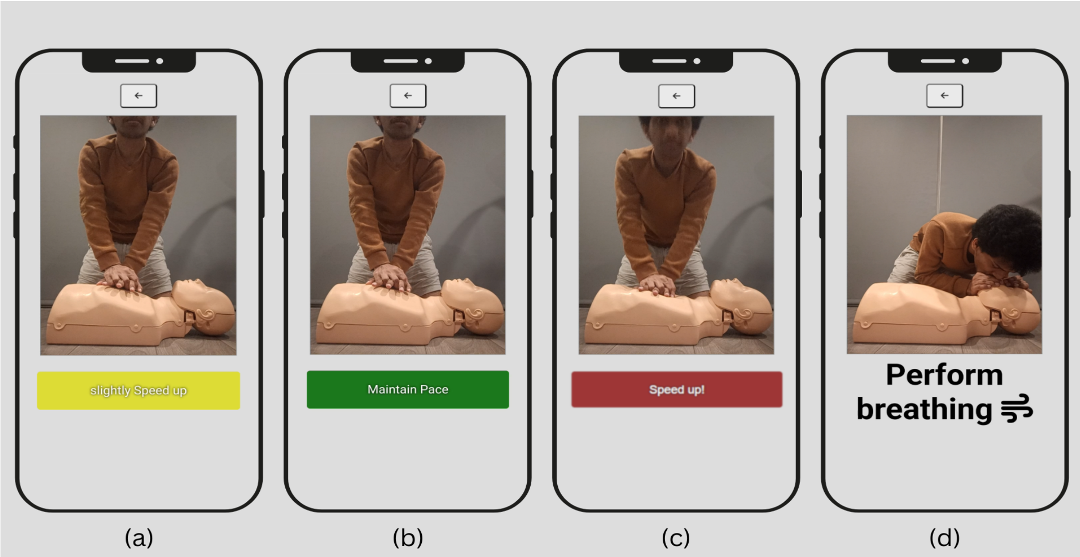


Figure 3.5: Training Session Interface (a) Slight Variation and Increase (b) Maintain Speed (c) Major Variation and pace needs to be sped up (d) Start Resuscitation Breaths

Before training begins, users have the flexibility to choose whether they want real-time feedback during the session, as shown in Fig:3.4.c. This is to enable the user to practice without feedback as well, to have a gauge of how they will perform without assistance. Users can also select between performing CC-CPR or WB-CPR. This choice accommodates different training scenarios and helps trainees master maintaining both CPR rate and CPR fraction.

The live CPR rate is computed based on the time intervals spanning the most recent three compressions, which begins and the start of the 3rd rep and ends when the user finishes their session. This interval, in milliseconds (ms), is the difference between the timestamps of the third and first compressions.

$$\text{Interval(ms)} = \text{Timestamp of third compression} - \text{Timestamp of first compression} \quad (3.1)$$

Since our measurements are taken when the user rises after a compression, a 500-millisecond adjustment is made to approximate the descent for the initial compression and the ascent post the third one.

The CPR rate, measured in compressions per minute (cpm), is then:

$$\text{CPR rate (cpm)} = \frac{3}{(\text{Interval} + 500)\,/60000} \tag{3.2}$$

During a session, if feedback is enabled, the user will receive both audio and visual feedback to maintain, speed up or slow down their compression speed (Fig:3.5.a, b and c). If resuscitation breaths are enabled, the system will prompt the user after 30 seconds to perform breathing for 9 seconds (Fig:3.5.d). Over a 1-minute period, this timing is designed to bring the CCF to around 70% and help the user identify the time gap they posses to perform resucitation.

Play Game Mode: Users can participate in a game designed to reinforce their CPR training, acceptance of the T&C is again required as the live camera feed is required, and their best score would be displayed on the leaderboard.

Once the user initiates the game and begins performing CPR, the system actively monitors their compression rate. Upon reaching the optimal rate of 100-120 compressions per minute, the system prompts the user with the command "HOLD". This command signals the user to maintain that optimal rate for as long as possible.

The game's score is determined by the duration for which the user sustains the optimal compression rate. The challenge lies in maintaining the precise rhythm, reflecting real-world scenarios where consistent and accurate compressions are crucial. Should the user's rate fall outside the optimal range, the game automatically concludes, recording the time maintained as the final score.

View Report: Users have access to their individual reports, detailing the performance of their previous CPR training sessions (Fig:3.6.a). This self-monitoring feature enables continuous improvement and goal-setting.

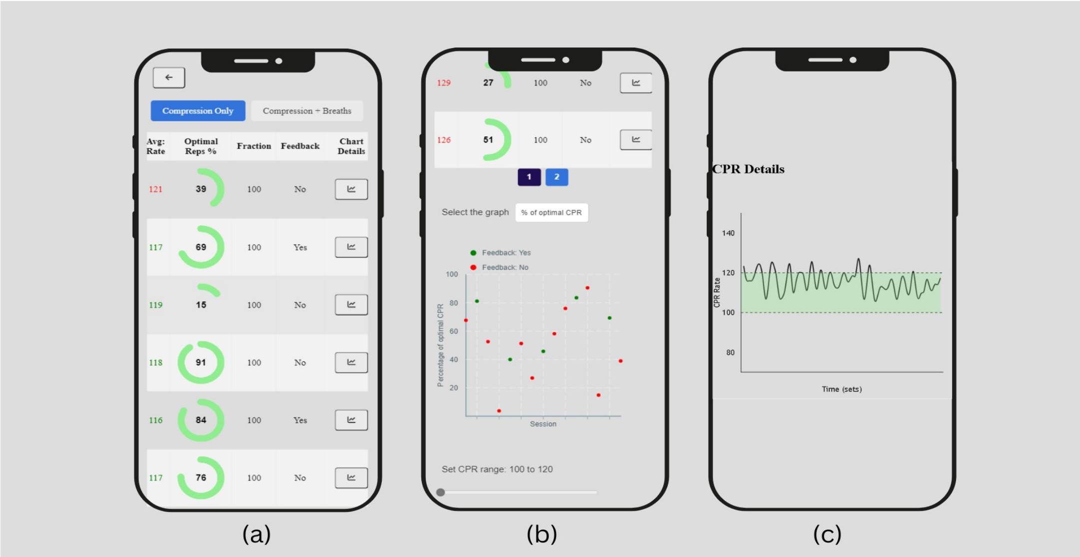


Figure 3.6: Interface of (a) Report Table (b) Report Graph with the y-axis representing the optimal percentage and the x-axis representing the session (c) Session Performance Plot with the y-axis indicating CPR rate and the x-axis indicating time

Within the report, users can filter between sessions performed with CC-CPR and WB-CPR. This categorization aids in the specific analysis of training types. Detailed data from previous sessions are displayed, including an essential metric known as "Optimal CPR %." This percentage represents the frequency with which the user's CCR fell within the optimal range of 100-120 compressions per minute. The calculation is performed by grouping sets of 3 consecutive compressions and determining the rate within those groups. The overall percentage is then derived from the proportion of these sets that meet the optimal criteria.

$$\text{Optimal CPR \%} = \left(\frac{\sum_{i=1}^{n} \chi\{100 \leq \text{CCR}_i \leq 120\}}{n} \times 100 \right) \tag{3.3}$$

Where:

- χ is the indicator function, which is 1 if the condition inside the braces is true and 0 otherwise.
- CCR_i represents the compression rate of the i^{th} set of 3 consecutive compressions.
- n is the total number of sets of 3 consecutive compressions.

Graphical representation further aids users in visualizing their performance. A specific graph plots the rate of compressions (Y-axis) against time (X-axis), for each individual session (Fig:3.6.c). Another graph illustrates the percentage of optimal CCR and CCF maintained across different sessions, with the ability to adjust the acceptable range using a scroll bar (e.g., from 100-120 up to 90-130 as in Fig:3.6.b). These graphical tools provide subtle insights and allow Users to gauge whether deviations from the optimal range are significant or minor.

View Leaderboard: The User can view a leaderboard that ranks game scores of all users under their trainer who have played the game, fostering a competitive and engaging environment.

3.3.2 Trainer Interactions

Trainers interact with the application through a separate set of functionalities, defined as follows:

View Trainee Reports: Trainers can view the list of users assigned to them and their individual reports of their trainees (3.4.a). This feature includes the same report-viewing functionality as Users but extends it to multiple trainees, allowing the Trainer to oversee and support their trainees' progress.

Add Trainee: Trainers have the capability to add new trainees to their roster, thereby expanding their influence and reach within the training program.

4 Evaluation

4.1 Procedure

The evaluation of the application was conducted through a structured approach, ensuring both the reliability and validity of the results. The methodology was designed to capture the efficacy of the feedback system in enhancing the performance of CPR by the participants. Furthermore, user validation played a crucial role in this process, as their feedback determined the system's usability and potential for integration into real-world scenarios.

4.1.1 Participant Selection and Demographics

Participants were recruited from a close circle of acquaintances, primarily consisting of those who were available and willing to dedicate time for the study. Prior to the commencement of the evaluation, each participant was required to be physically capable of performing CPR and queried regarding their experience with CPR. Specifically, they were asked about their prior experience performing CPR and the duration for which they had known the CPR procedure. This was essential to account for any potential biases or variations in the results due to differing levels of expertise among participants [20]. Whereas for those whome had no prior experience were given a basic lesson on how to perform CPR followed by a visual demonstration.

4.1.2 Evaluation Design

The evaluation was structured over a span of 5 days, with each day comprising three distinct sessions. The reason behind this design was to gauge the initial proficiency of the participants on a given day and subsequently measure the improvements post the feedback session.

- **Session 1:** Participants performed CPR without any feedback. This session served as a baseline, capturing the participant's initial proficiency on that particular day.
- **Session 2:** Participants performed CPR with the feedback provided by the application. This session aimed to understand the immediate impact of the feedback system on the CPR performance.
- **Session 3:** Post the feedback session, participants again performed CPR without any feedback. This session was crucial in identifying the retention and application of the

feedback received in the previous session [21].

4.1.3 CPR Styles

To ensure a comprehensive evaluation, participants were made to perform the experiment using two distinct CPR techniques:

1. **CC-CPR:** This style focuses solely on chest compressions without any resuscitation breaths. Recent studies have highlighted its effectiveness, especially in cases where the bystander is untrained in full CPR [22].
2. **WB-CPR:** This traditional method combines chest compressions with rescue breaths. It is often recommended for victims of drowning, drug overdose, or prolonged cardiac arrest [23].

4.1.4 Rationale

The alternating feedback design was chosen to understand the immediate effects of the feedback system and its potential long-term benefits. By comparing the performance in the first and third sessions, it becomes feasible to comprehend the improvements facilitated by the feedback. Moreover, the decision to evaluate both CPR styles was influenced not only by the desire for a holistic understanding of the feedback system's applicability across different CPR scenarios but also by the system's inherent variability in accuracy for detecting compressions versus breaths [5, 24]. This variability underscores the importance of assessing the feedback mechanism in diverse CPR contexts to ensure its comprehensive efficacy.

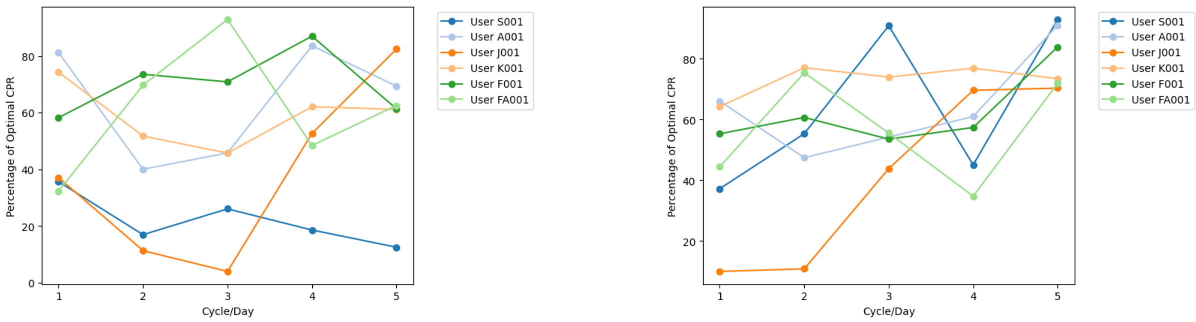
4.1.5 Open Interview

On the fifth day, after the completion of their sessions, participants were engaged in an open interview. This interview aimed to gather qualitative insights into the participants' experiences with the application. Questions covered various aspects, including their opinions on the user interface, the application's real-world usability, the effectiveness and utility of the feedback provided, the importance of the game mode implemented, and more. This qualitative approach was intended to complement the quantitative data, offering a holistic understanding of the application's impact on the participants [25].

4.2 Results

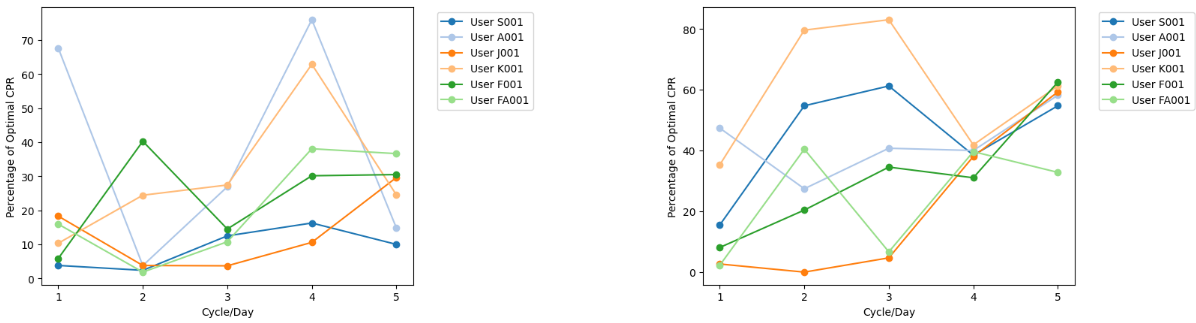
4.2.1 Graphical Analysis

Six line graphs were plotted to visually represent the performance of participants across different sessions and CPR styles for each user. Specifically, Fig:4.1 represents the sessions of the day where feedback was provided, Fig:4.2 showcases the performance during the first session of the day before any feedback, and Fig:4.3 illustrates the performance in the last session of the day after receiving feedback. The y-axis of these graphs represented the "Percentage of Optimal CPR" while the x-axis denoted the "Day or Cycle". Together, these graphs provide a comprehensive visual representation of the participants' performance trends over the evaluation period.



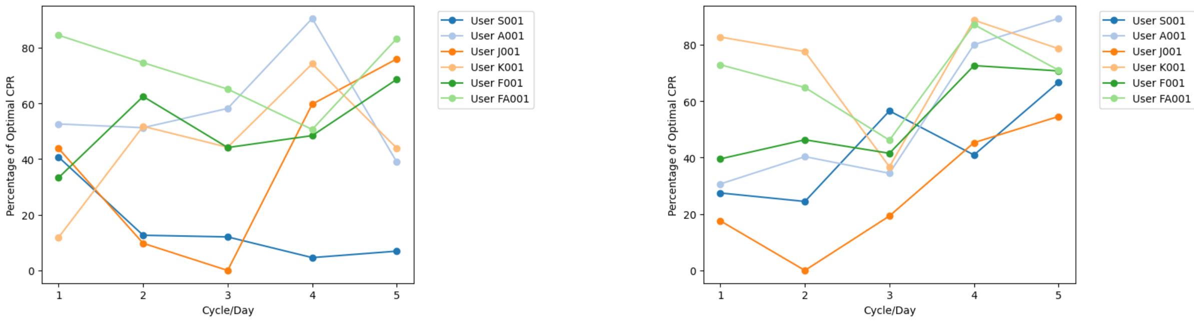
(a) CC-CPR with feedback (b) WB-CPR with feedback

Figure 4.1: Feedback sessions



(a) CC-CPR before feedback (b) WB-CPR before feedback

Figure 4.2: Sessions before feedback



(a) CC-CPR after feedback

(b) WB-CPR after feedback

Figure 4.3: Sessions after feedback

4.2.2 Dataset Construction

In need of further analysis, four datasets were constructed from the results of both CC-CPR and WB-CPR sessions:

1. The first session in the first cycle performed by the participant.
2. The highest-scoring first session from the last three cycles performed by the participant.
3. The third session in the first cycle performed by the participant.
4. The highest-scoring third session from the last three cycles performed by the participant.

These datasets were designed to capture various aspects of the participant's performance:

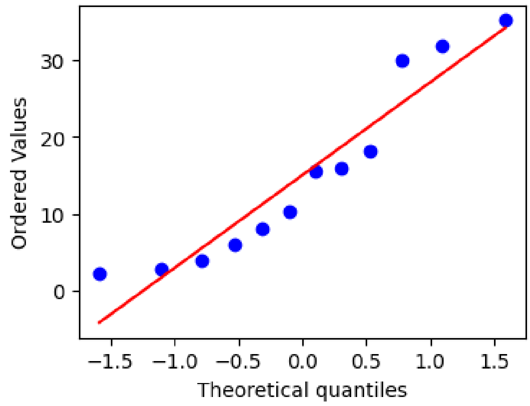
- **Dataset 1:** To gauge the initial performance of participants before any training.
- **Dataset 2:** To measure the retention and application of skills acquired over the training period.
- **Dataset 3:** To assess the immediate application of feedback received.
- **Dataset 4:** To evaluate the participants' ability to progressively utilize the feedback over time.

4.2.3 Statistical Analysis

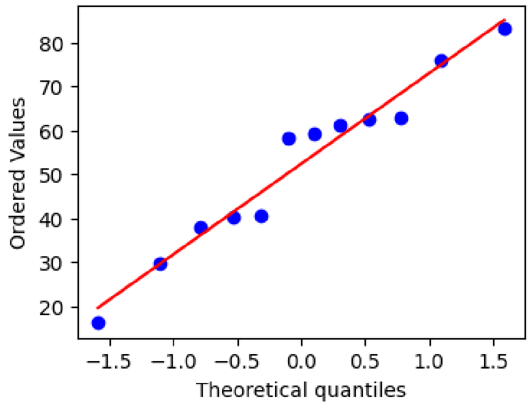
In this study, given the limited number of participants, it's essential to choose a statistical test that is robust for smaller datasets. The t-test emerges as a suitable choice, being specifically designed to handle and provide reliable results even with fewer data points [26].

Distribution Check

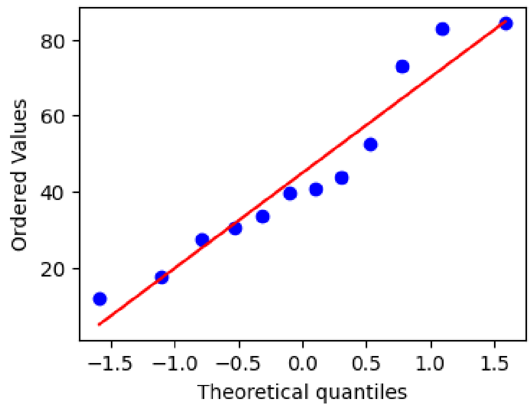
Before conducting the t-test, it's essential to ensure that the data meets the test's assumptions. One of the primary prerequisites for the t-test is the normal distribution of the datasets. To ascertain the normality, QQ plots were plotted as in Fig:4.4, and all datasets closely followed an approximate straight line, suggesting a normal distribution [27, 28].



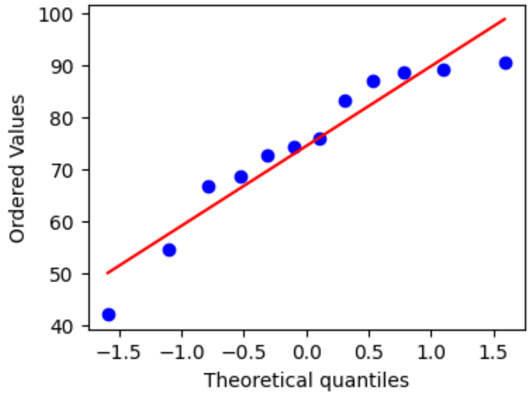
(a) Dataset 1



(b) Dataset 2



(c) Dataset 3



(d) Dataset 4

Figure 4.4: QQ Plots for Datasets

The Shapiro-Wilk test was further conducted to statistically confirm this observation:

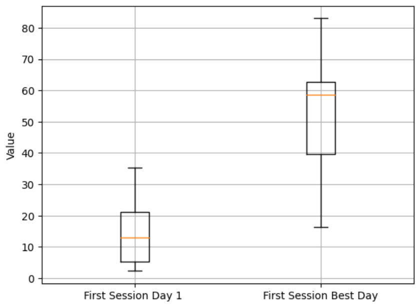
Dataset	Shapiro-Wilk p-value
First day after feedback	0.2956
First day before feedback	0.1071
Best day after feedback	0.1820
Best day before feedback	0.7355

Table 4.1: Shapiro-Wilk Test Results

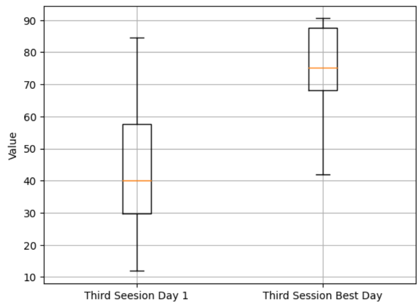
Given the conventional alpha level of 0.05, all datasets were found to be normally distributed as all p-values were greater than alpha [29].

Variance Check

Another prerequisite for the t-test is the homogeneity of variance between the datasets. To visually inspect the variance, box plots were generated, as shown in Fig:4.5. Both pairs exhibited similar shapes, suggesting homogeneity of variance across the datasets.



(a) Datasets 1 and 2



(b) Datasets 3 and 4

Figure 4.5: Box Plots for Variance Check

The Levene's test was conducted to statistically validate this observation:

Datasets Compared	Levene's Test p-value
Datasets 1 and 2	0.1985
Datasets 3 and 4	0.2137

Table 4.2: Levene's Test Results

Both p-values, being greater than the required alpha level of 0.05, confirm the homogeneity of variance across the datasets [30].

Hypothesis Testing

With the prerequisites met, a paired-sample t-test was conducted between datasets 1 and 2, and datasets 3 and 4:

Datasets Compared	t-test p-value
Datasets 1 and 2	5.17×10^{-6}
Datasets 3 and 4	4.3×10^{-3}

Table 4.3: Paired-sample t-test Results

Given the extremely low p-values, it can be inferred that the feedback system had a statistically significant impact on the participants' CPR performance [31].

4.2.4 Open Interview Feedback

After the completion of the evaluation sessions, participants were engaged in an open interview to gather qualitative insights into their experiences with the application. Their feedback provided a comprehensive understanding of the application's strengths and areas of potential improvement.

Positive Feedback: Participants expressed that the sessions with feedback were instrumental in helping them understand and maintain the correct rhythm for CPR. Many reported that they could retain some of this rhythm even on subsequent days, indicating the potential long-term benefits of the feedback system. The user interface (UI) was lauded for its user-friendliness, with participants finding it clean and straightforward, especially after an initial explanation. The graphical representations and reports were particularly appreciated for offering valuable insights into their performance. The game mode was highlighted as an innovative feature, with participants noting that it added an element of fun and competitiveness, potentially boosting morale during training sessions. Furthermore, several participants believed that the application could be particularly beneficial for training small societies or even first responders.

Areas for Improvement: While the feedback was largely positive, participants also highlighted areas where the application could be enhanced. Some suggested the incorporation of a blinker or beeper mechanism to assist in maintaining the correct CPR pace. A few participants found it challenging to keep up with the feedback, indicating a potentially steep learning curve associated with the system. This sentiment was further echoed by participants who felt that the UI, while user-friendly, required external assistance for initial navigation. Physical fatigue was another concern, with some participants feeling exhausted by the end of the second session. Is in turn affected their performance for the rest of the sessions on that same day. A few participants also voiced that while the application was beneficial for training, its utility might be limited in live emergency situations. Since to perform training a neutral background was recommended and unnecessary motion during a session was told to cause missed calculations. Lastly, suggestions were made to enhance the trainer's UI by incorporating more comprehensive statistics or additional information to provide a holistic view of the training sessions.

These insights from the open interview are invaluable, offering a user-centric perspective that can guide future iterations and improvements of the application [25].

5 Discussion

5.1 Inferences from Graphical Analysis

The visual aids not only depict the immediate impact of the feedback system but also shed light on the retention and application of the feedback over time.

5.1.1 Baseline Performance: Before Feedback

Our primary focus gravitates towards Fig:4.2 (illustrating sessions before any feedback). This session offers invaluable insights into the retention capabilities of the participants. There is a much evident upward trend, which is a promising outcome as it proves our case in highlighting the long-term retention and effective assimilation of CPR techniques, even in the absence of immediate feedback.

The performance in this session is particularly intriguing. While most users exhibited a struggle in their initial CC-CPR sessions, the WB-CPR sessions generally showcased better starting performances. This observation might be strongly influenced by the sequence in which participants were instructed to perform the CPR styles, with CC-CPR preceding WB-CPR.

5.1.2 Immediate Impact: Feedback Sessions

Turning our attention to Fig:4.1 (indicating sessions where feedback was provided), it becomes evident that the majority of participants showcased an improvement in the percentage of optimal CPR by the end of their cycles. However, there are exceptions, such as user S001 in Fig:4.1a (CC-CPR with feedback), who seemed to struggle with synchronizing their actions with the feedback. This could be attributed to the initial challenges faced by some participants in adapting to the feedback system and finding the right rhythm. An observation was made where participants, upon receiving feedback, often paused momentarily to process the information. This pause, although brief, disrupted their ongoing rhythm, making it challenging for them to resume CPR immediately [32]. This section of the study elucidates participants' adaptability and synchronization with the feedback over time.

5.1.3 Retentive Performance: Post-Feedback

Among the three sessions, the performance in Fig:4.3 (representing sessions post-feedback) stands out as particularly noteworthy. As anticipated, participants exhibited enhanced performance in this session, having just received feedback on the appropriate CPR technique. This trend underscores the immediate efficiency of the feedback system in guiding users towards optimal CPR performance. Notably, participants like F001 and FA001, who didn't fare exceptionally well during the feedback sessions, demonstrated improved performance in the subsequent non-feedback sessions. This phenomenon can be attributed to cognitive load theory [33]. When participants were provided with feedback, they had to juggle two tasks simultaneously: performing CPR (primary task) and adjusting their actions based on the feedback (secondary task). The increased cognitive load during the feedback sessions might have momentarily hindered their performance. However, the feedback provided them with valuable insights, enabling them to better understand and maintain the proper rate in subsequent sessions.

5.1.4 Case Analysis: Trained Participant

A unique case is that of user A001, the only participant with prior CPR training. Their performance trajectory suggests that while the feedback initially, in the first 2 cycles, disrupted their established rhythm, over time, they managed to integrate the feedback and refine their technique. This observation subtly indicates that even trained individuals, when exposed to new feedback systems, have the potential to further polish and enhance their existing technique.

5.1.5 External Influences and Variabilities

It's also worth noting that not all participants peaked in their performance on the final day. Such variations can be attributed to human error or external factors beyond the control of the study [34]. Whether it's the participant's physical or mental state on a particular day or external distractions, these uncontrollable elements reiterate the challenges of maintaining consistent performance across sessions.

5.2 Interpretation of Hypothesis Testing

The paired-sample t-test results strongly support the effectiveness of the feedback system in CPR training. The notably low p-values, 5.17×10^{-6} for Datasets 1 and 2 and 4.3×10^{-3} for Datasets 3 and 4, indicate a statistically significant improvement in participants' CPR performance post-feedback.

This data suggests that participants not only adapted to the immediate feedback but also retained these improvements in subsequent sessions. Such findings are consistent with existing literature, emphasizing the value of real-time feedback in skill acquisition [21].

In essence, the hypothesis testing validates the feedback system's potential in enhancing CPR training, making it more effective and targeted.

6 Limitations & Future Work

6.1 Sequence of CPR Styles

Having participants perform both CC-CPR and WB-CPR on the same day might have introduced unintentional biases or carry-over effects. The performance in one could have affected or influenced the participant's performance in the other, leading to skewed results. Splitting these sessions into separate days would have provided more precise data.

6.2 Comparison with Instructor

To truly gauge the efficacy of the feedback system, a comparison group trained by an experienced CPR instructor from the first responder's team would have been ideal. This would have allowed for a side-by-side comparison of the two methods, elucidating any key differences or similarities in performance outcomes.

6.3 Ground Truth Verification

The current study operated under the assumption that the algorithm would perform in alignment with its implementation as described by Corkery et al. [5]. However, to ensure the utmost accuracy and reliability of the system, it is imperative to have a ground truth mechanism in place. This would involve cross-referencing the system's feedback and results with a verifiable technique.

6.4 Comparison with Traditional Training

The suggestion from some participants to incorporate a blinker or beeper, akin to a metronome, to indicate the optimal CPR rhythm presents an avenue for further study. While the metronome style provides a consistent pace for users to follow, it possesses inherent challenges. If participants lose their rhythm, readjusting can be difficult without accelerating their rate substantially to catch up with the metronome's pace. This might risk the efficacy of CPR being delivered. However, despite these potential pitfalls, a simple auditory or visual cue like this has been proven to be a straightforward and effective technique for many users [35]. Comparing this method with the current feedback system could highlight the relative efficiencies and shortcomings of both methods.

6.5 Diversity in Participant Pool

The limited number of participants, especially those with prior CPR experience, restricts the generalizability of the results. A diverse group of participants encompassing various ages, backgrounds, physical abilities, and prior training experiences would provide a broader perspective and make the results more robust. Increasing the number of participants would not only enhance the diversity but also bolster the reliability of the statistical analysis performed, such as the t-test. Furthermore, with a larger participant pool, the study could explore other statistical tests like ANOVA for comparing more than two groups, or the Mann-Whitney U test for non-parametric data [36, 37]. These tests could provide additional insights into the data and further validate the findings.

6.6 User Interface and Experience Challenges

Participants praised the system's user interface for its clean and intuitive design during open interviews. However, many felt a heavy reliance on initial instructor explanations to understand the system's full capabilities. To address this, future versions could integrate a comprehensive tutorial module. This would guide users through the system's functionalities, reducing the need for external instruction and ensuring a smoother, more independent onboarding experience.

6.7 Evaluation Metric

The current metric, which quantifies solely based on the percentage of optimal CPR within the range of 100-120, may be overly strict. Participants who maintain a rhythm slightly below 100 or marginally above 120 aren't accurately acknowledged within this system, even though their performance lies near the optimal threshold. To better gauge the proficiency of participants, a more nuanced evaluation method is desirable. One approach could be to introduce a metric that considers the deviation or error from the optimal range. This way, a participant's performance would be judged based on the magnitude of deviation from the target, rather than a binary classification of optimal or not. Such a system would reward performances that are closer to the desired range, ensuring that even slight deviations are proportionally represented.

7 Conclusion

7.1 Summary of Findings

The study conclusively demonstrated that the feedback system effectively provides valuable insights to users during CPR training. Participants not only benefited from immediate feedback but also showcased an ability to retain and apply this knowledge in subsequent sessions. This retention was evident across a diverse set of users, highlighting the system's versatility. The varied interactions of participants with the system further underscored its adaptability and potential for widespread application.

7.2 Significance of the Study

This study highlights the system as a cost-effective alternative to expensive CPR dummies equipped with IoT devices. Its simplicity eliminates the complexities associated with setting up advanced systems. More importantly, in areas where trained CPR instructors are scarce, this system offers communities a viable and effective training solution, ensuring positive outcomes in CPR education.

7.3 Recommendations for Future Research

While this study primarily focused on feedback and retention, future research should delve into monitoring hand placement and CCD during CPR. These factors are crucial for effective CPR and were not extensively addressed in this study. Incorporating these variables could significantly enhance the training's efficiency and effectiveness.

Additionally, adapting the system for live emergency scenarios could be a valuable avenue for future research. This would involve stabilizing the video capture, especially when handheld, determining the optimal camera angle, and implementing techniques to minimize background noise interference. Additionally, exploring new video angles, such as from the sides of the CPR performer or from the head or feet of the victim, could prove viable, especially in scenarios involving two-rescuer CPR.

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A1 Appendix

A1.1 Use of AI Tools

A public subscription of ChatGPT developed by OpenAI, was utilized in the creation of the document. The AI tool was employed to retrieve a starting point for the structure of a few paragraphs and to provide suggestions for synonyms and alternative wording. This choice stemmed from the need to assist a non-native English speaking author, ensuring clear communication.

Additionally, ChatGPT was utilized in generating small code snippets, aiding the development process. Given that the technology stack was relatively unfamiliar, the AI-generated skeleton served as a valuable blueprint. Which assisted in the integration and understanding of the new technologies.