REVOLUTIONIZING REMOTE HEALTH MONITORING: AUTONOMOUS DETECTION OF PULMONARY AND CARDIAC ABNORMALITIES WITH CUSTOMIZED DIETARY PLANNING

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Project Proposal Report

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DECLARATION

I declare that this is my own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate is carrying out research for the undergraduate Dissertation under my supervision.

Signature of Supervisor
(Dr. Dilshan De Silva)

Date

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29/2/2024

ABSTRACT

Worldwide, cardiovascular diseases rank as the leading cause of mortality, and this has been true in America since 1950. The primary objective of this research is to develop an innovative, tablet-based mobile application that can generate a 12-Lead electrocardiogram signal using only the tablet’s camera, providing a reliable, contactless method for identifying cardiac rhythm through facial analysis. The proposed system aims to revolutionize remote health monitoring by utilizing advanced technologies like Convolutional Neural Networks and Generative Adversarial Networks. These technologies will be used for feature extraction from facial video data and for generating ECG signals respectively. The system will be designed to ensure high accuracy of the generated ECG signals, which is crucial for reliable diagnosis and monitoring of heart conditions. An application that enables users to monitor their cardiac health conveniently and accurately is the expected outcome of the study, should it be completed successfully. This could result in the early identification of cardiac abnormalities, which will allow prompt action, and improved patient outcomes. The system could also result in cost savings for the healthcare system by reducing the need for in-person consultations and specialized equipment. Furthermore, the study aims to make cardiac care more accessible, particularly for patients in remote areas or those with limited access to healthcare facilities. This study represents a significant advancement in the field of medical technology and has the potential to greatly improve patient care and outcomes in the field of cardiac health.

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LIST OF ABBREVIATIONS

Abbreviation	Description
WHO	World Health Organization
CVDs	Cardiovascular Diseases
TPU	Tensor Processing Unit
ECG	Electrocardiogram
ICRFA	Identification of Cardiac Rhythm through Facial Analysis
RAM	Random Access Memory
PPG	Photoplethysmographic
AF	Atrial Fibrillation
GAN	Generative Adversarial Network
CNN	Convolutional Neural Network
ROI	Region Of Interest
GPU	Graphical Processing Unit
VPG	Video plethysmography

1. INTRODUCTION

1.1 Background & Literature Survey

The World Health Organization (WHO) states that cardiovascular diseases (CVDs) account for 17.9 million deaths annually [1] and are the leading cause of death worldwide. This trend continues to this day, with coronary artery disease, one of the CVDs, ranking as the leading cause of death both as of today and thus far this year [2]. Moreover, 40% of deaths in Sri Lanka were due to CVDs with stroke and ischemic heart disease—both CVDs—representing the top two causes of death in 2021 [3]. CVDs like any other disease, can have their impact on health minimized [4] with early detection. The traditional 12-Lead Electrocardiogram (ECG) machine plays a vital role in the early detection [5] of cardiac abnormalities and is widely considered as the gold standard [6] by many.

However, there are several challenges associated with performing a 12-Lead ECG. One of the many challenges is the need for specialized, expensive equipment that is typically only available in a hospital setting. This necessitates a visit to the hospital, which may not always be feasible or convenient for all individuals. The process of performing an ECG also requires the individual to expose their upper body by removing their upper body clothing. This could potentially cause discomfort for some individuals, particularly females, due to privacy concerns. Furthermore, the procedure involves the placement of 10 electrodes, usually with a gel at the tip, onto the individual's body. The sensation caused by the gel might be uncomfortable for some individuals. Moreover, the procedure requires trained personnel [7] to correctly place the electrodes, operate the equipment, and ensure that the individual does not make any unnecessary movements which could affect the ECG reading. The individual must remain still [8] for about 5-10 minutes, which could be challenging for some, particularly those with certain health conditions or discomfort. Moreover, a 12-lead ECG captures information for only a few seconds. Therefore, there is a chance it may not detect abnormalities [13] that do not occur during the test itself. However, long-term, either continuous or periodic, monitoring of the heart's electrical activity can enhance [14] diagnostic results by increasing the probability of detecting irregularities. Currently there are noninvasive solutions which offer continuous monitoring such as smartwatches, ambulatory belts, and handheld devices. Smartwatches are an attractive choice due to their convenience and multifunctionality, not only do they tell time but also monitor health parameters, including heart rate and rhythm. While they offer continuous monitoring, it is important to note that they can be quite expensive and offer fewer comprehensive data compared to a 12-Lead ECG, as they only produce Lead I ECG [17] utilizing a single electrode [16]. Therefore, the reliability of the results may not be as high compared to the traditional 12-Lead ECG.

Ambulatory belts are designed to be worn around the chest for continuous ECG monitoring. However, wearing a belt continuously over an extended period might be uncomfortable for some users, as they can cause skin irritation or rashes, particularly in individuals with sensitive skin. This discomfort can also impact patient compliance, as some individuals may remove the device prematurely due to discomfort. Handheld devices offer the convenience of easily being able to carry it around for quick and convenient heart rate and rhythm checks. While they are more reliable alternatives to smartwatches and belts, they still do not offer a 12-Lead ECG reading. Based on the available information, the KardiaMobile 6L EKG [22] appears to be the most reliable handheld device currently on the market offering a 6-Lead ECG.

To successfully complete the research, understanding of video capture and processing techniques is required. It is crucial to know how to handle video data, extract frames, and perform operations such as scaling and cropping. Knowledge in computer vision will be beneficial here. Convolutional Neural Network (CNN) is primarily used to analyze visual data, they are particularly effective for tasks like image and video recognition. Therefore, it is necessary to understand the architecture of a CNN, including concepts like convolutional layers, pooling layers, and fully connected layers. It is also required to know how to train a CNN using techniques such as backpropagation and gradient descent. In addition to technical skills a solid understanding of cardiac rhythms and ECG signals is crucial.

1.2 Research Gap

The domain of Identification of Cardiac Rhythm through Facial Analysis (ICRFA) is relatively unexplored in literature. In fact, to the best of the existing knowledge, only one study has been conducted in this field, which was recently published. This is a study (Research A) proposed by Bin et al. [6] which present a novel noncontact method for the reconstruction of ECG signal based on facial videos. In the study, implicit and explicit supervision is used during the training of the network to successfully reconstruct an ECG signal. Short facial recordings are captured from a commercially available Logitech C930 web cam which is then fed into a motion disentanglement structure which aims to separate the facial region from the background and the noise. Techniques such as dense optical flow and median filtering is used to gather the motion features of the face and for removing the noise. Then the extracted facial region is fed into feature encoders which generate the relevant features such as the color changes in the skin, and irrelevant features such as the areas which may consists of hair or glasses. The two sets of features are then fed into a region generator which reconstructs the facial region to optimize the region of interest for physiological measurements. A reconstruction loss function is used to guide the network implicitly to learn the optimal features for physiological measurements.

Then there is a multiscale feature representation component, with the goal of creating feature maps of the desired facial region at various sizes. A feature extractor receives the input facial region and produces feature maps in various sizes. To assist the network to concentrate on the different impacts of light channels on physiological measures, the resulting feature maps are subjected to a channel aggregation attention technique. The feature maps are additionally processed through a frame aggregation attention mechanism, which strengthens the spatiotemporal association of the features in the network's shallow layers. The reconstructed facial region is then fed into another generator to extract the physiologically related features. Finally, these features are inputs to the convolution network based on the structure of a Generative Adversarial Network (GAN) which consists of a discriminator and a generator. Together the discriminator and generator generate a realistic ECG and heart rate. In the study, the correlation between the predicted and actual ECG signals, as measured by the Pearson correlation coefficient was 0.72 for the OBF dataset [10] and 0.85 for the FaceBio dataset [6]. However, the study does not provide information about the number of leads generated, nor the specific Lead generated. Additionally, there were instances where the system failed under conditions of significant changes in lighting.

There are other studies conducted on the detection of atrial fibrillation (AF) using facial video using smartphones. One such study by J.-P. Couderc et al. [20] used video plethysmography (VPG) to analyse facial pulsatile signals for AF detection. The objective of this study was to assess the precision in identifying AF using a smartphone and to evaluate its performance across different skin tones and recording conditions. The effectiveness of the monitoring was impacted by variables such as the patient's skin tone, light intensity, and the distance and angle of the camera from the patient's face. The study found that the VPG technology could detect AF with a sensitivity and specificity exceeding 90%. It is also stated that for the technology to consistently perform across all skin tones, the ambient level of illumination needed to be above one hundred lux. The study concluded that the detection of AF using facial video-based technology provides precise outpatient cardiac monitoring, with high accuracy in pulse rate and medical-grade performance for AF identification.

Another study by B. P. Yan et al. [21] presented a novel method for screening Atrial Fibrillation (AF) using an iPhone camera to detect and analyse photoplethysmographic (PPG) signals from the face without any physical contact. This method operates by extracting subtle beat-to-beat variations in skin colour that mirror the cardiac pulsatile signal. The Cardiio Rhythm smartphone application analysed the PPG measurements for heart rate regularity. Comparing the Cardiio Rhythm smartphone application to a 12-lead ECG, the study found that there was high sensitivity (95 percent; 95 percent confidence interval, 87 percent – 98 percent) and specificity (96 percent; 95 percent confidence interval, 91 percent – 98 percent) in differentiating between AF and sinus rhythm. The authors concluded that the detection of a facial PPG signal to determine pulse irregularity due to AF is feasible and holds potential for community screening and remote AF screening.

However, it is important to note that neither of the previous two studies deal with generating any ECG signals through facial analysis. The below table 1 shows a comparison of the related existing study against the proposed method.

Table 1 : Comparison with existing studies

Reference	**12-Lead ECG**	**Contactless approach**	**Portable device solution**
Research A	X	✓	X
Proposed System	✓	✓	✓

Given that the related existing study does not utilize a mobile camera as an input and does not generate a 12-Lead ECG, this proposed study aims to make cardiac health monitoring more accessible by leveraging devices that most people already possess.

1.3 Research Problem

Despite significant advancements in medical technology, CVD remain the leading cause of death globally. This is a complex issue with multiple contributing factors, including age, family history, smoking, bad eating habits, diabetes, and lack of exercise [18]. However, one key factor is that early detection of cardiac abnormalities can have a significant impact on health [4].

The primary challenge that this study aims to address is the development of a reliable, non-contact, hassle free method for identifying cardiac rhythm using facial analysis. Traditional methods for cardiac rhythm identification, while effective, require specialized equipment [7], trained personnel and time. This presents a barrier to regular monitoring, particularly for patients in remote areas or those with limited access to healthcare facilities. Traditional methods for cardiac rhythm identification, such as 12-lead ECG machines, while these provide accurate and detailed information about the heart's electrical activity, they are not without drawbacks. They require skin contact, can be uncomfortable to wear for an extended period, and need a healthcare professional to setup the equipment.

The more recent wearable ECG devices, though more convenient than conventional methods, have lower reliability [16] and higher cost. Hence the recent development of facial analysis presents a promising alternative for cardiac rhythm identification. It offers the ability for a non-invasive approach that can be used for convenient monitoring. Moreover, the development of a facial analysis-based approach for cardiac rhythm identification has significant implications. By providing regular cardiac health monitoring, it can transform patient care by facilitating the early diagnosis of cardiac problems, prompt intervention, and better patient outcomes. It could also result in cost savings [19] for the healthcare system by reducing the need for in-person consultations and specialized equipment.

One of the research questions in this domain is how to extract ECG signals from facial recordings, given that measuring ECG signal usually requires physical contact with electrodes. Another related question is how to obtain all 12 leads of ECG signal from facial recordings, considering that a traditional 12 Lead ECG machine uses 10 electrodes attached to various regions of the body. Other potential challenges include ensuring the quality and consistency of facial video data, dealing with motion, variations in lighting and skin tone.

If successfully addressed, this research problem could lead to significant advancements in the field of medical technology. It could improve patient care by enabling regular, non-invasive cardiac health monitoring. It could also lead to cost savings for the healthcare system and make cardiac care more accessible, particularly for patients in remote areas or those with limited access to healthcare facilities. Future development in this research area could potentially lead to monitoring cardiac health in public areas like shopping malls or airports. The system could assess the cardiac rhythms of multiple individuals simultaneously and alert medical personnel in case of cardiac events, enabling rapid intervention and potentially saving lives.

2. OBJECTIVES

2.1 Main Objectives

The main objective of this study is to create a tablet based mobile applications which will allow users to obtain a 12-Lead ECG signal of themselves with only the use of the tablet camera, and they will be able to visualize their ECG signals, share it with medical professionals. A video recording of their face captured from the tablet camera will be used as the input from which the ECG signal will be generated.

2.2 Specific Objectives

To achieve the main objective, there are several specific objectives that need to be addressed.

Identification of facial region

- After the video has been recorded, it's necessary to isolate only the face. This is because the ECG signal is produced from the features that are extracted from the face, a process that will be carried out using OpenCV. Part of this process will also involve identifying and ignoring areas of skin that are covered by hair or glasses, as these areas aren't suitable for feature extraction.

Extraction of physiologically related features from the face

- Once the desired region has been identified, relevant features need to be extracted, these features will then be used for the generation of the ECG. The extraction of these features will be performed using CNNs.

Generation of ECG signals

- Once the features are extracted, they will be fed into a GAN which will predict a realistic Lead II ECG signal. This generated signal will then be fed into an encoder-decoder structure which is a modified Attention U-Net framework [9] which is a CNN architecture, it will proceed to generate the remaining 11-Leads of ECG signals.

Creation of a tablet device-based system to visualize ECG data.

- After the generation of ECG signals, it's crucial for the user to have a way to view of them and have records of their previous readings. Given that there are 12 signals to display, a larger screen like that of a tablet would be ideal. Furthermore, a larger display aids medical professionals in evaluating a patient's condition more effectively due to the enhanced visualization of the signals.

3. METHODOLOGY

The proposed system will be capable of identifying the cardiac rhythm of an individual through facial analysis. Following section discusses the methodologies that will be used during the research period.

3.1 System Architecture

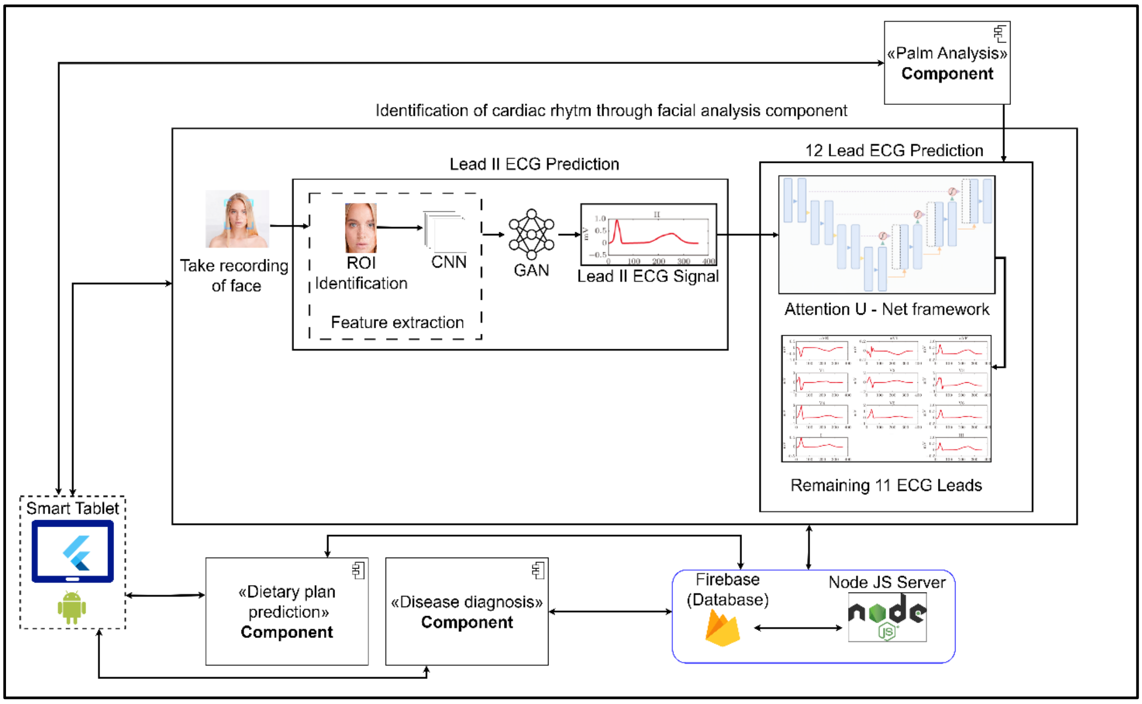

Figure 1 : Facial Analysis and ECG generation System Architecture

Figure 1 shows an overview of the proposed system for ICRFA. When the user wants to take an ECG reading, initially a video recording of the face must be taken from the Smart Tablet camera using the Flutter application, the duration of this video must be of at least 10 seconds. The captured video will be fed directly into the ICRFA component which consists of 2 main components, the Lead II ECG Prediction component, and the 12-Lead ECG Prediction component.

The first component receives the original input video, from which the region of interest (ROI) needs to be isolated. Then the region of skin that is not obstructed by hair or glasses needs to be identified. This identified region is fed into a CNN where the features that are most relevant are extracted. Then these features are fed into a GAN where it will generate the Lead II ECG signal. This predicted Lead II ECG signal will be fed into the 12 Lead ECG prediction component which consists of a modified Attention U-Net framework [9]. This framework consists of an encoder and decoder section, it is a modified version of the Attention U-Net framework suggested by Oktay et al. [12]. The modified version consists of three main components. In the downscaling component the input signal is repeatedly convolved and down sampled to extract high-level features and reduce the spatial dimension. In the upscaling component the down sampled signal is repeatedly deconvolved and up sampled to restore the spatial dimension and generate the output signal. Finally, the Attention-gated skip connections link the corresponding layers of the downscaling and upscaling paths and pass the low-level features from the input signal to the output signal. Once the Lead II signal is passed into the framework, it will predict the 11 remaining ECG Leads. Once the prediction has been made, the results will be updated in firebase through the Node JS Server.

To carry out with the project, securing access to the OBF dataset [10] is crucial. This dataset is needed for training and testing the models. Once the dataset is obtained, the existing method proposed by Bin et al. [6] will be recreated. This serves as a baseline for the study. Next, modifications will be made to the network to make it suitable for predicting the Lead II ECG signal from the video feed coming from a tablet camera. The accuracy of this prediction is vital, as it impacts the reliability of the prediction of 11 remaining ECG leads. Once a reliable Lead II ECG prediction is achieved, the remaining 11 ECG leads will be predicted. It’s important to note that any errors in the Lead II ECG prediction could be reflected in these predictions, making them unreliable. Throughout this process, the performance of the models will be continually evaluated, and necessary adjustments will be made.

The tasks and sub-tasks identified to achieve the identified objectives involve filtering out the facial region from the input video using OpenCV. This step is essential as it isolates the region of interest, allowing for more focused and accurate analysis. Then the suitable areas of for feature extraction needs to be identified. After the features have been extracted, architecture of the GAN needs to be defined. GANs consist of two parts: a generator and a discriminator. The discriminator is then trained on real Lead II ECGs for several epochs. Next, the generator predicts the Lead II ECG signals, which the discriminator evaluates. Initially, the discriminator will correctly identify these signals as fake. However, as the training progresses, the generator improves its ability to create realistic Lead II ECG signals. then training of the discriminator on real Lead II ECGs needs to be done for several epochs. Then the generator will predict the Lead II ECG signals and discriminator will correctly predict them as fake. The goal of this process is to generate a Lead II ECG signal that is as accurate and realistic as possible.

Materials needs to carry out the project include a tablet for testing purposes. It provides a larger screen for visualizing the ECG signals. A powerful Graphics Processing Unit (GPU) is needed to train models. Training deep learning models is computationally intensive and can be significantly accelerated with a GPU. Services like Google Colab and Kaggle Notebook provide access to GPUs (NVIDIA Tesla P100, NVIDIA T4 * 2) as well as a Tensor Processing Unit (TPU) which can be leveraged for this purpose. A large amount of Random Access Memory (RAM) is needed to load videos. Video files are large and require substantial memory to process. Kaggle Notebook provides sufficient RAM (30 GB) for this task.

The data needed for the study includes two types of datasets, the first type of data needed is a dataset that includes facial recordings along with simultaneous ECG readings. This data is crucial for training the model to predict ECG signals from facial video feeds. There are two datasets available for the purpose of facial analysis, OBF and FaceBio. However, access to the FaceBio dataset is currently restricted as it is incomplete. Therefore, the OBF dataset will be the primary source of data for this part of the study. The second type of data needed is a dataset consisting of all 12-Lead ECG signals. This data will be used to train the model to predict the remaining 11 ECG leads from the Lead II ECG signal. The PTB-XL dataset [11] is a publicly available resource that can be used for this purpose. It is one of the largest publicly available ECG datasets and includes a wide variety of heart conditions, making it ideal for this study. Data collection will involve requesting access to the necessary datasets and downloading them for use in the study.

Accessing and preprocessing the dataset can take a few days to a week depending on the size and complexity of the dataset. Facial recordings tend to be large therefore it could take up to a week. To recreate existing methods, the time taken will be based on the complexity of the method and the level of documentation available, this could take 1-2 weeks. Modifying the network and predicting Lead II ECG is a complex task that could take several weeks to a few months. It involves not only modifying the network but also training and fine-tuning it to ensure accurate predictions. Predicting the remaining 11 ECG Leads could also take several weeks to a few months, as it involves training a model to predict multiple outputs.

Once the project is successfully completed, the anticipated results would include an application which is capable of accurately predicting all 12-Leads of an ECG in a noninvasive, contactless manner. It will be allowing users to monitor their cardiac health using just a tablet camera which is particularly useful for patients in remote areas with limited access to healthcare facilities, and for those who need regular monitoring of their heart condition.

Below is a summary of the technologies, techniques, architectures, and algorithms to be used for the ICRFA mentioned in the table (Table 2).

Table 2 : Technologies, techniques, architectures, and algorithms used.

Technologies	Flutter, Python, TensorFlow, Node JS, OpenCV, Jupyter Notebook, Keras
Techniques	Feature extraction
Algorithms	CNN, GAN
Architectures	Attention U-Net Framework

4. PROJECT REQUIREMENTS

4.1 Functional requirements

1. High accuracy of generated Lead II ECG - The system must ensure that the generated Lead II ECG is highly accurate. The predicted ECG should closely match the actual ECG of the user. High accuracy is crucial for reliable diagnosis and monitoring of heart conditions. The accuracy of the system should be validated using appropriate evaluation metrics and compared against a clinically obtained gold standard 12-Lead ECG.
2. 10-Second duration for lead II ECG - The system should generate a Lead II ECG reading of 10-second duration. A 10-second reading is a standard length for an ECG and provides an extensive view of the heart's electrical activity.
3. High accuracy and 10-Second duration for remaining ECG leads - The system must also maintain high accuracy and a 10-second duration for the predicted 11 remaining ECG leads. This ensures that the system provides a complete and accurate representation of the heart's electrical activity, as seen from different angles. Like the Lead II ECG, the accuracy of these leads should be validated using appropriate evaluation metrics.
4. Quick generation of predicted results - The system should generate predicted results quickly. This is important for providing real-time feedback to the user and for enabling timely intervention in case of any detected abnormalities.

4.2 System requirements

- Flutter to create mobile application.
- Jupyter Notebook to create python scripts.
- Keras to implement neural networks.
- OpenCV for ROI identification.
- Node server to send notifications to users.
- OBF and PTB XL dataset to train models.

4.3 User requirements

- Patients
    - They would use the application to record a video of their face using their tablet's camera. The application would then analyze the video to generate a 12-lead ECG signal.
- Doctors
    - They would use the application to review and interpret the ECG data generated of their patients. Based on their evaluation, they would recommend appropriate medical interventions or lifestyle changes to the patients.

4.4 Non-functional requirements

1. User-friendliness - The design should be clean and uncluttered, with clear instructions and feedback. It should provide a consistent user experience. Furthermore, the system should be responsive to adjust its layout based on the device and screen size to ensure optimal usability.
2. Reliability - The system should be robust and dependable. It should function correctly and consistently under all expected conditions. Mechanisms for elegantly handling mistakes and recovering from failures without losing data should be built into the system. The system should implement strong encryption methods to protect sensitive information.
3. Performance - The system should be efficient and responsive. It should process and display the ECG signals quickly and accurately, without noticeable delays. The system should also be scalable.
4. Availability - The system should be accessible to all users, whenever it is needed, with minimal downtime.

4.5 Use Cases

User

- Record facial video.
- Generate ECG signal.
- View ECG signal
- Save ECG signal.
- Share ECG signal.

Doctor

- Review ECG signal.
- Provide feedback.

4.6 Test Cases

- Check if tablet camera meets minimum requirements (720p or 1080p).
- Check if the application can successfully record a 10-second video using the tablet’s camera.
- Check if there is sufficient light (200-500 lux) to carry out facial analysis.
- Check if the application can successfully generate 12-lead ECG signals from the recorded video.
- Check if the generated ECG signals are correctly displayed on the tablet.
- Check if the user can successfully save or share their ECG report.

4.7 Wireframes

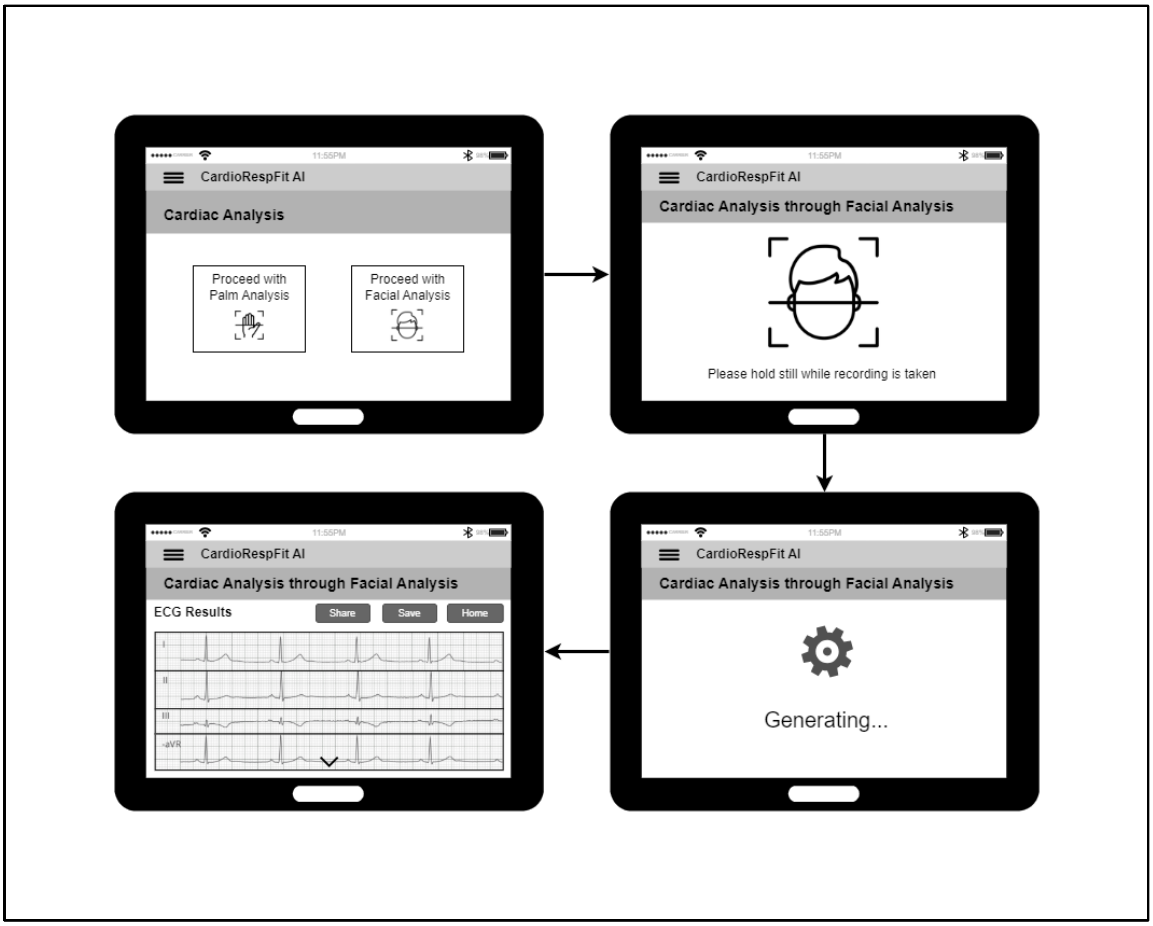

Figure 2 : Wireframe of Facial Analysis Process

5. WORK BREAKDOWN STRUCTURE

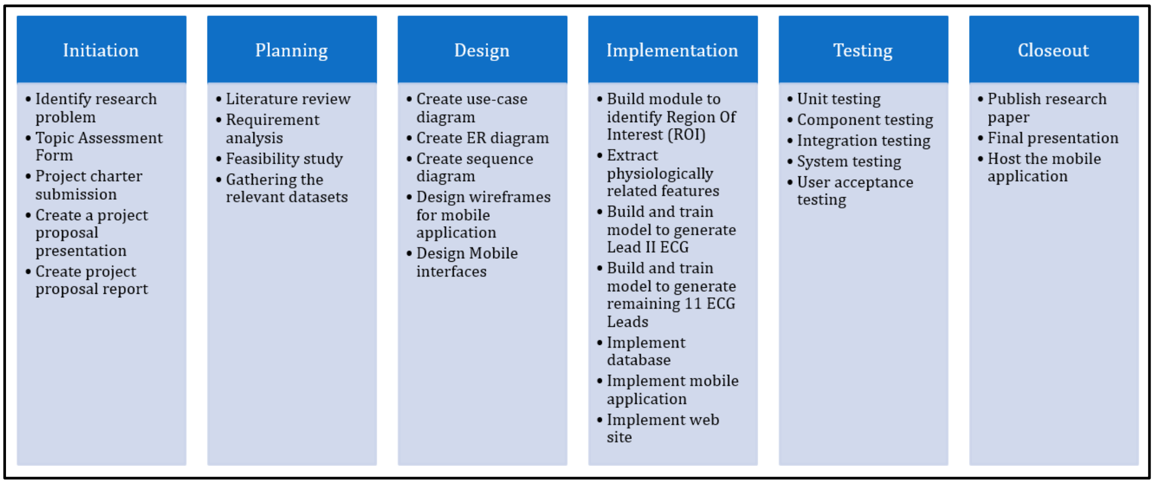

Figure 3 : Work Break Down Structure of Facial Analysis Component

6. BUDGET AND BUGET JUSTIFICATION

Table 3 below shows the overall budget for the proposed system.

Table 3 : Estimated expenses for the proposed system

Expenses	
Requirement	**Cost**
Telemedicine kit	500 USD
Subscription fee	29 USD / month
Doctor consultation fee	49 USD / month
Research and Development	150,000 LKR per annum
Cloud hosting	25,000 LKR per annum
Other costs	30,000 LKR per annum

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APPENDICES

Appendix - A : Plagiarism Report