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

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DECLARATION

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ABSTRACT

Worldwide, cardiovascular diseases remain the leading cause of mortality. The primary objective of this research was to develop an innovative, non-invasive method to reconstruct a 12-Lead electrocardiogram signal using novel approaches for cardiac rhythm identification. Initially, the focus was on creating a tablet-based mobile application that could generate the electrocardiogram signal through facial analysis using the tablet's camera. This approach aimed to utilize advanced technologies like Convolutional Neural Networks and Generative Adversarial Networks for feature extraction from facial video data and for generating electrocardiogram signals, respectively. However, due to challenges in obtaining reliable remote photoplethysmography signals necessary for accurate facial analysis, the research pivoted to an alternative method. The project was adapted to obtain a Lead I electrocardiogram signal via palm analysis using a three disposable electrode setup, an AD8232 single Lead Heart Rate Monitor, an Arduino UNO Rev3 microcontroller board, and an ATmega328p microcontroller. This approach maintains the objective of providing a non-invasive, cost-effective, and accessible solution for cardiac health monitoring. The expected outcome of the study includes the development of a reliable system for reconstructing a 12-Lead electrocardiogram signal from a Lead I electrocardiogram signal obtained from the palms. This system could enable early identification of cardiac abnormalities, allowing for prompt action and improved patient outcomes. The change in approach is also important in highlighting the adaptability of the research in addressing real-world challenges while attempting to increase the ease and availability of cardiovascular services for patients who live in areas that are rural or do not have good access to medical facilities. This study represents a significant advancement in medical technology and has the potential to improve patient care and outcomes in the field of cardiac health.

Keywords– Non-invasive ECG, Palm-based ECG acquisition, 12-Lead ECG reconstruction, Cardiac monitoring

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LIST OF ABBREVIATIONS

Abbreviation	**Description**
WHO	World Health Organization
CVDs	Cardiovascular Diseases
CVD	Cardiovascular Disease
ECG	Electrocardiogram
PPG	Photoplethysmography
GAN	Generative Adversarial Network
CNN	Convolutional Neural Network
ROI	Region Of Interest
ROIs	Region Of Interests
GPU	Graphical Processing Unit
rPPG	Remote photo plethysmography

1. INTRODUCTION

1.1 Background Literature

1.1.1 Overview of cardiovascular diseases

Cardiovascular diseases (CVDs) include a broad spectrum of disorders that affect the heart and blood vessels, including coronary artery disease, heart failure, arrhythmias, and hypertension. These diseases are collectively the leading cause of death worldwide, responsible for 17.9 million deaths [1] in 2019, which accounts for 32% of all global deaths. A significant majority of these deaths, approximately 85%, result from heart attacks and strokes. In the WHO European Region alone, CVDs claim the lives of 10,000 people every day [2], and the situation is particularly serious in low- and middle-income countries, where over three-quarters of CVD-related deaths occur, often in younger populations. Over recent decades, the presence of CVDs in Sri Lanka has been increasing. According to the World Health Organization (WHO), CVDs were responsible for over 40% of deaths in Sri Lanka in 2021. Ischemic heart disease and stroke were the primary causes of death, contributing to approximately 20% and 10% of fatalities, respectively [3]. CVDs have long been recognized as a significant public health challenge due to their high prevalence, chronic nature, and the significant economic burden they force on healthcare systems.

Chronic diseases, particularly cardiovascular diseases, have a profound impact on global health, contributing significantly to the overall burden of mortality and morbidity. CVDs alone are responsible for more deaths annually than any other cause [1], surpassing even infectious diseases, which have historically been the leading cause of death. This shift in the global health landscape reflects changes in lifestyle, aging populations, and the epidemiological transition from communicable to non-communicable diseases as primary health concerns.

The extensiveness of CVDs is not confined to any particular demographic or geographical region, making them a global concern. However, the burden of these diseases is particularly high in low- and middle-income countries, where access to healthcare services is often limited, and awareness of heart health is generally lower. This inequality is further worsened by lifestyle factors such as poor diet, physical inactivity, and tobacco use [4], which are more prevalent in regions with limited public health infrastructure.

Early detection and continuous monitoring of cardiovascular conditions are crucial for managing these diseases effectively. Unfortunately, many cases of CVDs remain undiagnosed until they progress to a critical stage, leading to life-threatening events such as heart attacks or strokes [5]. This highlights the importance of developing reliable methods for early detection and regular monitoring, which can significantly reduce mortality rates and improve patient outcomes. The growing recognition of this need has fueled research into innovative technologies that can make cardiovascular monitoring more accessible, especially in resource-limited settings.

1.1.2 Global health impact of diseases

The impact of CVDs extends beyond the direct health effects on individuals. These diseases place a significant strain on healthcare systems, particularly in developing countries where resources are already scarce. The cost of treating CVDs, including hospitalizations, surgeries, and long-term medication, is a significant financial burden for both patients and healthcare providers. Moreover, the loss of productivity [6] due to cardiovascular disease (CVD) related morbidity and mortality has broad economic implications, affecting communities and nations as a whole.

In high-income countries, where healthcare systems are more robust, CVDs still represent a major challenge. The rising incidence of obesity, diabetes, and sedentary lifestyles has led to an increase in the incidence of cardiovascular conditions, despite advances in medical treatment and preventive care. As a result, there is a growing emphasis on preventive measures and the development of technologies that can facilitate early detection and management of CVDs. This approach aims to reduce the burden on healthcare systems by shifting the focus from reactive treatment to proactive health management.

1.1.3 Importance of continuous health monitoring

Continuous health monitoring plays a vital role in the early detection and management of cardiovascular diseases. Unlike traditional diagnostic methods, which often rely on periodic check-ups and tests, continuous monitoring provides ongoing data on a patient’s cardiovascular status, allowing for the timely identification of abnormalities that may indicate the onset of disease. This proactive approach to health management is particularly important for individuals at high risk of developing CVDs, such as those with a family history of heart disease, hypertension, or diabetes.

The need for continuous monitoring is further emphasized by the fact that many cardiovascular conditions have no symptoms of illness or disease in their early stages. For example, hypertension, often referred to as the “silent killer,” can lead to severe complications such as stroke or heart attack if left undiagnosed and untreated. Similarly, arrhythmias, which are irregular heart rhythms, can occur rarely and may not be detected during routine check-ups. Continuous monitoring allows for the detection of these conditions as they develop, enabling early intervention and reducing the risk of serious outcomes.

In recent years, there has been a growing interest in developing technologies that can facilitate continuous health monitoring outside of traditional healthcare settings. This includes wearable devices, mobile applications, and remote monitoring systems that can track vital signs in real-time and transmit data to healthcare providers. These technologies have the potential to revolutionize the management of cardiovascular diseases by providing patients with convenient and accessible tools for monitoring their heart health.

1.1.4 Role of remote health monitoring systems

Remote health monitoring systems have emerged as a critical component of modern healthcare, particularly in the management of chronic diseases like cardiovascular conditions. These systems allow for the continuous collection and analysis of health data from patients in their own homes or other non-clinical settings, reducing the need for frequent in-person visits to healthcare facilities. The increasing role of remote monitoring is driven by advances in technology, including the development of wearable devices, mobile applications, and cloud-based platforms that enable real-time data transmission and analysis.

One of the primary benefits of remote health monitoring systems is their ability to provide timely information to healthcare providers, allowing for early detection and intervention in the case of abnormal health parameters. For cardiovascular diseases, this can include monitoring vital signs such as heart rate, blood pressure, and electrocardiogram (ECG) signals, all of which are critical for assessing heart health. Remote monitoring systems can alert both patients and healthcare providers to potential issues before they escalate, facilitating prompt treatment and reducing the risk of unfavorable outcomes.

The COVID-19 pandemic has further accelerated the adoption of remote health monitoring systems as healthcare systems around the world sought to minimize in-person interactions to reduce the spread of the virus [7]. During this time, remote monitoring provided a lifeline for many patients with chronic conditions, including cardiovascular diseases, allowing them to continue receiving care without the need to visit healthcare facilities. This experience has highlighted the potential of remote monitoring to play a central role in the future of healthcare, particularly as the demand for more accessible and patient-centered care continues to grow.

Despite these advancements, challenges remain in the widespread acceptance of remote health monitoring systems. Issues such as data privacy, the need for reliable internet access, and the integration of monitoring systems with existing healthcare infrastructure must be addressed to fully realize the potential of these technologies.

Furthermore, there is a need for robust validation studies to ensure that remote monitoring devices and systems are accurate and reliable, particularly in the context of diagnosing and managing cardiovascular diseases.

1.1.5 ECG and its importance

The ECG is a fundamental tool in the diagnosis and monitoring of heart conditions. It measures the electrical activity of the heart through electrodes placed on the skin, providing a visual representation of the heart's rhythm and function. The standard 12-Lead ECG, which records electrical activity from twelve different angles, is considered the gold standard in cardiac care [8]. It provides comprehensive information about the heart's electrical impulses, helping clinicians diagnose a wide range of conditions, including arrhythmias, myocardial infarction (heart attack), and other cardiac abnormalities.

The importance of the 12-Lead ECG lies in its ability to provide a detailed view of the heart's electrical activity, capturing data from multiple perspectives. Each lead represents a different angle of electrical activity, allowing clinicians to pinpoint specific areas of the heart that may be affected by disease or injury. This makes the 12-Lead ECG an invaluable tool for both diagnosing and guiding the treatment of cardiovascular conditions. Figure 1.1 showcases the 12 signals captured in a standard 12-Lead ECG test.

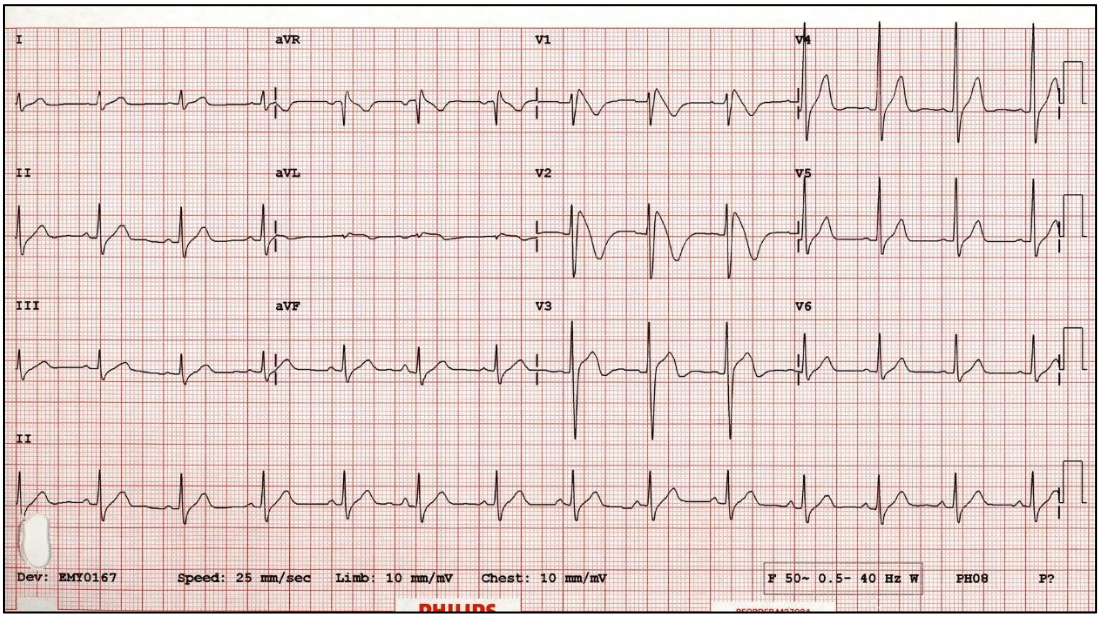

Figure 1.1 : Standard 12-lead ECG

Source: [10]

It consists of three standard limb leads (I, II, III), three augmented limb leads (aVR, aVL, aVF), and six precordial (chest) leads (V1-V6). Each lead provides a unique view of the heart's electrical activity, allowing for the detailed assessment of various cardiac functions. The limb leads capture the heart’s electrical impulses from the frontal plane, while the precordial leads provide a view from the horizontal. The ECG tracing shows the different waves (P, QRS, T) that correspond to specific events in the cardiac cycle, such as atrial depolarization (P wave), ventricular depolarization (QRS complex), and ventricular repolarization (T wave) as shown in Figure 1.2.

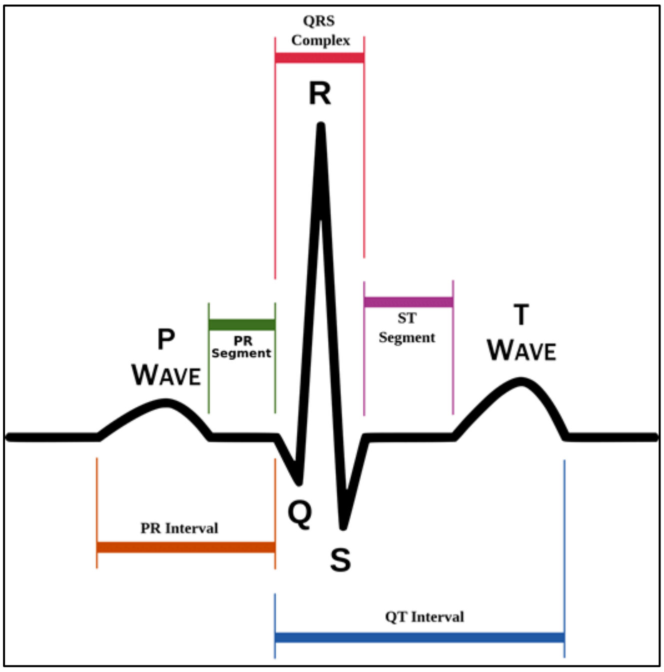

Figure 1.2: PQRST complex of an ECG

Source [11]

Given its critical role in cardiac care, the 12-Lead ECG is used considerably in both emergency settings and routine examinations. It is a standard part of the evaluation process for patients presenting with chest pain, shortness of breath, or other symptoms suggestive of heart disease [9]. Additionally, the ECG is used in preventive care, particularly for individuals with risk factors for cardiovascular disease, to detect potential issues before they become symptomatic.

Despite its widespread use and clinical importance, traditional ECG methods require physical contact with the patient and the placement of electrodes on specific areas of the body. This can be a barrier to accessibility, particularly in remote or underserved areas where access to healthcare facilities and specialized equipment is limited. As a result, there has been growing interest in developing alternative methods for ECG acquisition that are non-invasive and more accessible, potentially expanding the reach of this critical diagnostic tool.

1.1.6 Non-invasive methods for ECG acquisition

Traditional ECG acquisition methods involve placing electrodes (V1-V6) on the patient's chest, limbs (RA, LA, RL and LL), and torso, which requires contact with the skin and specialized equipment. While effective, this approach can be uncomfortable for patients and is not always feasible in remote or resource-limited settings. Figure 1.3 shows the placement of electrodes in a standard 12-Lead ECG test. Four limb electrodes are positioned on the right arm (RA), left arm (LA), right leg (RL), and left leg (LL). The right leg electrode usually serves as a ground. Additionally, six chest electrodes (V1-V6) are strategically placed across the chest.

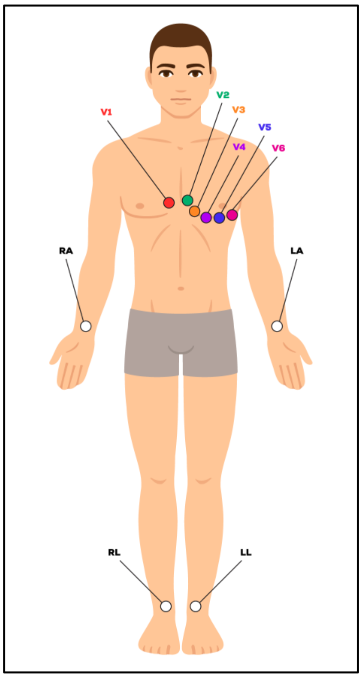

Figure 1.3 : Standard 12-lead ECG electrode placement

Source: [12]

One promising avenue of research has been the use of remote photoplethysmography (rPPG) to capture cardiovascular signals through facial analysis. rPPG operates by detecting changes in skin color caused by the pulsing of blood vessels, which can be captured by a camera and analyzed to extract heart rate and other vital signs [13]. This technology has the potential to provide a contactless and convenient method for obtaining ECG signals, particularly when integrated into mobile applications that use the cameras of smartphones or tablets.

However, while rPPG offers significant promise, it also presents challenges. The quality and accuracy of rPPG signals can be affected by external factors such as lighting, movement, and individual differences in skin tone [14]. These challenges have made it difficult to achieve the level of reliability required for clinical use, particularly in generating a full 12-Lead ECG signal. Despite these challenges, research continues to explore ways to improve rPPG technology and its application in cardiac monitoring.

Given the challenges associated with facial analysis for ECG acquisition, alternative non-invasive methods have also been explored. One such method involves obtaining ECG signals from the palms using disposable electrodes and a small monitoring device. This approach, while still requiring contact with the skin, offers a more accessible and user-friendly option compared to traditional ECG methods. By placing electrodes on the palms, it is possible to capture a Lead I ECG signal, which can then be used to generate a full 12-Lead ECG through advanced algorithms and machine learning models.

This shift from facial analysis to palm-based ECG acquisition represents an important evolution in the search for non-invasive cardiac monitoring methods. While the initial goal of using facial analysis to generate ECG signals faced significant challenges, the alternative approach of palm-based acquisition offers a practical solution that still aligns with the broader objective of making cardiac monitoring more accessible. As research in this area continues, the potential for non-invasive ECG acquisition methods to transform cardiac care remains a promising avenue for innovation.

1.2 Research Gap

The area of face-based ECG acquisition is an emerging field with limited research available. One notable study in this area is detailed by Bin Li et al. [15]. This research investigates the feasibility of generating ECG signals from facial videos using remote rPPG. The study employed a combination of explicit and implicit methods to reconstruct ECG signals from the rPPG data extracted from facial recordings. The researchers used deep learning models to analyze the facial video data, applying algorithms to correlate the facial pulse signals with ECG waveforms.

In this study, researchers developed a method to reconstruct ECG signals using a combination of advanced image processing and machine learning techniques. The facial recordings were processed to separate relevant physiological features from background noise, after which these features were analyzed and refined to optimize the quality of the physiological data. The final step involved using a Generative Adversarial Network (GAN) to generate realistic ECG signals from the processed facial data. The study demonstrated a moderate to strong correlation between the predicted and actual ECG signals but did not provide details on the number and types of ECG leads generated, leaving some questions about its practical applicability.

The results from this study demonstrated that while it is possible to reconstruct ECG signals from facial videos, the reliability and accuracy of these signals are significantly influenced by various factors. The study highlighted that environmental conditions, such as lighting and camera quality, as well as subject movement, greatly affect the quality of the rPPG signals. These limitations suggest that while the approach holds potential, it is still in the early stages of development and may not yet be suitable for clinical applications.

There was another notable study done by Zhu et al [16] which worked on ECG reconstruction via photoplethysmography (PPG), where researchers achieved a high accuracy of 0.98 averaged correlation in reconstructing ECG signals from PPG data using a discrete cosine transform (DCT) mapping approach. This inspired me to obtain a high-quality rPPG signal from facial videos, similar to PPG signals, so that it would be possible to generate accurate ECG signals.

Given these findings, there was initially a motivation to explore face-based ECG acquisition in this research. The potential for a non-invasive, accessible monitoring technology that could utilize everyday devices like smartphones or tablets was particularly appealing. However, the research on face-based ECG acquisition remains limited, with significant gaps in practical and clinical applicability. The scarcity of comprehensive studies in this area underscores the challenges of developing a reliable method for generating ECG signals from facial analysis. Despite the initial promise, the field is still in its infancy, and more research is needed to address the technical limitations and ensure that the method can be used reliably in real-world scenarios.

Given the challenges encountered with facial analysis for ECG acquisition, it became evident that alternative non-invasive methods were necessary. Facial analysis, while innovative, faced significant obstacles such as unreliable signal quality due to environmental factors like lighting and motion, as well as difficulties in obtaining consistent rPPG signals. These challenges limited the practicality of face-based methods, making it difficult to achieve the accuracy required for reliable ECG monitoring.

This led to the exploration of palm-based ECG acquisition as a viable alternative. To my knowledge, there are only two studies done that explore obtaining ECG signals from the palms, including the studies done by Lourenço et al. [17] and Adil et al. [18]. These studies highlight the potential of using palm-based systems to acquire ECG signals with fewer electrodes, making the process more comfortable and less intrusive for users. The device described by Lourenço et al. utilized dry Ag/AgCl (silver/silver chloride) electrodes to acquire ECG signals from the palms. Notably, this approach was primarily intended for biometric identification purposes rather than for medical diagnostics. The study demonstrated that ECG signals captured from the palms could be used as a unique biometric identifier, providing an additional layer of security in biometric systems. However, the focus on biometrics means that the system was not specifically designed or validated for clinical use, which introduces limitations when considering its application for medical ECG monitoring.

The study done by Adil et al. [18] further explores the use of palm-based systems by proposing a real-time ECG acquisition system that uses just two electrodes. This system addresses common issues such as impedance matching, power-line noise, and muscle activity interference, which are often encountered in traditional ECG setups. The use of an analog front end (AFE) such as the AD8232 and a microcontroller

(ATmega328p) allows for the efficient processing and digitization of the ECG signals, making the system portable and suitable for integration into various health monitoring applications. One of the key advantages of palm-based ECG acquisition is its accessibility and simplicity. By placing electrodes on the palms, this method avoids the discomfort and inconvenience associated with traditional electrode placements on the chest and limbs. The use of portable devices like the AD8232 and Arduino UNO Rev3 further enhances the system's usability, allowing for easy integration into various applications, including remote health monitoring and IoT-based systems.

This approach aligns with the broader goal of making cardiac monitoring more accessible, particularly in remote or resource-limited settings where traditional ECG equipment may not be available. By simplifying the process and reducing the number of electrodes needed, palm-based ECG systems offer a practical solution for continuous and unobtrusive health monitoring.

Despite its potential, several research gaps remain in the development of palm-based ECG systems. First, there is a need for more extensive validation studies that compare the accuracy of palm-based ECG acquisition with traditional 12-lead systems. These studies should include diverse populations and a variety of clinical scenarios to ensure the reliability and generalizability of the results. Second, challenges in miniaturizing the technology for truly portable and user-friendly applications need to be addressed. While current systems demonstrate feasibility, further advancements in hardware design and signal processing are required to create devices that are both compact and robust enough for everyday use.

Finally, issues related to signal interference and consistency must be thoroughly investigated. Factors such as skin impedance, electrode placement variability, and environmental conditions can significantly impact the quality of the ECG signals obtained from the palms. Research focused on optimizing electrode materials, improving noise reduction techniques will be crucial in overcoming these challenges.

While palm-based ECG acquisition offers a promising alternative to traditional methods by simplifying the process of obtaining lead I from the palms, its true potential lies in its ability to be integrated with advanced techniques for reconstructing a full 12-lead ECG from this single lead. This integration could significantly enhance the practicality and effectiveness of palm-based ECG systems, making comprehensive cardiac monitoring more accessible and user-friendly. However, reconstructing a 12-lead ECG from fewer leads, particularly from just a single lead like lead I, presents its own set of challenges.

The current state of research in 12-lead ECG reconstruction has made significant strides. Techniques using Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs) have shown promising results. For example, Kapfo et al. [19] proposed networks to predict the standard 12-lead ECG from just three input leads. They study reported an impressive average correlation coefficient of 0.98, suggesting that their model effectively captured the general trends of the ECG signals. However, their work also had significant drawbacks, particularly the high root mean squared error (RMSE) of 78, indicating substantial deviations between the reconstructed and actual signals, which raises concerns about the accuracy of their reconstructions despite the high correlation.

Another study conducted by Jangjay et al. [20] contributed to the field by using LSTM networks to achieve an average correlation coefficient of 0.95 for their reconstructed signals. This was a solid performance, showing that their model could effectively reconstruct ECG signals with high fidelity. However, like Kapfo et al., Jangjay et al.'s work was dependent on multiple input leads, which limits its practical applicability.

Yoon et al. [21] employed a GAN that utilized a U-Net as the generator and a patch discriminator as the discriminator to reconstruct the 12-lead ECG from a single lead. The study achieved a mean Frechet Distance (FD) score of 11.321 and a mean squared error (MSE) of 0.038, indicating moderate success in producing accurate reconstructions. However, their approach was complicated by the inherent instability and high computational demands of GAN training. Additionally, they relied on 11 separate models, each responsible for reconstructing one of the 11 leads, and further limited their approach by segmenting the ECG signals to only 2.5 seconds. This segmentation is a significant drawback, as comprehensive and accurate interpretation, especially in a clinical setting, generally requires a 10-second ECG recording [22].

Another study carried out by Gundlapalle et al. [23] proposed a method that combined CNNs, LSTMs, and multi-layer perceptrons (MLPs) to reconstruct the 12-lead ECG from just one lead, reporting a correlation coefficient of 0.973 and a regression coefficient of 0.959. Their approach was innovative, but the complexity of the model made it difficult to implement and like Yoon et al., they also used 11 different models, each to reconstruct a single lead. Additionally, the model segments the ECG signals into 1-second intervals which is a drawback as previously mentioned.

Lastly a study carried out by Garg et al. [24] presented a novel approach using a modified Attention U-Net framework for single-lead to multi-lead ECG reconstruction. Their model used only lead II as input to reconstruct the entire 12-lead ECG, achieving a Pearson correlation coefficient of 0.805, an MSE of 0.0122, and an R-squared value of 0.639. While their correlation coefficient was slightly lower than some previous studies, their model excelled in maintaining low reconstruction errors and practical applicability. Their approach had significant advantages, such as the ability to reconstruct a full 10-second ECG signal in one pass and using a single combined model for all 11 leads. This reduces the complexity, and computational resources compared to models that reconstruct each lead individually. Furthermore, they demonstrated that their reconstructed signals were effective in real-world scenarios by maintaining comparable performance to original signals in a cardiovascular disease classification task. The original signals achieved an accuracy of 45.6% and an AUROC (Area Under the Receiver Operating Characteristic Curve) of 0.810, while the reconstructed signals achieved an accuracy of 42.6% and an AUROC of 0.752.

The comparison in Table 1.1 highlights the distinct capabilities of the proposed system in relation to existing studies. While Adil et al. [18] focused on acquiring a single ECG lead from the palm and Garg et al. [24] developed a method for reconstructing a 12-lead ECG from a single lead, our system integrates these functionalities into a unified platform. It not only acquires a palm-based ECG signal but also reconstructs the full 12-lead ECG at a higher accuracy, displays it on a smart tablet. This comparison underscores the comprehensive and practical nature of our proposed solution, aimed at enhancing accessibility and usability in cardiac health monitoring.

Table 1.1 : Comparison of key features between the proposed system and existing studies

Reference	**Ability to acquire ECG**	**Ability to Obtain 12-Lead ECG**	**System for ECG Visualization**
Adil et al. [18] (Two-Electrode Palm ECG)	✓	X	X
Garg et al. [24] (12 Lead ECG reconstruction)	X	✓	X
Proposed System	✓	✓	✓

In conclusion, integrating palm-based ECG acquisition with robust 12-lead reconstruction techniques holds great promise for the future of cardiac monitoring. However, to fully realize this potential, ongoing research must address the challenges of improving accuracy of reconstructed signals and further validating the clinical applicability of the reconstructed signals. By overcoming these challenges, the combination of palm-based acquisition and 12-lead reconstruction could significantly enhance the accessibility and reliability of cardiac health monitoring, particularly in rural or underserved areas where access to comprehensive medical facilities is limited. This would represent a substantial step forward in providing cost-effective and non-invasive cardiovascular services to a broader population, improving patient outcomes and overall public health.

1.3 Research Problem

The core problem that this research aimed to address is the need for a non-invasive, cost-effective, and accessible method for obtaining a reliable 12-lead ECG. The 12-lead ECG is a crucial tool for the early detection and continuous monitoring of cardiac conditions, which are among the leading causes of death globally. Traditional methods of obtaining a 12-lead ECG involve using multiple electrodes placed on specific parts of the body, which require direct skin contact, specialized equipment, and trained personnel to operate [25]. This approach, while effective, is often impractical in many settings, particularly in remote or resource-limited environments where access to healthcare facilities and advanced medical devices is limited.

The significance of this problem lies in the global burden of CVDs, which account for a substantial portion of mortality and morbidity worldwide. Despite advances in medical technology, CVDs remain the leading cause of death, claiming millions of lives each year. Early detection and monitoring of cardiac abnormalities are essential for improving patient outcomes, yet the limitations of traditional ECG acquisition methods create barriers to widespread and regular use. In many remote or underdeveloped regions, the lack of access to standard ECG equipment and healthcare professionals worsens the challenge of managing heart conditions effectively. Thus, there is a critical need to develop a method that not only matches the diagnostic accuracy of traditional 12-lead ECG systems but is also easier to deploy, more affordable, and capable of reaching a broader population.

The research initially focused on using facial analysis to obtain a 12-lead ECG. This approach was highly innovative, leveraging rPPG signals extracted from facial video data. The concept was to develop a contactless method for ECG acquisition, where advanced image processing and machine learning techniques could analyze subtle changes in skin color caused by blood flow and reconstruct these signals into a comprehensive 12-lead ECG. This method had the potential to revolutionize cardiac monitoring by integrating ECG acquisition into everyday devices like smartphones or tablets, making it accessible to a wide audience without the need for specialized equipment or direct skin contact.

However, as the research progressed, significant challenges emerged that ultimately rendered this approach impractical. The reliability of rPPG signals was found to be heavily influenced by external factors such as lighting conditions, facial motion, and skin tone variations, which affected the consistency and accuracy of the data. Additionally, the complexity of processing and reconstructing ECG signals from facial videos proved to be a formidable technical hurdle. These issues highlighted that while the idea was theoretically sound, the practical application was fraught with difficulties that made it unlikely to produce a reliable, clinically useful 12-lead ECG. This realization led to a deeper understanding that the problem was not merely about innovating a new method but about finding a solution that was both technically feasible and reliable in real-world scenarios.

Faced with the challenges of facial analysis, the research pivoted to an alternative method which was palm-based ECG acquisition. This approach involved using a three-electrode setup placed on the palms to obtain lead I of the ECG, which could then be used as the input for reconstructing the full 12-lead ECG using an advanced deep learning model. The decision to shift to palm-based ECG was driven by the need for a more reliable and straightforward method of acquiring ECG signals that still adhered to the principles of non-invasiveness and accessibility. The palm-based approach offered several advantages, including better control over signal quality, reduced susceptibility to environmental factors, and easier integration with portable, low-cost monitoring devices like the AD8232 and Arduino UNO Rev3 microcontroller.

This change in focus also refined the research problem. Originally, the goal was to develop a new, contactless method for ECG acquisition using facial analysis. However, the shift highlighted a bigger challenge: creating a non-invasive method to obtain a reliable 12-lead ECG using minimal leads and simple, accessible technology. The problem evolved to not just focus on innovation but also on practical use, balancing advanced technology with real-world feasibility. This revised problem shaped the research, directing efforts toward integrating palm-based ECG acquisition with methods for reconstructing the full 12-lead ECG in a way that could be easily used in various settings.

This research is important because it could significantly improve non-invasive cardiac monitoring. By tackling the challenges of signal acquisition and reconstruction, this work helps create practical solutions that can impact patient care. The proposed system, which combines palm-based ECG acquisition with 12-lead reconstruction, offers a promising alternative to traditional methods, especially in places where standard ECG equipment is hard to find. This technology could be used in remote or resource-limited areas, making cardiac health monitoring more accessible and effective, which could lead to better patient outcomes.

1.4 Research Objectives

Initially, the primary objective of this research was to develop a tablet-based mobile application that could obtain a 12-lead ECG signal using only the tablet's camera through facial analysis. However, due to the challenges encountered with facial analysis, as outlined in the Research Problem section, the focus of the research was shifted to developing a non-invasive, accessible method for obtaining a reliable 12-lead ECG using palm-based ECG acquisition. The revised objectives reflect this change in direction.

1.4.1 Main objective

The main objective of this study is to develop a system that can reliably acquire a lead I ECG signal from the palms and use it to reconstruct a 12-lead ECG essentially obtaining a 12-lead ECG from the palms. The system will also allow users to visualize their ECG signals thereby enabling early detection and continuous monitoring of cardiac conditions.

1.4.2 Specific objectives

To achieve this main objective, the following specific objectives are identified:

Acquisition of lead I ECG from palms:

- Develop a method for reliably obtaining a lead I ECG signal using a simple, non-invasive setup with electrodes placed on the palms. This will involve the use of the AD8232 AFE and an Arduino UNO Rev3 microcontroller.

Reconstruction of 12-lead ECG signals:

- Implement and refine a deep learning model to reconstruct the remaining 11 leads of the ECG from the acquired lead I signal. This model will ensure that the reconstructed signals are accurate and clinically useful.

Development of a system for visualization of ECG data:

- Create a user-friendly interface, optimized for tablets or similar devices, that allows users to visualize their ECG signals in real-time.

2. METHODOLOGY

2.1 Introduction to the Methodology

This study was initially begun with the goal of developing a non-invasive, accessible method for obtaining a reliable 12-lead ECG through innovative approaches. The initial methodology focused on facial analysis, leveraging the potential of rPPG signals extracted from facial video recordings to reconstruct ECG signals. This approach was inspired by emerging research that suggested the feasibility of using facial videos for physiological monitoring. However, due to significant challenges in achieving reliable and accurate results, the methodology evolved. The focus shifted to a more practical solution which was obtaining lead I ECG from the palms and reconstructing the remaining 11 leads using advanced deep learning models, specifically a modified Attention U-Net framework. This transition reflects the adaptability of the research approach, balancing the need for innovation with practical applicability to ensure reliable and clinically useful outcomes.

2.2 Previous Component System Architecture

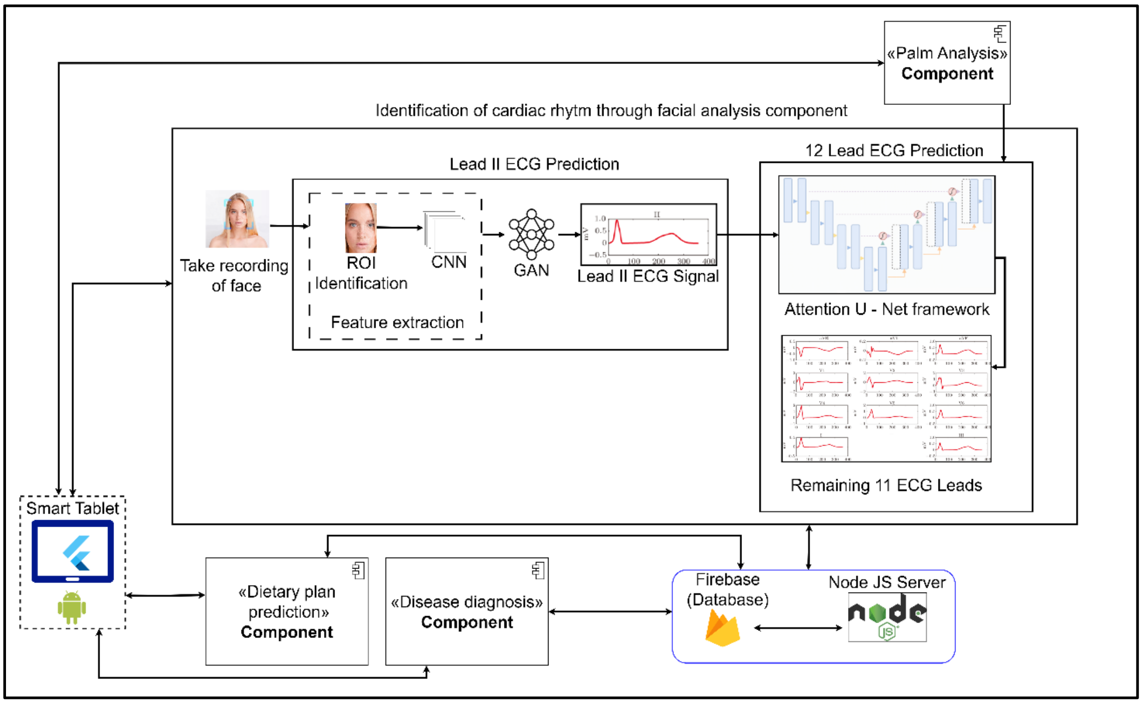

Figure 2.1 : Facial Analysis and ECG generation System Architecture

Figure 2.1 shows an overview of the previously proposed system for the initial facial analysis component. 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 identification of cardiac rhythm through facial analysis component which consists of 2 main components, the Lead II ECG Prediction component, and the 12-Lead ECG Prediction component.

2.3 Initial Approach

The facial analysis component was the starting point of the research, aiming to explore the possibility of extracting ECG signals from facial videos. The inspiration for this approach came from the paper proposed by Bin Li et al. [15]. This approach utilized advanced techniques, including multiscale feature representation and the application of GANs for ECG signal reconstruction. The process also incorporated dense optical flow to capture subtle facial movements correlating with cardiac activity. However, the complex methodologies posed significant challenges. Moreover, the paper did not provide a comprehensive explanation of the entire methodology, parts were left out making it challenging to fully replicate the process. Despite the promising results demonstrated in this paper, the methodology presented was complex and challenging to replicate without access to specific datasets and advanced understanding of the techniques used. Nonetheless, the initial efforts focused on replicating and understanding the process.

2.3.1 Challenges in understanding and implementation

The paper presented a sophisticated approach, integrating multiple advanced machine learning and computer vision techniques. Replicating these methods proved difficult due to the complex nature of the mathematical models and algorithms involved. Furthermore, the specific datasets used in the paper, such as OBF [33] and FaceBio [15], were not publicly accessible, complicating the replication efforts. Consequently, the approach had to be adapted, utilizing alternative datasets and methodologies.

Due to the unavailability of the OBF and FaceBio datasets, the UBFC dataset was chosen as an alternative. The UBFC dataset [26], though not originally intended for ECG reconstruction from facial analysis, provided RGB facial video recordings and synchronous physiological signals, making it a suitable candidate for the initial experiments.

The UBFC dataset included RGB facial video recordings and PPG signals. The first task was to understand the structure of this dataset and how to effectively extract and utilize the relevant data for the research objectives. This involved preprocessing the video data to isolate the facial regions and preparing the physiological data for analysis.

2.3.2 Face isolation using DeepFace

To isolate the face from the video frames, the DeepFace library was employed. This library is known for its state-of-the-art facial recognition capabilities. This library was applied to the frame depicted in Figure 2.2 which illustrates an unprocessed video frame from the UBFC dataset. DeepFace successfully identified and isolated the facial region in each frame of the video sequences, providing a critical starting point for further analysis. This step was essential in ensuring that the subsequent signal extraction processes focused solely on the relevant facial areas. While the library is user-friendly and provided good results for facial recognition, it provided cropped square images of the detected face. As a result, the final output as it can be seen in Figure 2.3 often excluded certain parts of the face as well as included background elements that were not part of the face, potentially introducing noise when extracting the rPPG signal. Additionally, DeepFace occasionally flipped the face upside down, which further complicated the signal extraction process.

Figure 2.2: Video frame from UBFC dataset

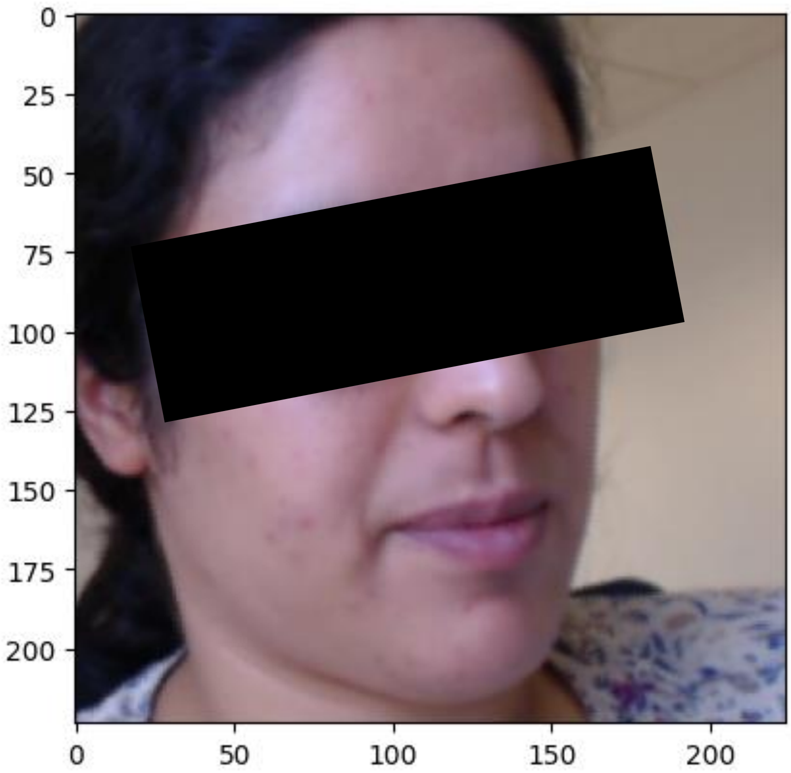

Figure 2.3: Video frame after DeepFace library processing

2.4 Creation of a Custom Facial Video Dataset

Recognizing the lack of suitable datasets, a decision was taken to create a custom dataset to ensure the data aligned with the specific needs of the research. Figure 2.4 illustrates the custom dataset collection setup, showing a participant being recorded with a smartphone while simultaneously being connected to an ECG measurement device.

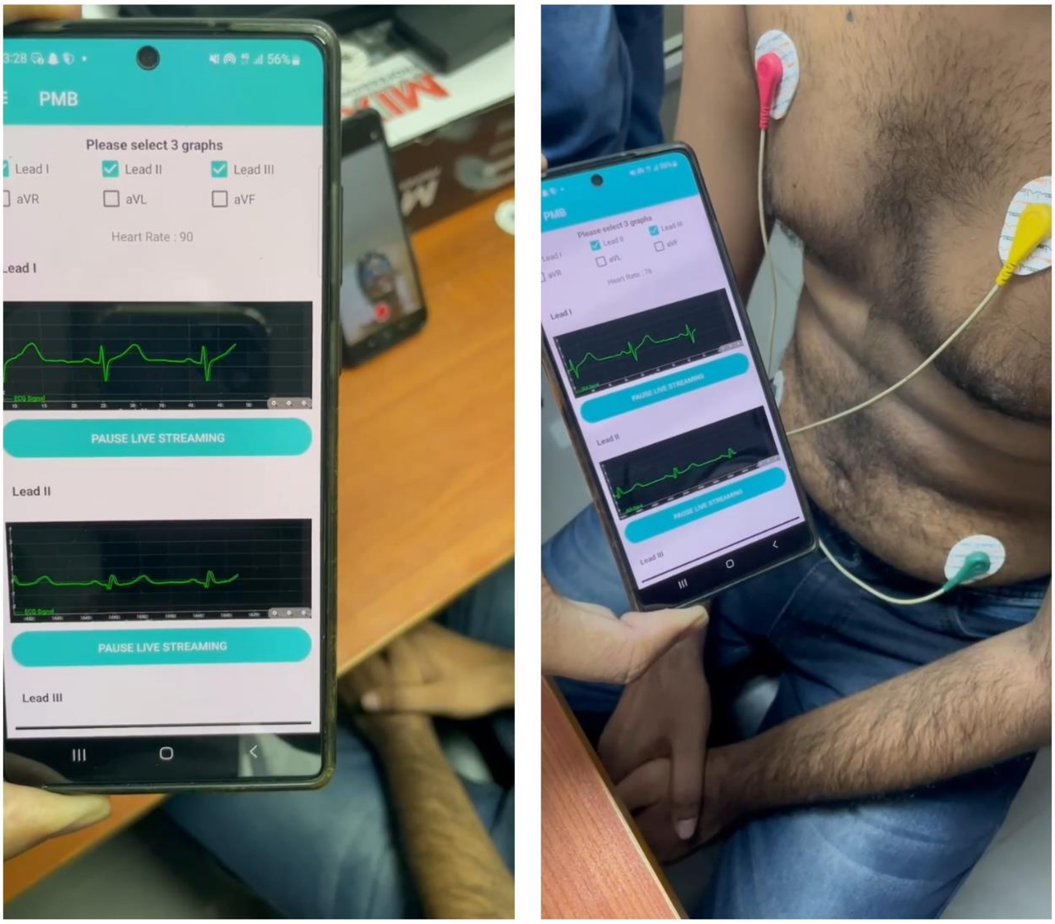

Figure 2.4: Custom dataset creation

The custom dataset was collected using a Redmi Note 10 Pro smartphone, which consists of a 16MP front camera capable of recording video at 1080p and 30 frames per second. The recordings were conducted in an indoor setting with controlled lighting conditions (approximately 50-55 lux). Seven participants volunteered, with a diverse range of skin tones, facial hair, and eyewear to ensure a varied dataset. Each participant was recorded for one minute, and a simultaneous 6-lead ECG was captured to provide a reference for heart rate and cardiac activity.

One of the significant challenges encountered during this phase was the synchronization of the video recordings with the ECG signals. Accurate synchronization was crucial for correlating facial movements with ECG data. Despite efforts to manually align the signals based on visible markers in the data, this step introduced potential errors that could affect the accuracy of the subsequent analysis.

2.5 Exploration of Dense Optical Flow

Inspired by the approach outlined in the reference paper, dense optical flow techniques were applied to the facial videos. Dense optical flow, specifically the Farneback method [27], is commonly used to estimate motion within video sequences, capturing subtle changes that may correlate with cardiac activity.

2.5.1 Implementation of the Farneback method

The Farneback method was applied to the isolated facial regions in an attempt to capture the subtle facial movements associated with the heartbeat. However, the exact role of dense optical flow in reconstructing ECG signals was unclear from the literature, and without a concrete understanding of its application, this approach proved challenging leading to the decision to abandon this technique in favor of more direct approaches to signal extraction. Figure 2.5 shows a visual representation of dense optical flow applied to a facial video frame, illustrating the vector field that represents motion.

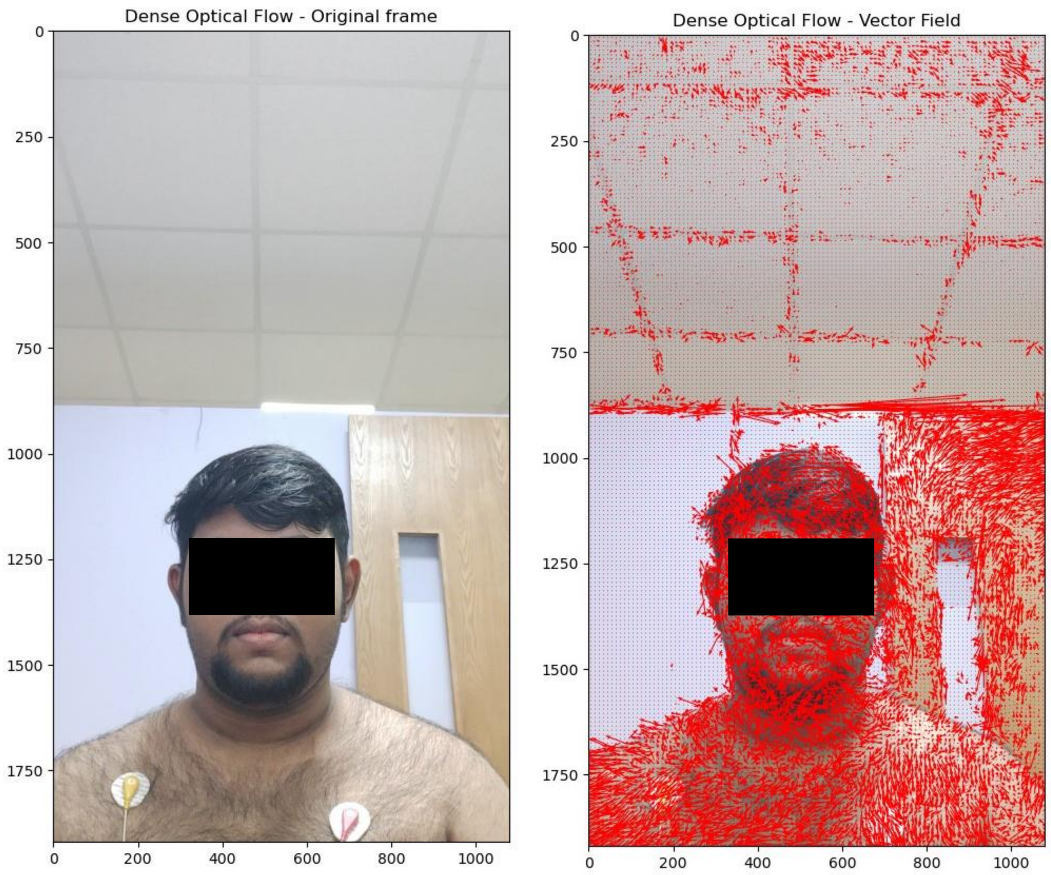

Figure 2.5: Visual representation of dense optical flow

2.6 rPPG Signal Extraction

Due to the challenges faced with dense optical flow, the focus was shifted towards extracting a reliable rPPG signal from the facial videos. rPPG, a non-contact method, estimates heart rate by analyzing color changes in the skin caused by blood circulation.

The rPPG signal was initially extracted using the Haarcascade classifier, a machine learning-based approach typically employed for object detection, which was applied to identify the region of interest (ROI) on the face, specifically targeting the forehead. The extracted signal was subsequently processed with a Butterworth Bandpass filter to reduce noise and enhance the relevant frequency components associated with heart rate. Figure 2.6 compares the raw rPPG signal with the filtered signal, demonstrating the effects of the filtering process.

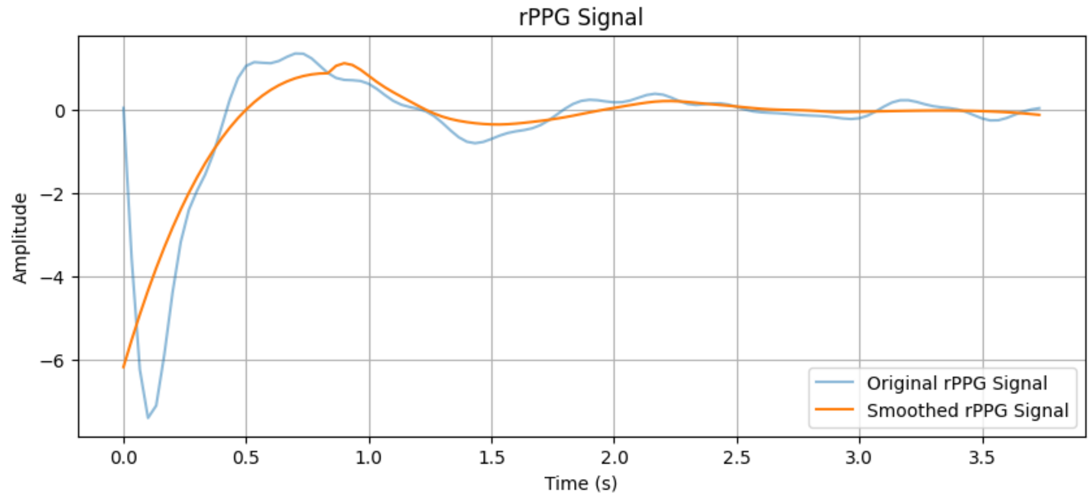

Figure 2.6: rPPG signal (forehead ROI) vs. filtered signal

The filtered rPPG signal was examined using Fast Fourier Transform (FFT) to find the main frequency components. The frequency spectrum of the rPPG signal, as illustrated in Figure 2.7, provides a visual representation of these frequency components. A peak detection algorithm was then used to estimate the heart rate from the rPPG signal. However, the initial results were not as expected, with an average heart rate of 49.77 beats per minute (bpm) from a 4-second video—much lower than anticipated. This suggested there might be problems with how the signal was extracted. Figure 2.8 displays the detected peaks within the rPPG signal, illustrating the results of the peak detection algorithm.

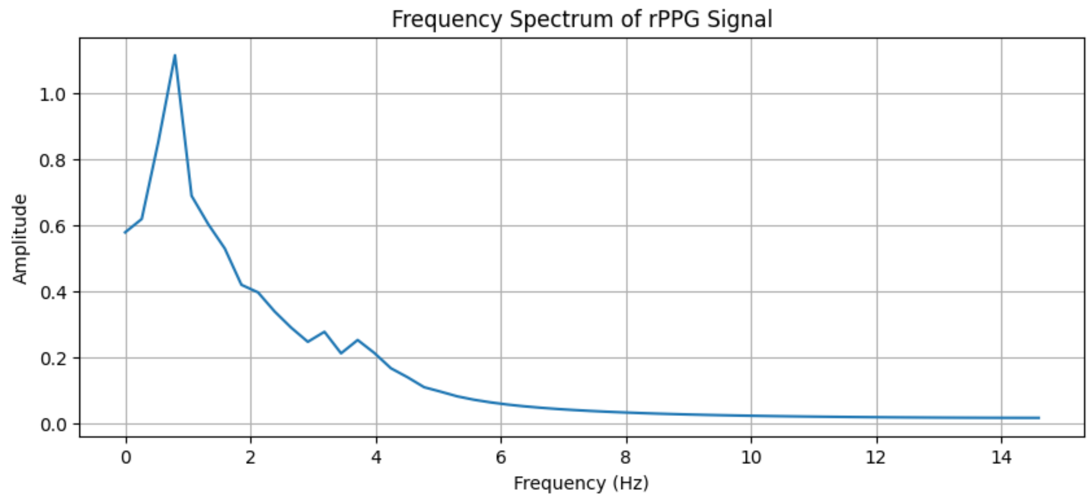

Figure 2.7: Frequency spectrum of rPPG signal using FFT

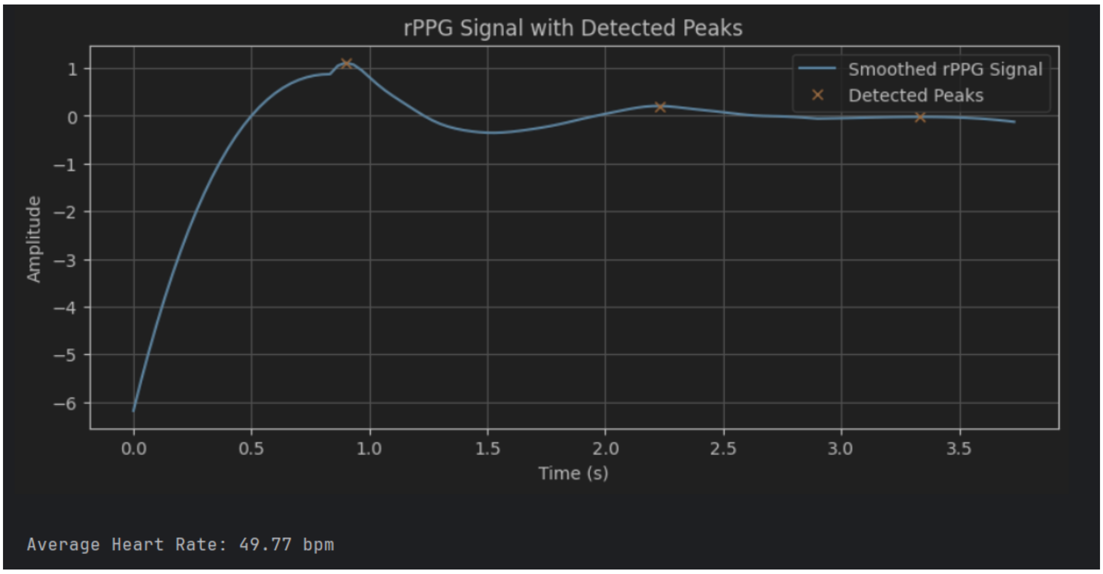

Figure 2.8: Smoothed rPPG signal with detected peaks

2.7 rPPG Extraction with Mediapipe Face Mesh

To improve the accuracy of the rPPG, the research transitioned to using MediaPipe, a more sophisticated tool developed by Google. MediaPipe's Face Mesh offered a dense set of 468 facial landmarks, allowing for precise identification of multiple Regions of Interest (ROIs) such as the forehead, cheeks, and nose. The choice of the forehead, cheeks, and nose as ROIs for rPPG signal extraction was strategic due to several key factors. These areas are relatively large, flat, and less prone to rapid movement compared to other parts of the face, which helps in obtaining more stable signals. The forehead is typically free from obstructions like facial hair or glasses, making it an ideal site for capturing consistent skin color changes related to blood flow. Similarly, the cheeks provide a broad surface area that is also less affected by facial expressions and movements, ensuring reliable signal acquisition. The nose, being centrally located and less mobile during subtle facial expressions, adds another stable region for capturing rPPG signals. By selecting these specific areas, the research aimed to maximize the quality of the rPPG signal by focusing on regions that offer the best combination of stability, accessibility, and minimal interference, which are crucial for accurate heart rate estimation and potential ECG reconstruction.

Mediapipe Face Mesh tool was more robust in handling real-world conditions, providing better accuracy in detecting facial landmarks even in the presence of obstructions. As illustrated in Figure 2.9, MediaPipe successfully identifies a comprehensive array of facial landmarks, facilitating more accurate analysis of the face compared to previous methods.

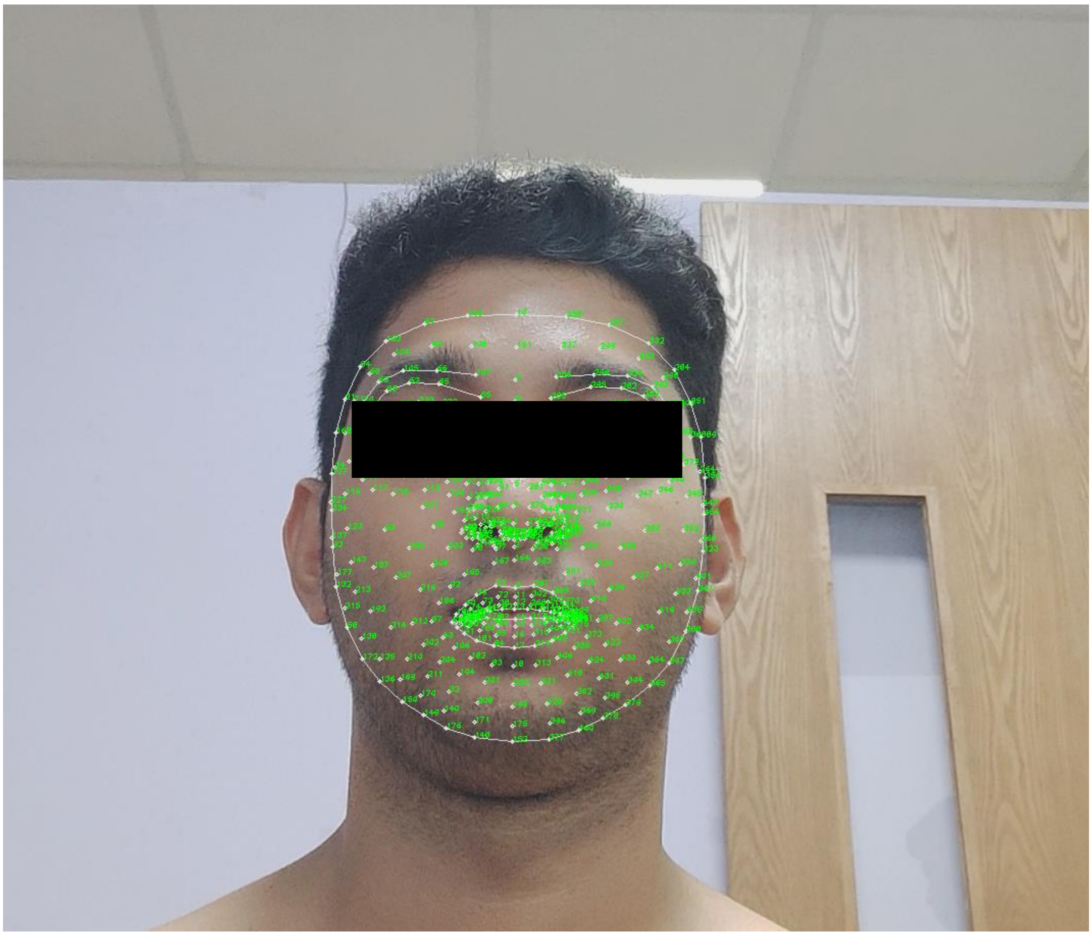

Figure 2.9: FaceMesh applied to a facial video frame

2.7.1 Multiple ROI signal extraction

Mediapipe Face Mesh enabled the identification of ROIs on the face, including the forehead, cheeks, and nose. The rPPG signals extracted from these individual ROIs—depicted in Figures 2.10, 2.11, and 2.12—were averaged to reduce the impact of facial hair, glasses, and other obstructions. This approach enhanced the overall quality of the rPPG signal, offering a more accurate representation of the participant's heart rate. The combined rPPG signal, shown in Figure 2.13, illustrates the improved accuracy achieved through this method.

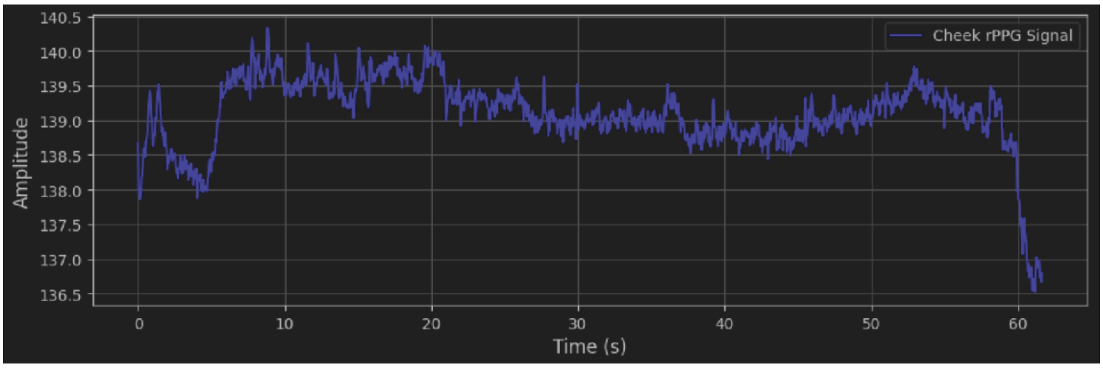

Figure 2.10: rPPG signal obtained from cheek ROI

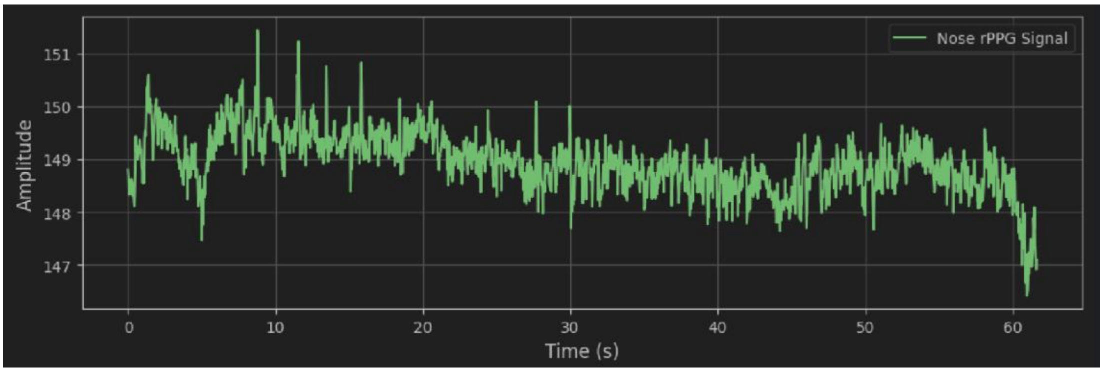

Figure 2.11: rPPG signal obtained from nose ROI

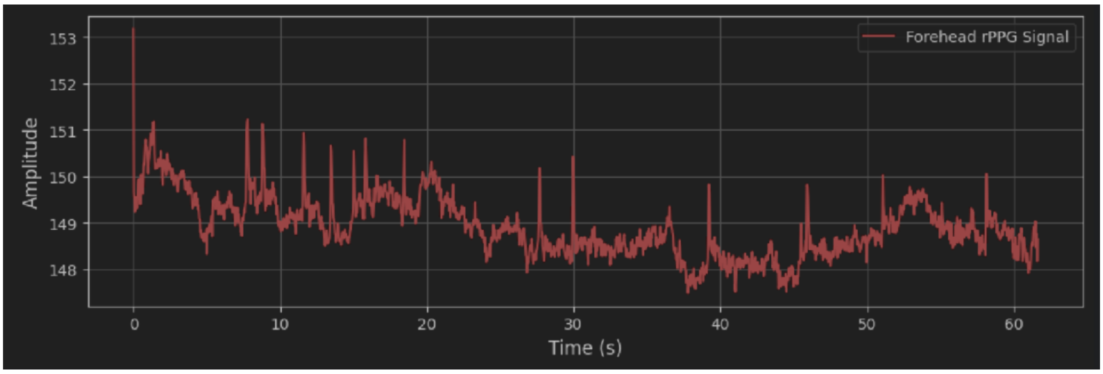

Figure 2.12: rPPG signal obtained from forehead ROI

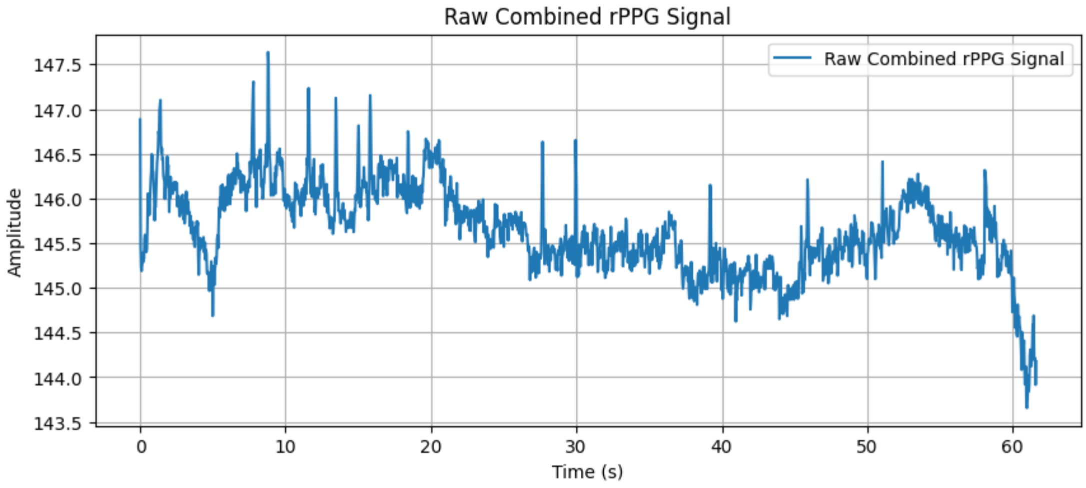

Figure 2.13: Combined rPPG signal from multiple ROIs

2.7.2 Signal smoothing and heart rate calculation

The extracted rPPG signals were further processed using the Savitzky-Golay filter to smooth out any noise and enhance the clarity of the heart rate signal. Reapplication of the peak detection algorithm to this smoothed signal yielded a more accurate heart rate estimation. For a one-minute video recording, the estimated heart rate was 64.06 bpm, which was closer to the actual ECG-derived heart rate of 71 bpm, though not perfectly accurate. Figure 2.14 illustrates the effect of the Savitzky-Golay filtering on the rPPG signal and the improved peak detection results.

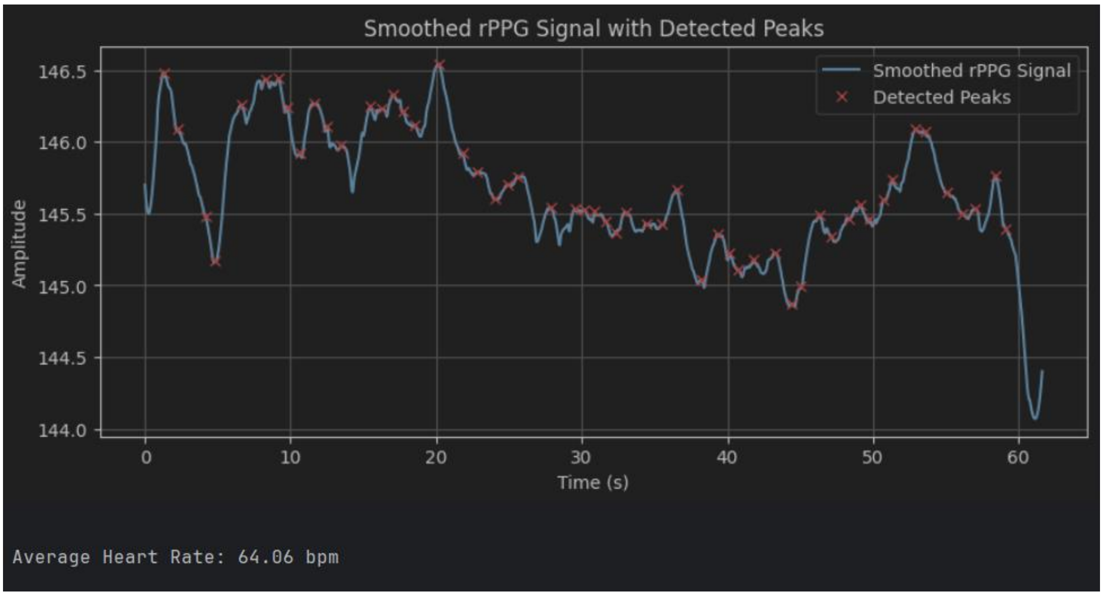

Figure 2.14: Peaks detected from combined rPPG signal with heart rate

2.8 Exploration of Research Paper Methodology

In another attempt to enhance the accuracy of the rPPG-based heart rate estimation, I explored the methodology outlined in a study done by Macwan et al. [28]. The study described a multi-objective optimization approach to rPPG-based heart rate estimation, reporting a Pearson's correlation coefficient of 0.99, a mean absolute error of 0.55, and a signal-to-noise ratio of 2.98. I attempted to replicate their methodology, focusing on the key components such as signal preprocessing, feature extraction, and optimization. However, during the process, I encountered an error related to the calculation of negentropy—a measure of signal disorder used to optimize the heart rate estimation.

2.8.1 Termination of the facial analysis component

The challenges encountered with negentropy calculation, combined with the overall complexity of the method, led to the decision to discontinue further efforts on the facial analysis component. Despite the promising direction, the limitations in time, resources, and technical expertise necessitated a pivot to a more feasible approach—palm-based ECG reconstruction.

2.9 Palm-Based ECG Acquisition

Following the challenges with facial analysis, the research pivoted to a palm-based ECG acquisition approach. This method involved developing a system that could reliably acquire a lead I ECG signal from the palms, which would then be used as the basis for reconstructing the full 12-lead ECG. As shown in Figure 2.15, this component diagram illustrates the process flow of the palm-based ECG acquisition and 12-lead reconstruction system.

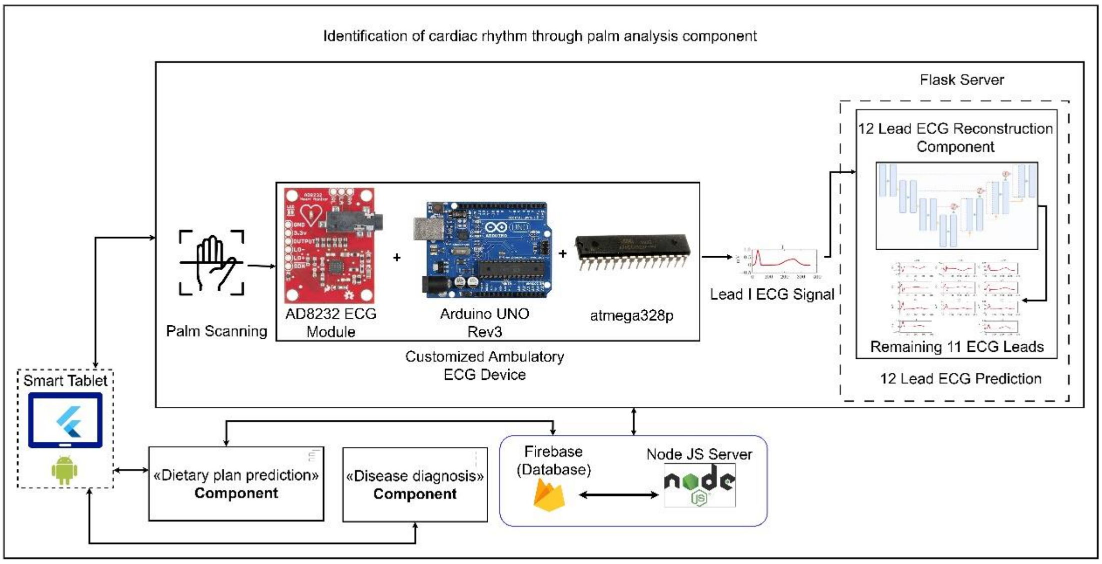

Figure 2.15: Palm Analysis and ECG generation System Architecture

Initially, the ECG acquisition device, consisting of an AD8232 ECG module and an Arduino UNO Rev3 with an ATmega328p microcontroller, is connected to a smart tablet running the system's interface. Disposabele gel electrodes are placed strategically: the positive electrode (LA) on the left palm, the negative electrode (RA) on the right palm, and the reference electrode (RL) on the right leg. The reference electrode can be attached to the right thigh near the knee area or the right ankle if the user is wearing long trousers.

The system captures the Lead I ECG signal, which serves as the input for the next stage. This signal is sent to the 12-lead ECG reconstruction component, hosted on a Flask server. Here, the modified Attention U-Net deep learning model processes the Lead I signal to generate the remaining 11 ECG leads, thus reconstructing a full 12-lead ECG.

This seamless integration of hardware and software components allows for accurate and portable ECG monitoring, making it a valuable tool for remote health assessments and telemedicine applications.

2.9.1 System design

The palm-based ECG acquisition system was designed with an emphasis on portability, cost-effectiveness, and simplicity. The system utilized an AD8232 AFE for signal amplification and conditioning, paired with an Arduino UNO Rev3 equipped with an ATmega328p microcontroller for digitization. Data transmission to a personal computer (PC) was facilitated through a USB connection. The AD8232 was chosen due to its high common-mode rejection ratio (CMRR) and low power consumption, making it ideal for portable applications. The high CMRR helps in reducing noise from external sources, which is critical in a mobile ECG monitoring setup. The low power consumption aligns with the design goal of creating a system that could be powered by a small battery, making it practical for everyday use in remote or home-based settings. The Arduino UNO was selected for its ease of use, widespread support, and sufficient processing power to handle the Analog-to-Digital Conversion (ADC) and initial signal processing tasks. The ATmega328p microcontroller on the Arduino UNO is well-suited for handling the relatively simple processing tasks required for this project, and its open-source nature allows for easy customization and integration with other components. Disposable gel electrodes were chosen for their ability to provide stable and reliable contact with the skin, ensuring consistent signal acquisition. Gel electrodes reduce skin impedance, which is crucial for obtaining clear biopotential signals such as those required for ECG. The use of disposable electrodes also enhances hygiene, particularly important in a consumer product intended for regular use .

The three-electrode configuration was specifically chosen to optimize signal acquisition and minimize noise. The positive electrode was placed on the left palm, the negative electrode on the right palm, and the reference electrode on the right leg. This configuration was selected based on its ability to provide a clean lead I ECG signal while minimizing interference from other sources. Placing the positive (LA) and negative (RA) electrodes on the palms simplifies the setup process, making it easy for users to apply the electrodes themselves. The palms provide a stable surface with sufficient electrical conductivity to capture the heart's electrical signals. This placement also avoids the need for exposing the chest, making the system more user-friendly and less invasive. The reference electrode (RL) was placed on the right leg, specifically near the knee or ankle, to provide a stable reference point for the ECG signal. These areas are typically less prone to movement compared to other parts of the body, reducing the risk of introducing noise into the signal. This placement also allows the user to comfortably position the electrodes while sitting, which is often how they would use the device.

The decision to utilize Lead I for ECG acquisition was based on several key considerations. Lead I is one of the simplest and most commonly used leads in ECG monitoring. It measures the electrical activity of the heart between the left arm (LA) and the right arm (RA), providing a clear and straightforward view of the heart's electrical axis. This simplicity makes Lead I an ideal choice for a portable system designed for ease of use. While Lead I alone does not provide a complete view of the heart's electrical activity, it is highly informative for monitoring the heart's rhythm and detecting basic abnormalities [34]. Since the primary goal was to reconstruct the full 12-lead ECG using a deep learning model, Lead I serves as a sufficient starting point, capturing essential data that can be expanded into a comprehensive 12-lead ECG. Given that the deep modified Attention U-Net is designed to reconstruct the full 12-lead ECG from Lead I, this lead was chosen to ensure the model had a reliable and consistent input signal to work with, facilitating accurate reconstruction.

2.9.2 Signal acquisition and processing

The signals acquired from the electrodes were biopotentials, which are naturally weak and highly susceptible to noise. To address this, the AD8232 played a crucial role in amplifying and conditioning the signals before they were digitized. The Arduino UNO Rev3, operating at a sampling rate of 200 Hz, performed the Analog-to-Digital Conversion (ADC). The chosen sampling rate ensured that the ECG signal was captured with sufficient resolution, providing detailed data necessary for subsequent analysis.

To further reduce noise during the digitization process, the Arduino was configured to operate in ADC noise reduction mode. This mode minimized the noise introduced by the microcontroller during ADC operations, ensuring that the digital signal remained as true to the original analog signal as possible.

2.9.3 Noise reduction techniques

To enhance the quality of the ECG signal, several noise reduction techniques were implemented. A 50 Hz notch filter was applied in software to mitigate power-line interference, a common issue in ECG signal acquisition, particularly in environments with electrical noise. The notch filter specifically targets this frequency, effectively removing the interference without affecting the integrity of the ECG signal.

Baseline drift, typically caused by respiration and other low-frequency movements, was addressed using a high-pass filter with a cutoff frequency of 0.5 Hz. This filter effectively removed low-frequency noise while preserving the essential components of the ECG signal. By setting the cutoff frequency at 0.5 Hz, the filter preserves the higher-frequency components of the ECG signal that are critical for accurate analysis while removing the low-frequency noise.

Muscle noise and other high-frequency artifacts can obscure the ECG signal. The low-pass filter with a 40 Hz cutoff frequency was chosen to reduce these unwanted components while maintaining the important diagnostic features of the ECG signal. The use of second-order and fourth-order filters provides a balance between effective noise reduction and the preservation of signal fidelity, ensuring that the ECG signal remains clear and useful for further analysis.

2.9.4 Transmission and processing

Once the ECG signals were filtered and digitized, they were transmitted to a PC via USB for further processing. A custom Python script was developed to handle this data, applying additional digital filters as necessary to refine the signal further. The processed data was then prepared for the next phase of the project—reconstructing the full 12-lead ECG using a deep learning model. This step was critical in transforming the acquired lead I ECG signal into a comprehensive 12-lead ECG, which is vital for more detailed cardiac analysis and diagnosis.

2.10 12-Lead ECG Reconstruction

With the lead I ECG signal acquired from the palms, the next step was to reconstruct the remaining 11 leads using a deep learning model. Working collaboratively with a fellow team member, we decided to use the modified Attention U-Net framework for this task, known for its ability to capture complex patterns in time-series data, making it particularly suitable for ECG signal reconstruction. Since there was no available source code or pre-existing model that met our requirements, we had to build the model from scratch. I focused on the encoding part of the model, where hierarchical features were extracted from the input signal, while my team member handled the decoding part, where these features were used to reconstruct the additional ECG leads. Additionally, several modifications were made to the model to further improve its accuracy, tailoring it specifically to the unique challenges of ECG signal reconstruction.

2.10.1 Dataset and pre-processing

The PTB-XL dataset [29] was selected for training and validating the deep learning model. This dataset contains over 21,000 clinical 12-lead ECG recordings from nearly 19,000 patients, providing a diverse and robust foundation for model development. The raw ECG signals were preprocessed to standardize data formats, correct artifacts, and enhance signal clarity. This included applying Butterworth filters to remove low-frequency and high-frequency noise, as well as using a Savitzky-Golay filter to smooth the waveforms. Min-Max Normalization was applied to scale the signals between 0 and 1, ensuring consistency across the dataset.

2.10.2 Model architecture

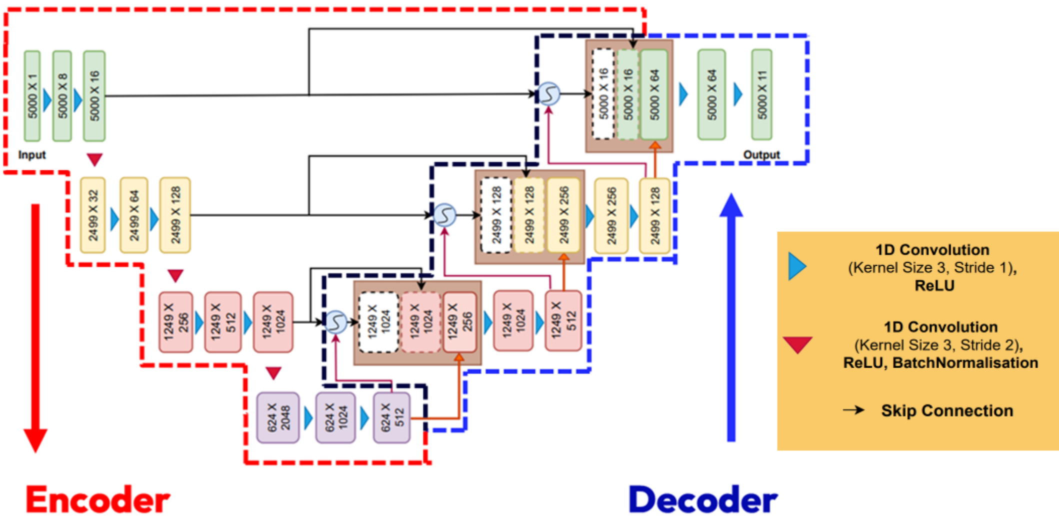

Figure 2.16: Garg et al.'s Modified Attention U-Net Architecture

Source: [24]

The deep learning model was adapted to reconstruct 12-lead ECG signals from a Lead I input, whereas it was initially designed for Lead II input. The model architecture, as shown in Figure 2.16, is based on the modified Attention U-Net framework. My primary focus was on the encoding phase of this model.

The encoder section of the model is responsible for taking the Lead I ECG signal as an input and extracting the most relevant features necessary for reconstructing the remaining ECG signals. These features primarily include edges and repeating signal patterns, such as the QRS complex, which are crucial for accurate ECG reconstruction.

The encoding phase consists of multiple convolutional layers with ReLU activation functions, followed by batch normalization to stabilize the learning process. In the first layer, two 1D convolution layers create feature maps from the input Lead I ECG signals. The ReLU activation function in these layers enables the model to learn complex nonlinear relationships between the Lead I ECG signal and the other 11 ECG signals. The output feature maps generated by this process are preserved through skip connections, which are critical during the decoding process to mitigate data loss.

Subsequently, the output is processed through a 1D convolution layer with BatchNormalization, which downscales the input data by reducing the length of the ECG signal through strided convolutions. This downsampling reduces the computational complexity of the network, thereby enhancing the speed and stability of the training process. The signal then undergoes two more 1D convolutions with ReLU activation to generate additional feature maps.

This sequence is repeated two more times in subsequent layers, resulting in the signal being downscaled three times in total. By the end of the encoding phase, the input signal has been refined to retain only the most essential features required for the reconstruction of the remaining ECG leads. The skip connections play a vital role in counteracting the data loss that occurs during this downsampling by reintroducing information from earlier layers.

Following that the decoder part of the model takes the encoded features and reconstructs the ECG signals. The combination of the encoding and decoding phases formed a comprehensive model capable of accurately predicting the remaining ECG leads from the lead I input.

2.10.3 Model training

Once the model's architecture was complete, including both the encoding and decoding phases, the training process was undertaken by a fellow team member. The model was trained over 50 epochs, with a batch size of 32 and a learning rate of 0.0001, using the ADAM optimizer. The training was conducted in a Kaggle notebooks environment, leveraging the computational power of an Nvidia Tesla P100 GPU. Throughout the training process, the model iterated over the dataset multiple times, allowing it to learn and capture the intricate patterns within the ECG signals.

Performance was evaluated using metrics such as the overall Pearson correlation coefficient and the R^2 value, which are critical indicators of the model's accuracy in reconstructing ECG signals. The proposed model demonstrated a significant improvement over the baseline, with an overall Pearson correlation coefficient of 0.883 compared to 0.805 for the modified Attention U-Net. Additionally, the proposed model achieved an R^2 value of 0.779, surpassing the modified Attention U-Net's R^2 value of 0.636. These metrics highlight the enhanced performance of the proposed model in accurately reconstructing the 12-lead ECG signals from the Lead I input.

2.10.4 Extracting and calculating 12 Leads

Following the training, the model—now fully trained with both the encoding and decoding components—was used to generate the additional ECG leads (II, V1-V6) from the lead I input. The remaining four leads (III, aVR, aVL, aVF) were calculated using Einthoven's law [35] and Goldberger's equations [36], ensuring that all 12 leads were accurately reconstructed for comprehensive cardiac monitoring.

2.11 Development of Visualization Interface

The final component of the project involved developing a comprehensive and user-friendly interface designed to handle the entire ECG capturing, visualization process as seen in Figure 2.17. This interface was intended to be deployed on tablets and other portable devices, providing a seamless platform for real-time ECG monitoring, immediate feedback on electrode connectivity.

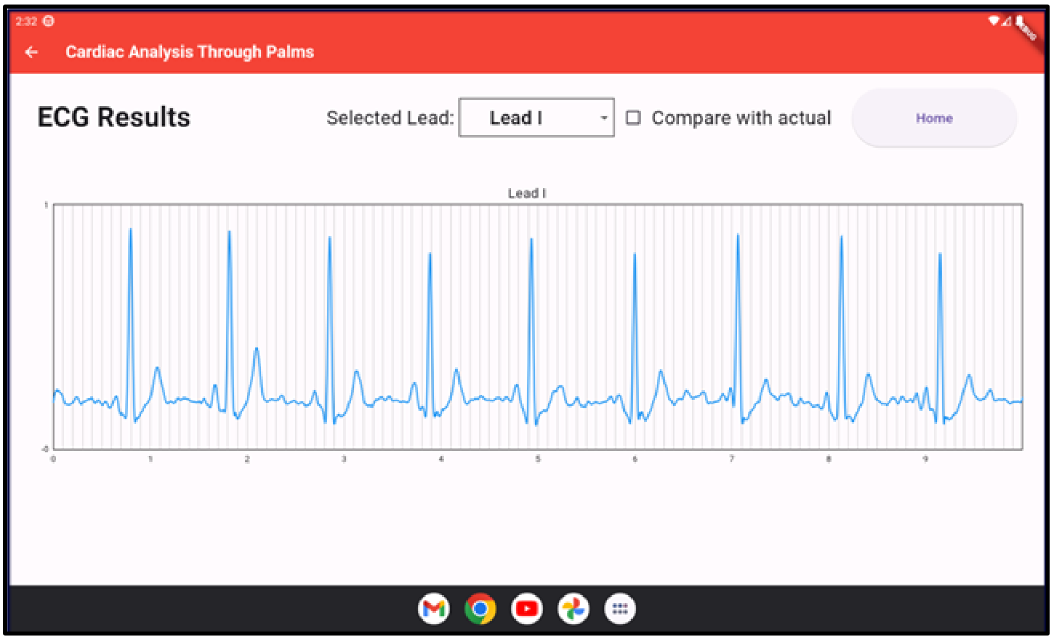

Figure 2.17: Lead I ECG visualization

2.11.1 Design process

The design process prioritized usability and functionality, ensuring that users could easily interact with the system from the moment the palm ECG capturing device was connected. The interface was designed to provide immediate feedback on the status of the electrodes. If both electrodes were correctly connected, the app would allow the user to initiate ECG measurement. If the electrodes were not properly connected, the app would alert the user, preventing inaccurate data capture. Once the ECG was captured, the interface provided clear, organized visualization of all 12 leads simultaneously. Flutter was chosen as the development framework due to its flexibility and ability to create responsive interfaces that function seamlessly across various devices.

2.11.2 Data management functionality

Beyond visualization, the interface was designed to include robust data management features. Users could store historical ECG readings within the app, allowing for easy access and review of past data. Comprehensive visualization made the interface a powerful tool for personal health management.

Finally, below mentioned in the Table 2.1 is a summary of all the technologies, techniques, architectures, and algorithms used for developing the proposed system.

Table 2.1 : Technologies, techniques, architectures, and algorithms used.

Technologies	Flutter, Python, TensorFlow, Node JS, Jupyter Notebook, Keras, Arduino IDE, Kaggle
Techniques	Feature extraction, Signal Filtering, Data normalization, Signal Processing
Algorithms	CNN, Peak Detection, Fast Fourier Transform, Batch Normalization
Architectures	Attention U-Net Framework
Activation Functions	ReLU

2.12 Commercialization Aspects of the Product

2.12.1 Market analysis

The demand for non-invasive cardiac monitoring solutions has been steadily increasing, driven by the global rise in CVDs and the growing need for accessible, cost-effective healthcare technologies. Cardiovascular diseases remain the leading cause of death worldwide, underscoring the critical need for early detection and continuous monitoring of cardiac health. The market for ECG monitoring devices, particularly those that are portable and non-invasive, is expected to grow significantly in the coming years. This growth is fueled by several factors, including the aging population, increasing awareness of heart health, and the expansion of telemedicine and remote healthcare services.

The proposed product, a palm-based ECG acquisition device coupled with a 12-lead ECG reconstruction system, is positioned to meet this growing demand. Unlike traditional ECG devices that require multiple electrodes to be attached to various parts of the body, this product offers a simpler and more convenient solution by acquiring ECG signals from the palms. This approach not only enhances patient comfort but also makes it easier to perform frequent monitoring, particularly in home settings or for individuals in remote areas with limited access to healthcare facilities.

The potential market for this palm-based ECG acquisition product spans several key segments. First, there is the home healthcare market, where individuals are increasingly seeking convenient ways to monitor their heart health from the comfort of their homes. This product’s ease of use and portability make it an ideal choice for such users, offering them a way to conduct regular, comprehensive cardiac checks without the need for clinical visits. Additionally, the product is well-suited for remote healthcare, serving healthcare providers who offer services to patients in remote or underserved areas where access to traditional ECG devices may be limited. By enabling reliable ECG monitoring outside of hospital settings, this device supports broader access to quality cardiac care.

Moreover, the product has potential in the portable devices market, where there is a growing interest in integrating medical-grade sensors into everyday devices. As consumer demand for health monitoring tools that blend seamlessly into daily life increases, this product’s ability to provide a 12-lead ECG in a portable form factor gives it a competitive edge. Finally, the product can integrate with telemedicine platforms, supporting remote monitoring and consultation services. This allows healthcare providers to continuously monitor patients’ cardiac health, offering timely interventions when necessary. The product's unique ability to deliver reliable 12-lead

ECG signals, typically only available in clinical settings, positions it to capture significant market share across these segments.

2.12.2 Competitive landscape

The competitive landscape for ECG monitoring devices is diverse, ranging from traditional clinical ECG machines to modern wearable devices like smartwatches and fitness trackers that include basic ECG functions. However, these competitors often fall short in certain areas where the proposed product excels.

Traditional 12-lead ECG machines, while accurate and reliable, are typically bulky, expensive, and require professional operation. They are generally used in hospitals and clinics, making them less accessible for regular monitoring by the average consumer. The proposed product addresses these limitations by offering a compact, portable alternative that can be used at home without the need for professional assistance.

In recent years, there has been a surge in wearable devices that offer ECG monitoring, such as smartwatches. While these devices are convenient and widely adopted, they generally only provide single-lead ECG readings, which are less comprehensive than 12-lead ECGs. Additionally, the accuracy of these readings can vary significantly, especially in non-clinical settings. The proposed product, with its ability to reconstruct a full 12-lead ECG from a palm-based acquisition, offers a much more detailed and reliable cardiac assessment, making it a superior option for users who require more thorough monitoring.

In terms of competition, several existing products occupy the ECG monitoring space. AliveCor's KardiaMobile 6L [30] is their most advanced device, offering a six-lead ECG that provides more detailed cardiac insights than single-lead devices. This portable and user-friendly device allows users to take ECG readings at home or on the go, with data instantly available via a smartphone app. While the six-lead capability offers improved diagnostic utility over single-lead devices, it still falls short of the comprehensive analysis provided by a 12-lead ECG, which is the gold standard in cardiac diagnostics.

Similarly, the Apple Watch includes a single-lead ECG function as part of its broader suite of fitness tracking features [31]. However, while the Apple Watch is widely adopted for general health monitoring, its medical applications are limited, and it cannot offer the detailed cardiac insights that a 12-lead ECG provides. Another competitor, the iRhythm Zio Patch, is a wearable ECG monitor designed for continuous monitoring over extended periods, typically up to 14 days [32]. Although effective for diagnosing arrhythmias, the Zio Patch is primarily targeted at short-term monitoring for specific conditions and is not designed for ongoing daily use by consumers. These competitors highlight the current market gap that the proposed product aims to fill by offering a portable, comprehensive, and user-friendly solution for 12-lead ECG monitoring.

2.12.3 Commercialization strategy

The primary differentiation of this product lies in its ability to offer a 12-lead ECG from a palm-based acquisition, a feature that is currently not available in any portable or consumer-oriented devices. This unique selling point will be emphasized in all marketing and promotional activities, positioning the product as a cutting-edge solution for comprehensive cardiac monitoring.

To bring the palm-based ECG device to market in Sri Lanka, securing approval from the National Medicines Regulatory Authority (NMRA) is essential. The NMRA ensures all medical devices meet safety and performance standards. This process requires submitting technical documentation, clinical data, and proof of compliance with international standards like ISO 13485. Aligning with global standards such as ISO 13485 and IEC 60601 is also crucial for both local and international commercialization. These certifications not only ease NMRA approval but also support future market expansion into regions like Europe and the United States. Obtaining regulatory approval will build consumer trust, ensuring the product meets high safety standards, which is vital for adoption in both the healthcare sector and among individual users. This trust is particularly important in the growing market for non-invasive, at-home health monitoring.

The product will be priced competitively to balance affordability with the advanced features it offers. A tiered pricing model may be employed, offering different packages based on additional services such as cloud storage of ECG data, real-time monitoring by healthcare professionals, or integration with other health monitoring devices.

The proposed palm-based ECG acquisition and 12-lead reconstruction system is well-positioned to capture a significant share of the growing market for non-invasive cardiac monitoring. By leveraging its unique capabilities, strategic partnerships, and a comprehensive commercialization strategy, the product has the potential to make a substantial impact on how individuals monitor and manage their heart health.

2.13 Testing & Implementation

2.13.1 Implementation of the palm-based ECG acquisition system

The implementation of the palm-based ECG acquisition system focused on creating a portable, cost-effective solution for capturing and reconstructing 12-lead ECG signals. The system was designed using key components such as the AD8232 AFE and the Arduino UNO Rev3 with an ATmega328p microcontroller. The development process involved several critical steps to ensure the system's functionality, accuracy, and usability.

2.13.2 System design and hardware integration

The ECG acquisition system was built with portability and simplicity in mind. The AD8232 AFE was chosen for its ability to amplify and condition the weak biopotential signals captured from the body, specifically the palms. The Arduino UNO Rev3, equipped with the ATmega328p microcontroller, was responsible for digitizing the amplified signals at a sampling rate of 200 Hz. The three-electrode configuration, with the positive electrode on the left palm, the negative electrode on the right palm, and the reference electrode on the right leg, was selected to optimize signal clarity and minimize noise. The hardware components were integrated into a compact setup as shown in Figure 2.18, allowing for easy deployment in various environments.

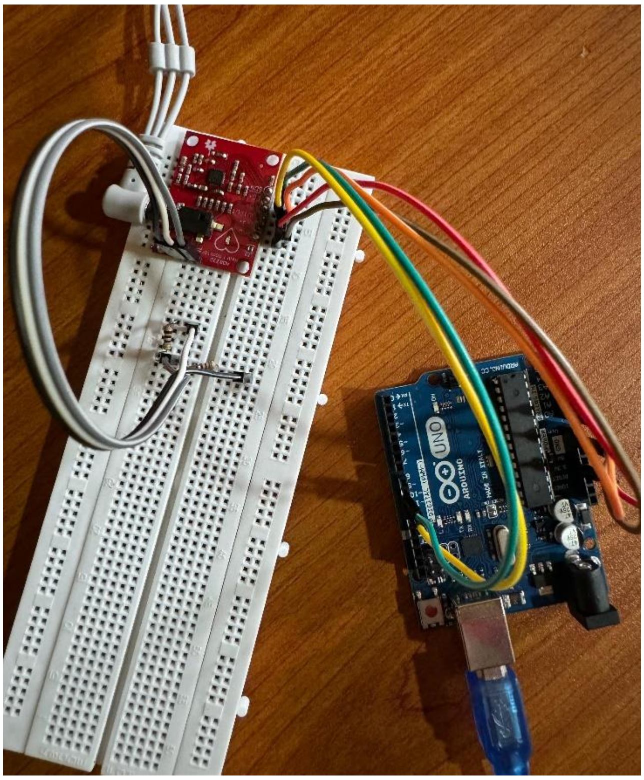

Figure 2.18: Palm ECG acquisition system

2.13.3 Signal processing and filtering techniques

The signals acquired from the electrodes were processed to remove noise and enhance the quality of the ECG data. The AD8232 provided initial amplification, but additional noise reduction techniques were applied during and after digitization. A 50 Hz notch filter was implemented to mitigate power-line interference, while baseline drift and muscle noise were addressed using high-pass and low-pass filters, respectively. Both second-order and fourth-order filters were employed to balance effective noise reduction with signal preservation. Figure 2.19 shows a noisy signal before processing, highlighting the need for these noise reduction techniques to improve signal clarity.

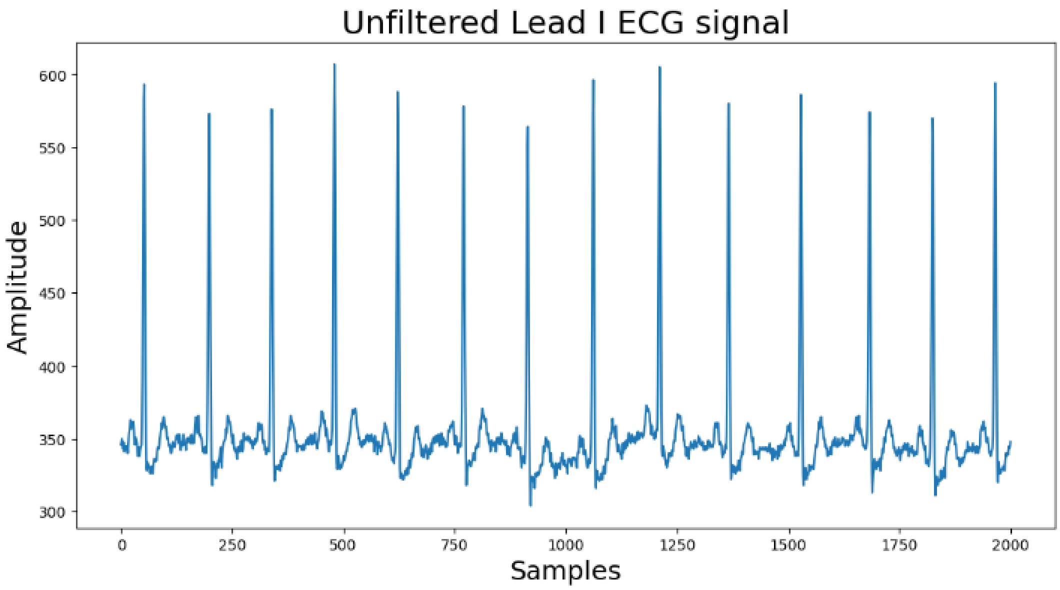

Figure 2.19: Unfiltered lead I ECG signal acquired from palms

2.13.4 Software development for data transmission and analysis

Once the signals were filtered and digitized, they were transmitted to a PC via USB. A custom Python script was developed to handle this data, applying additional digital filters and preparing the signals for further analysis as seen in Figure 2.20. The script was designed to be efficient and user-friendly, allowing for seamless integration with the subsequent deep learning models used for 12-lead ECG reconstruction.

```python
def apply_savitzky_golay_filter_x(data):
  window_length = 11
  polyorder = 3
  x = data
  x = x.squeeze()
  x = savgol_filter(x, window_length, polyorder)
  return x[:, np.newaxis]

def butter_highpass_filter(data, cutoff_frequency, fs, order=4):
    nyquist = 0.5 * fs
    normal_cutoff = cutoff_frequency / nyquist
    b, a = butter(order, normal_cutoff, btype='highpass', analog=False)
    filtered_data = lfilter(b, a, data)
    return filtered_data

def butter_lowpass_filter(data, cutoff_frequency, fs, order=4):
    nyquist = 0.5 * fs
    normal_cutoff = cutoff_frequency / nyquist
    b, a = butter(order, normal_cutoff, btype='lowpass', analog=False)
    filtered_data = lfilter(b, a, data)
    return filtered_data

def apply_butterworth_filters_x(data):
  x = data[np.newaxis, :, np.newaxis]
  x = butter_highpass_filter(x, cutoff_frequency_high, fs, 4)
  x = butter_lowpass_filter(x, cutoff_frequency_low, fs, 4)
  return x

def apply_notch_filter(data):
    sig = data.squeeze()
    b, a = iirnotch(f0, Q, fs)
    sig = filtfilt(b, a, sig)
    sig = sig[:, np.newaxis]
    return sig
```

Figure 2.20: Filters implementation for palm acquired ECG signals

2.13.5 Testing of the system

The testing phase was crucial for validating the functionality and accuracy of the palm-based ECG acquisition system. This phase involved making use of an Arduino sketch (Figure 2.21) to ensure proper connectivity of the palm electrodes and to verify that the system could reliably capture and process ECG signals. The code was designed to monitor the connection status of the electrodes and provide feedback on their status, ensuring consistent and accurate signal acquisition.

```
void setup() {
  // initialize the serial communication:
  Serial.begin(9600);
  pinMode(10, INPUT); // Setup for leads off detection LO +
  pinMode(11, INPUT); // Setup for leads off detection LO -

}

void loop() {
  if((digitalRead(10) == 1)||(digitalRead(11) == 1)){
    Serial.println('!');
  }
  else{
    // send the value of analog input 0:
    Serial.println(analogRead(A0));
  }
  //Wait for a bit to keep serial data from saturating
  delay(1);
}
```

Figure 2.21: Lead off detection

2.13.6 Reconstruction of 12-lead ECG

The core objective of the testing phase was to verify the accuracy of the reconstructed 12-lead ECG signals. The deep learning model, specifically the modified Attention U-Net framework, was trained and validated using the PTB-XL dataset. The model's performance was assessed by comparing the reconstructed ECG leads with the original signals from the dataset.

2.13.7 Test Case Design

The below mentioned test cases were also made to make sure of the reliability of the system.

Table 2.2: Test case to verify whether both electrodes are connected

Test Case Id	01
Test Case	Verify electrode connection
Test Scenario	Verify that both electrodes are properly connected, and the system can detect disconnection
Precondition	Both electrodes should be attached to the palms of the user and the system should be powered on
Input	Electrodes connected to the left and right palms
Expected Output	1. System should confirm that both electrodes are connected 2. If an electrode is disconnected, the system should alert the user and stop data collection
Actual Result	1. System confirmed both electrodes were connected 2. System alerted the user when an electrode was disconnected and paused data collection
Status (Pass/Fail)	Pass

Table 2.3: Test case to verify data transmission to the mobile application

Test Case Id	02
Test Case	Verify data transmission to the mobile application
Test Scenario	Test whether the ECG data captured from the electrodes is successfully transmitted to the mobile application for further analysis
Precondition	Electrodes must be properly connected, and the mobile application should be running and ready to receive data
Input	ECG signal captured from the palms
Expected Output	1. ECG data should be successfully transmitted to the mobile application 2. The mobile application should display the ECG signal in real-time
Actual Result	1. ECG data was transmitted successfully 2. The mobile application displayed the ECG signal in real-time without any lag
Status (Pass/Fail)	Pass

Table 2.4: Test case to check the integrated mobile application

Test Case Id	03
Test Case	Testing the integrated mobile application
Test Scenario	Testing the mobile application's ability to handle signal acquisition, processing, and 12-lead ECG reconstruction
Precondition	The system should be integrated, with all hardware and software components connected and functioning
Input	ECG signal captured from the palms, processed through the Arduino, and transmitted to the mobile application
Expected Output	1. Accurate lead I ECG signal display 2. Correct reconstruction of the 12-lead ECG in the application 3. Smooth user interaction with no application crashes
Actual Result	1. Lead I ECG was accurately displayed 2. 12-lead ECG was reconstructed correctly 3. The mobile application operated smoothly without crashes
Status (Pass/Fail)	Pass

Table 2.5: Test case to validate noise filtering and signal quality

Test Case Id	04
Test Case	Validate noise filtering and signal quality
Test Scenario	Ensure that the system effectively filters out noise and preserves the integrity of the ECG signal
Precondition	System should be active with electrodes attached and ready for signal acquisition
Input	ECG signal captured in a typical environment with potential noise sources (e.g., electrical interference)
Expected Output	1. The system should apply noise filtering techniques to produce a clean ECG signal \\ 2. The ECG signal should be free from significant artifacts and suitable for diagnostic purposes
Actual Result	1. Noise filtering effectively removed interference \\ 2. The resulting ECG signal was clean and suitable for analysis
Status (Pass/Fail)	Pass

3. RESULTS & DISCUSSION

3.1 Results

3.1.1 Facial analysis component

The initial approach of using facial analysis through rPPG for ECG signal acquisition faced significant challenges that ultimately led to its abandonment. The primary issue was the reliability of the rPPG signals, which were highly susceptible to various forms of interference, including noise, lighting variations, and facial movements. These factors made it difficult to obtain consistent and accurate signals, which are crucial for reliable ECG reconstruction. Advanced techniques such as Dense Optical Flow and Haar cascade were employed to enhance the detection of subtle facial changes related to cardiac activity. However, these methods failed to achieve the necessary accuracy and consistency, further compounding the challenges. The average heart rate derived from the facial recordings was consistently lower than expected, and the noise levels remained prohibitively high, rendering the signals unsuitable for further processing into ECG data. These persistent issues highlighted the technological limitations of the facial analysis approach in its current state, leading to the decision to discontinue this line of investigation and shift focus to a more feasible method for ECG signal acquisition.

3.1.2 Palm-based ECG acquisition

The palm-based ECG acquisition system successfully captured Lead I ECG signals (Figure 3.1) using the AD8232 AFE and Arduino UNO Rev3. The design of the system prioritized portability and simplicity, employing a straightforward three-electrode setup that was both user-friendly and highly effective for ECG signal acquisition. This setup, which involved placing electrodes on the palms and the reference electrode on the leg, allowed for consistent and reliable signal capture across different users and environments.

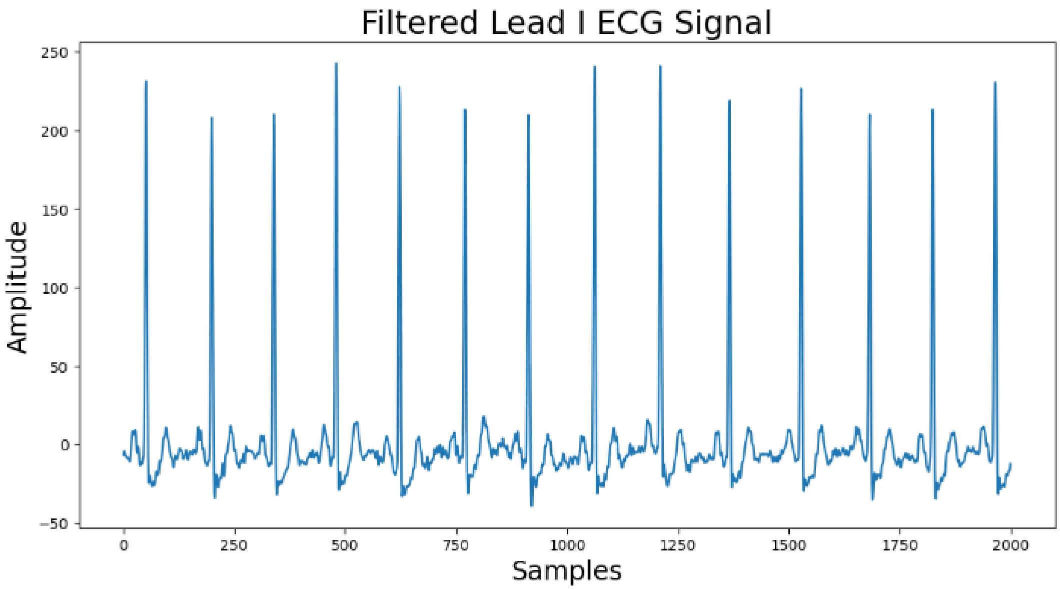

Figure 3.1: Filtered lead I ECG signal acquired from palms

To ensure the quality and reliability of the captured signals, a series of noise reduction techniques were applied. These included the use of a 50 Hz notch filter to eliminate power-line interference, which is a common issue in environments with multiple electronic devices. Additionally, high-pass and low-pass filters were implemented to address baseline drift and muscle noise, respectively. The high-pass filter, with a cutoff frequency of 0.5 Hz, effectively removed slow, low-frequency movements such as those caused by respiration, while the low-pass filter, set at 40 Hz, reduced high-frequency muscle artifacts. Together, these filtering techniques resulted in ECG signals that were free from significant noise and artifacts, ensuring that the signals retained their clinical relevance.

To further validate the effectiveness of the system, a frequency spectrum analysis was conducted, comparing the downscaled Lead I signal obtained from the system with the original 500 Hz signal from the PTB-XL dataset, which is widely regarded as the gold standard in ECG data. As illustrated in Figure 3.2, this comparison revealed that the developed system effectively retains all essential frequency components of the ECG signal.

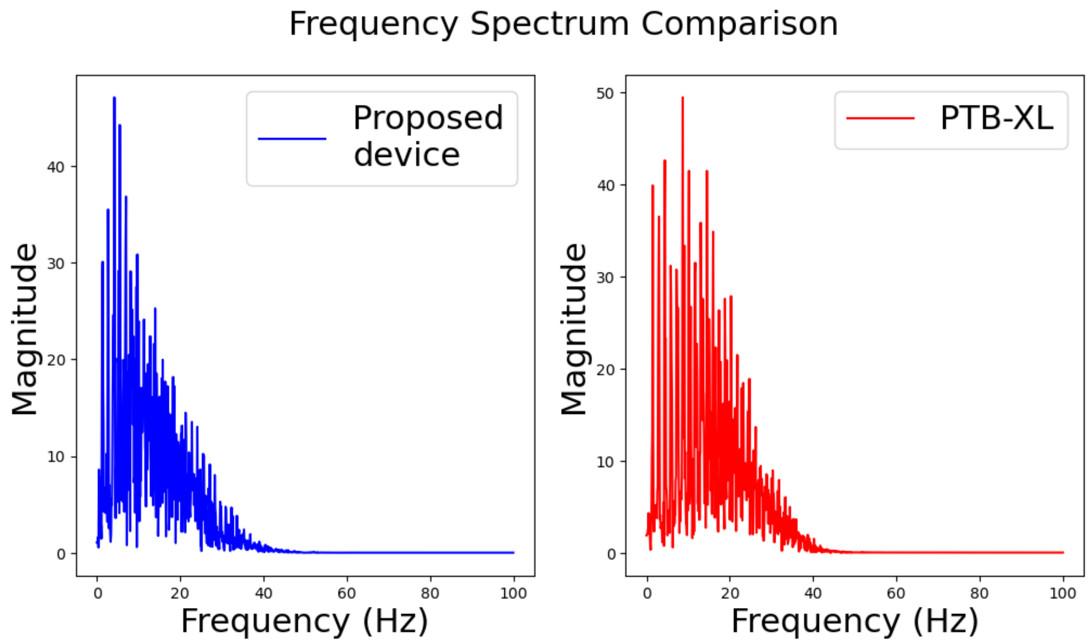

Figure 3.2: Frequency spectrum comparison

Specifically, the system preserved the low-frequency elements associated with the P-wave and T-wave, which are critical for assessing atrial and ventricular repolarization, respectively. Additionally, the system accurately captured the higher frequencies related to the QRS complex, which are crucial for analyzing ventricular depolarization. This retention of critical signal components is vital for maintaining the diagnostic integrity of the ECG signals, ensuring they are suitable for subsequent analysis and the reconstruction of the full 12-lead ECG.

The results of this comprehensive validation confirm that the palm-based system not only captures high-quality Lead I ECG signals but also processes these signals in a way that preserves their clinical relevance. The successful application of noise reduction techniques, combined with the system's ability to retain essential frequency components, highlights its potential as a reliable tool for non-invasive cardiac monitoring. This makes the system particularly valuable for portable and remote healthcare applications, where maintaining signal integrity is crucial for accurate diagnosis and patient care. The palm-based method provided reliable Lead I ECG signals, which were successfully used for reconstructing the remaining 11 leads.

3.1.3 12-Lead ECG reconstruction

The deep learning model, specifically the modified Attention U-Net, demonstrated a strong capability in accurately reconstructing the 12-lead ECG signals from the Lead I input. This was evidenced by high correlation coefficients and low RMSE.

Figures 3.3, 3.4, and 3.5 further illustrate the effectiveness of the model by comparing all 11 reconstructed ECG leads against their corresponding original leads from the PTB-XL dataset. The visual comparisons presented provide a clear, side-by-side evaluation of the reconstructed leads versus the original leads, offering a comprehensive overview of the model's performance. These comparisons are critical for confirming that the reconstructed signals not only visually resemble the original ECG signals but also maintain the diagnostic integrity necessary for clinical applications. These figures showcase the similarity between each reconstructed signal and its original counterpart, quantified as a percentage.

The high similarity observed in the reconstructed signals suggest that the model was highly successful in capturing the essential characteristics of the original ECG signals.

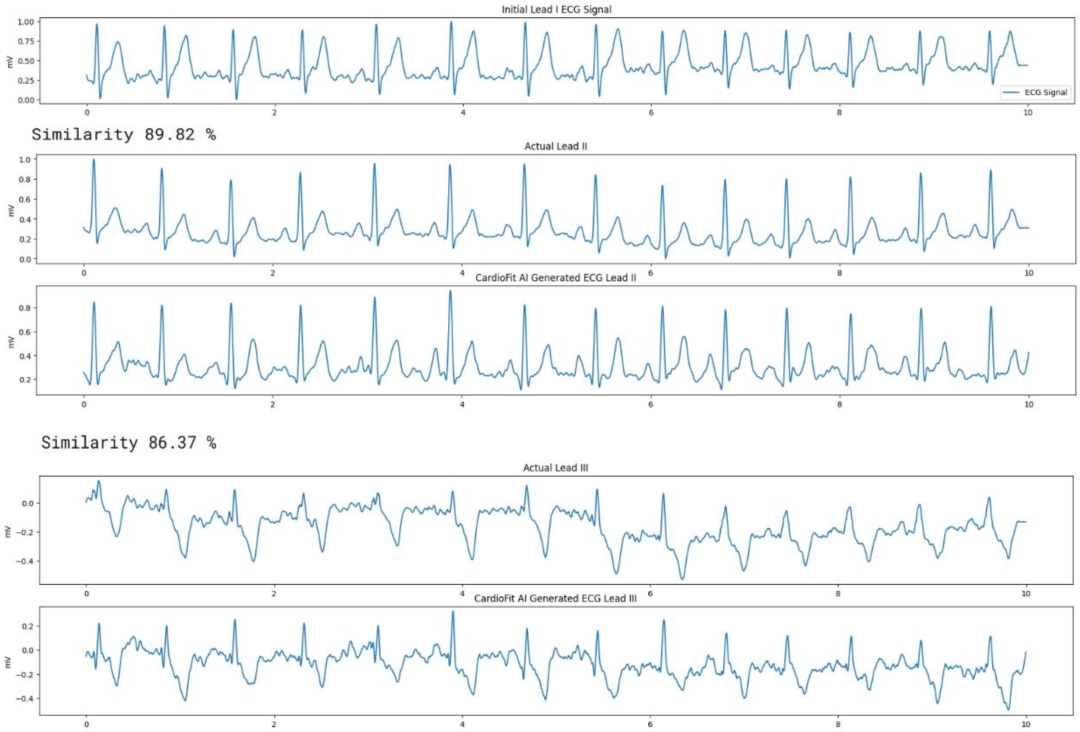

Figure 3.3: Comparison of Lead II and III

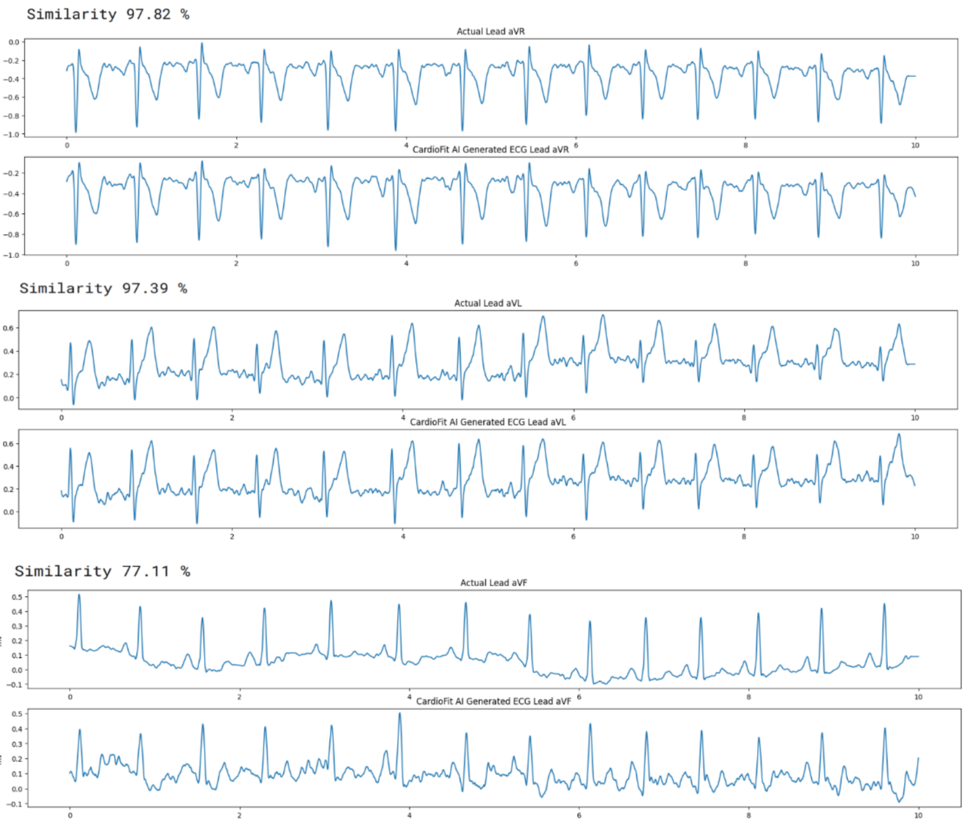

Figure 3.4: Comparison of leads aVR, aVL and aVF

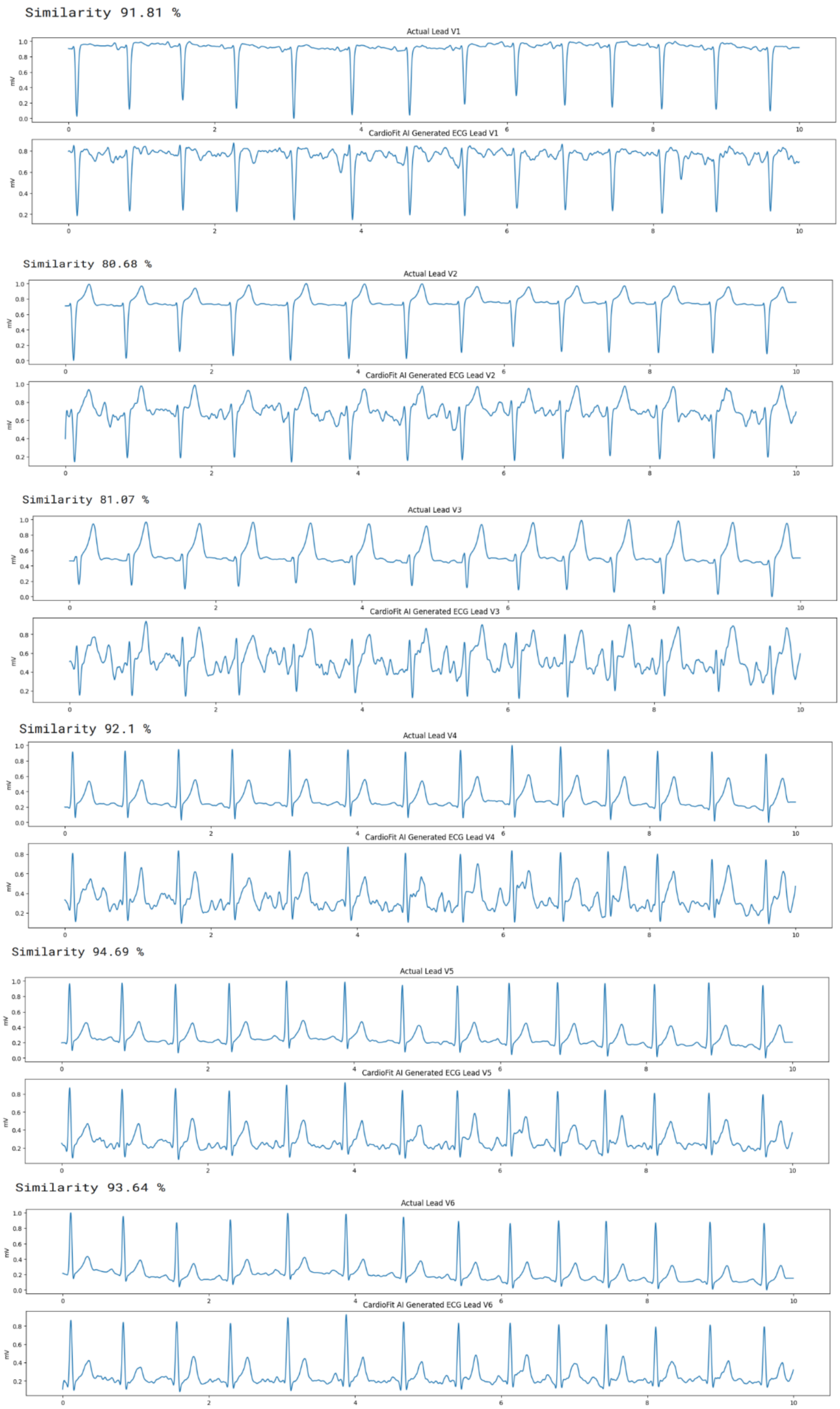

Figure 3.5: Comparison of leads V1-V6

The model demonstrated the feasibility of using a single-lead ECG signal for comprehensive cardiac assessment, validating the effectiveness of the palm-based acquisition method.

3.2 Research Findings

The initial phase of the research focused on exploring the feasibility of reconstructing ECG signals from facial videos, a non-contact method that promised significant advancements in the field of cardiac monitoring. However, the results revealed that current technologies face substantial limitations in this area. Specifically, the reliability of the rPPG signals obtained from facial recordings was inconsistent, particularly in varying lighting conditions and among individuals with different skin tones. Despite extensive efforts, including the application of advanced signal processing techniques and the utilization of datasets like the UBFC-rPPG, the quality of the extracted signals was insufficient for accurate ECG reconstruction. This finding highlighted the need for further research and development in non-contact ECG acquisition technologies, suggesting that while the concept holds promise, the current state of technology is not yet mature enough for practical application in clinical settings.

In response to the challenges encountered with facial video-based ECG acquisition, the research pivoted to a more conventional but equally innovative approach—palm-based ECG acquisition. This shift proved highly effective, demonstrating that a simple three-electrode setup could reliably capture high-quality Lead I ECG signals. The palm-based method utilized the AD8232 AFE and Arduino UNO Rev3 microcontroller, emphasizing portability and ease of use. The system was designed to be both cost-effective and accessible, making it suitable for a wide range of applications, from home-based monitoring to telemedicine. The ECG signals acquired through this method were subjected to rigorous validation processes, including frequency spectrum analysis, which confirmed that the system retained all essential frequency components necessary for accurate diagnostic use. The success of this approach suggests that palm-based ECG acquisition could play a significant role in expanding the reach of cardiac monitoring technologies, particularly in remote or resource-limited settings.

Building on the high-quality ECG signals obtained from the palm-based acquisition system, the research then explored the potential of deep learning in enhancing non-invasive cardiac monitoring techniques. A modified Attention U-Net deep learning model was developed and trained to reconstruct the full 12-lead ECG from the single Lead I input. The model's performance exceeded expectations, with high correlation coefficients and low RMSE values indicating strong alignment between the reconstructed and original signals from the PTB-XL dataset. Figures 2.24, 2.25, and 2.26 provided a visual comparison, showcasing the similarity between the reconstructed leads and their original counterparts, with the model retaining critical features such as the P-wave, T-wave, and QRS complex. This finding underscores the transformative potential of AI in the field of cardiac monitoring, suggesting that deep learning models could significantly improve the accuracy and accessibility of ECG technology. The successful application of this model not only highlights the feasibility of reconstructing comprehensive ECG data from minimal inputs but also opens up new avenues for the development of portable, non-invasive cardiac monitoring devices that could be deployed in a variety of healthcare settings.

3.3 Discussion

The research demonstrated that while innovative approaches like facial ECG acquisition hold theoretical promise, practical challenges significantly limit their current applicability. The susceptibility to environmental factors and the complexity of accurately capturing physiological signals from facial videos highlighted the need for more robust methods.

The pivot to palm-based ECG acquisition was a strategic decision driven by the need for reliability and practicality. The system's success underscores the importance of a solid hardware foundation combined with effective signal processing techniques. The results suggest that with careful design and implementation, even simple, portable systems can provide high-quality ECG data, making them suitable for remote monitoring and telemedicine applications.

The deep learning model's success in reconstructing the 12-lead ECG from a single-lead input offers exciting possibilities for the future of cardiac care. This approach not only simplifies the process of obtaining comprehensive ECG data but also reduces the invasiveness of traditional methods. The ability to accurately predict multiple leads from a single source could revolutionize how ECGs are performed, particularly in settings where traditional 12-lead systems are impractical.

CONCLUSION

This research aimed to explore innovative methods for non-invasive cardiac monitoring, starting with the ambitious goal of reconstructing a 12-lead ECG signal from facial video recordings. The initial approach, inspired by the potential of rPPG signals captured from facial videos, encountered significant challenges. These included difficulties in obtaining consistent and accurate signals due to variables such as lighting conditions, facial movement, and the inherent complexity of signal extraction from facial frames. These challenges highlighted the limitations of the current state of technology in reliably using facial analysis for ECG reconstruction.

Recognizing these limitations, the research strategically pivoted towards a more practical and reliable solution—palm-based ECG acquisition. This method focused on capturing a Lead I ECG signal from the palms using a straightforward three-electrode setup, combined with an AD8232 AFE and an Arduino UNO Rev3 microcontroller. The system was designed to be portable and cost-effective, addressing the need for accessible cardiac monitoring solutions in various settings. Signal processing techniques, including the application of noise reduction filters, were crucial in ensuring the acquisition of a Lead I signal that effectively retains the essential frequency components of the ECG signal, including the P-wave, T-wave, and QRS complex. This Lead I signal was then used to reconstruct the remaining 11 leads of the ECG.

The deep learning component of the research involved implementing a modified Attention U-Net model to reconstruct the full 12-lead ECG from the single Lead I input. The model demonstrated strong performance, accurately predicting the remaining ECG leads and providing results that closely matched those obtained through traditional methods obtaining a Pearson correlation coefficient of 0.883 and an R^2 value of 0.779. This success underscores the potential of AI and machine learning in enhancing non-invasive cardiac monitoring, particularly in simplifying the process while maintaining diagnostic accuracy.

In addressing the research objectives outlined in the introduction, the project successfully developed a practical and reliable method for ECG signal acquisition and reconstruction. The pivot to palm-based acquisition provided a solution to the challenges encountered with facial analysis, ensuring that the research met its goal of developing an accessible and effective cardiac monitoring system. The introduction highlighted the need for innovative, non-invasive methods to improve cardiac care, particularly in remote or resource-limited settings. The conclusion affirms that this research has made significant strides towards that goal, offering a viable alternative to traditional ECG acquisition methods and laying the groundwork for future advancements in this field.

This report provides a cohesive narrative of the research journey, from the initial exploration of facial analysis to the successful implementation of palm-based ECG acquisition and reconstruction. The solutions presented in this study directly address the problems raised in the introduction, demonstrating how adaptive research strategies can lead to meaningful advancements in medical technology. The findings and solutions proposed in this report contribute to the broader field of non-invasive cardiac monitoring, offering new possibilities for improving patient outcomes and making comprehensive cardiac care more accessible.

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APPENDICES

Appendix - A : Plagiarism Report