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

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The dissertation was submitted in partial fulfilment of the requirements for the B.Sc. (Honors) degree in Information Technology Specializing in Software Engineering

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DECLARATION

I declare that this is my own work, and this dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. Also, I hereby grant to Sri Lanka Institute of Information Technology the non-exclusive right to reproduce and distribute my dissertation in whole or part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as article or books).

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....23/8/2024..........

Signature of Supervisor
(Dr. Dilshan De Silva)

Date

ABSTRACT

The growing prevalence of cardiac diseases worldwide underscores the critical need for early detection and intervention, especially in resource-limited settings. This research explores a novel approach for diagnosing cardiac diseases using 12-lead Electrocardiograms (ECGs) captured through electrodes applied to the palms, diverging from conventional placement. By leveraging deep learning techniques, this study aims to validate the effectiveness of this unconventional method in accurately diagnosing a range of cardiac conditions. **CardioFit AI** system, built on a Convolutional Neural Network (CNN) architecture, incorporates a baseline model that has been fine-tuned with low pass filtering and moving average methods to improve ECG signal clarity before diagnosis. The project involves a mobile application developed using Flutter, supporting both Android and iOS platforms, where real-time patient status notifications, including live location tracking, are sent to loved ones in case of emergencies. This application, deployed on a Flask server hosted on PythonAnywhere, processes ECG data, reconstructs the leads, and predicts possible conditions. The deployment leverages Firebase for model storage and a geolocation service for precise tracking. The findings reveal that this palm-based ECG system holds promise for reliable cardiac diagnosis, with significant potential for real-world deployment. The integration of innovative diagnostic methods and mobile technologies provides a comprehensive, user-friendly solution to improve cardiac care accessibility and efficiency.

Keywords - Cardiac Disease Diagnosis, 12-lead ECG, Machine Learning, Palm Electrode Placement, Flutter, Firebase, Real-time Notifications, ECG Data Preprocessing, Flask Server Deployment

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LIST OF ABBREVIATIONS

Abbreviation	Description
WHO	World Health Organization
CVD	Cardiovascular diseases
ECG	Electrocardiography
ReLU	Rectified Linear Unit
CNN	Convolutional Neural Network
RNNs	Recurrent Neural Networks
AUC	Area Under the ROC Curve
GAP	Global Average Pooling
LVH	Left Ventricular Hypertrophy
NDT	Non-Diagnostic
LAFB	Left Anterior Fascicular Block
AFIB	Atrial Fibrillation
ISC	Ischemia
EMA	European Medicines Agency
NMRA	National Medicines Regulatory Authority
SaaS	Software-as-a-service
FDA	Food and Drug Administration
CAGR	Compound Yearly Growth Rate
PVC	Premature Ventricular Contractions
RBBB	Right Bundle Branch Block

1. INTRODUCTION

1.1 Background Literature

Globally, cardiac disorders are the primary cause of morbidity and mortality, significantly affecting both personal health and public health systems. The World Health Organization (WHO) reports that cardiovascular diseases (CVDs) continue to be the world's leading cause of mortality, taking about 32 percent of all fatalities. This means that there are more than 17 million fatalities annually, highlighting the urgent need for efficient diagnosis and treatment plans [1].

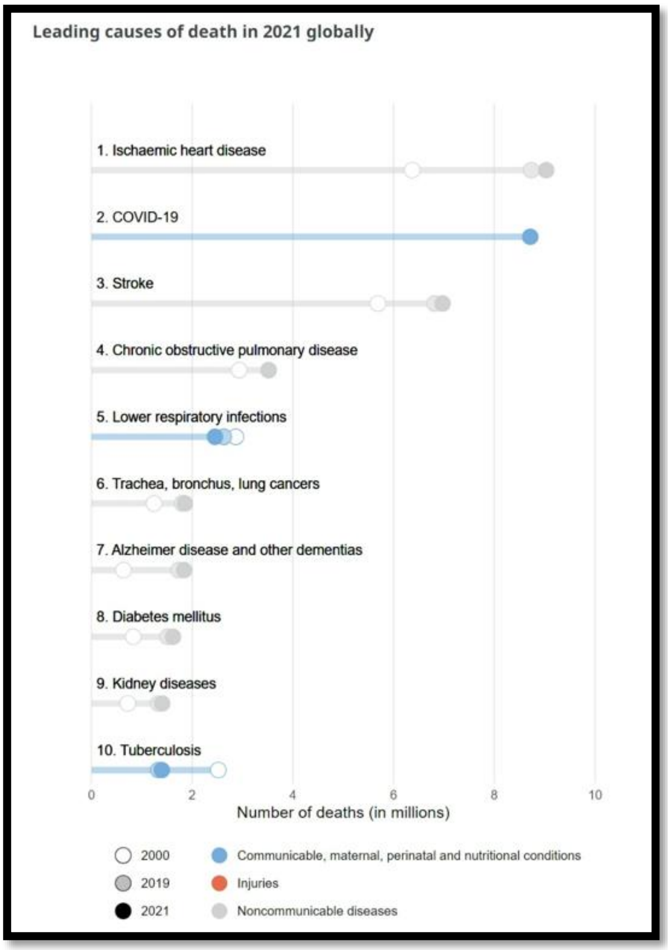

Figure 1:Leading cause of death

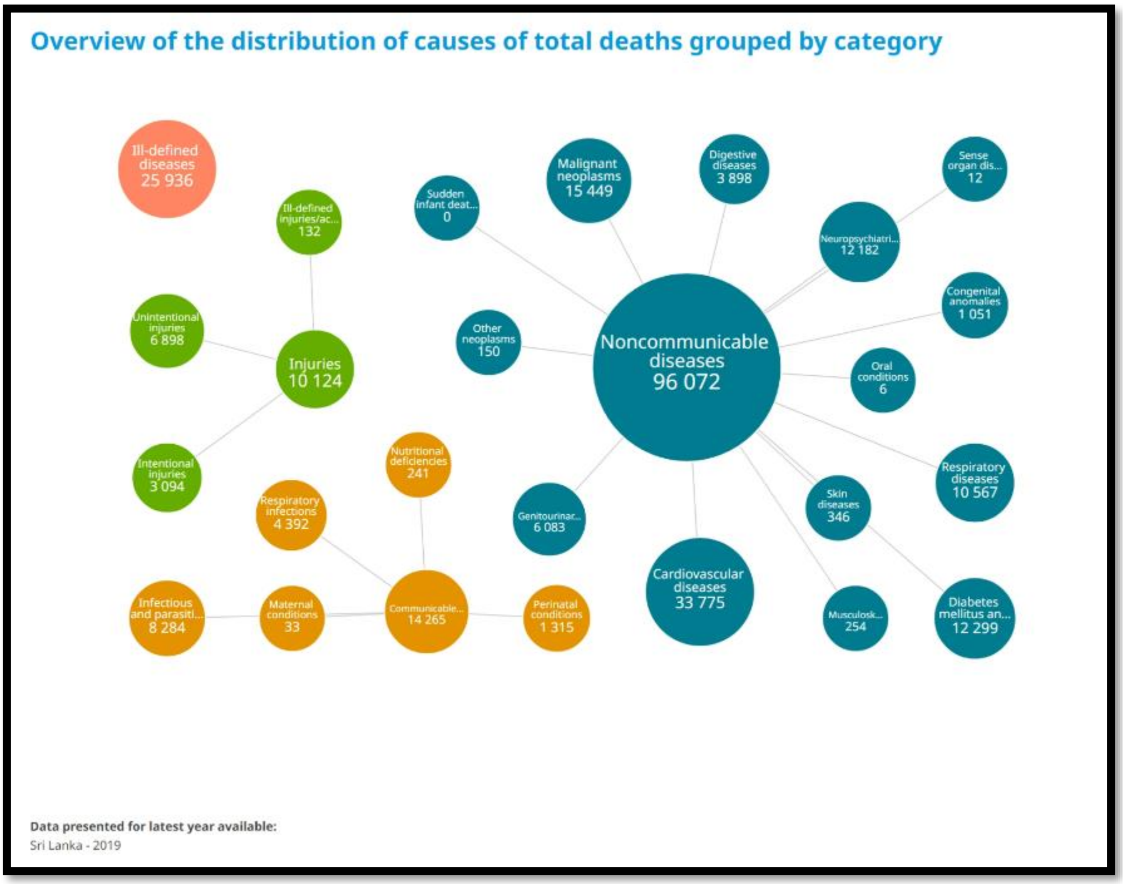

Figure 2:Causes of death marked by category

The increased burden of CVDs is highlighted by recent figures. As per the American Heart Association's 2024 report, almost half of the adult population in the US suffers from cardiovascular diseases such as heart failure, coronary artery disease, and hypertension. Due to shifting lifestyles and rising rates of risk factors including obesity and diabetes, this prevalence is becoming more common in middle-class and low-income countries and other high-income ones.

Beyond only affecting mortality, cardiovascular illnesses have a major negative influence on quality of life and healthcare expenditures worldwide. Individuals with chronic cardiac diseases often deal with long-term health issues, expensive treatment and management expenses, and many physician visits [2]. Healthcare systems and economies are under pressure due to the direct and indirect costs of CVDs, which emphasizes the pressing need for creative solutions to enhance early identification, preventative care, and overall disease management.

Considering this, the creation and application of cutting-edge diagnostic technologies, like the recently stated machine learning models and innovative ECG recording techniques, constitute a critical progress in tackling the worldwide threat of cardiovascular disease. These advances can greatly lower the burden of CVDs and improve patient outcomes globally by enabling prompt intervention and improving diagnostic accuracy.

The electrical activity of the heart is continuously recorded by electrocardiography (ECG), a vital diagnostic tool in cardiology. It offers insightful data regarding the electrical conduction, rhythm, and general health of the heart. With a typical 12-lead ECG, electrodes are positioned on the chest, limbs, and occasionally other parts of the body to obtain a complete picture of the electrical activity of the heart. Diagnosing ischemic heart disease, myocardial infarction, arrhythmias, and other cardiac disorders has been made possible by this standard procedure.

ECG-based diagnostics are now considerably more capable because to recent developments in machine learning and ECG technologies. ECG data contains complex patterns that may suggest a variety of heart problems. Machine learning models, especially those that make use of deep learning architectures, have shown remarkable effectiveness in this regard. To increase diagnosis accuracy and predictive modeling, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to evaluate time-series ECG data.

The application of these cutting-edge methods to increase diagnostic accuracy and promote early cardiac anomaly diagnosis has drawn more attention in recent years. Research has indicated that the amalgamation of machine learning with electrocardiogram analysis can result in enhanced precision and promptness in diagnosis, an essential aspect of efficient patient care and therapy.

ECGs are typically acquired by placing conventional electrodes on the limbs and chest. Nonetheless, novel methods for obtaining ECG data are becoming more prevalent. Utilizing ECG readings from unorthodox locations, such the palms, is a fresh and exciting development in non-invasive cardiac monitoring. This method is based on the ideas that different body surfaces can record the electrical activity of the heart and that distinct anatomical locations may offer insights into cardiac health.

It is a novel idea to use ECG electrodes on the hands for diagnostic purposes. Potential benefits of this innovative approach include improved patient comfort and ongoing cardiac health monitoring in various contexts. These unusual lead placements may be able to record significant ECG signals and offer useful diagnostic data, according to preliminary studies. However, more investigation is required to confirm these results and improve the strategy. The cardiac diagnosis of these methods of retrieving ECG has never been addressed. Hence, this new approach of research aims to diagnose cardiac diseases from the 12 lead ECG obtained from the and palms.

1.2 Research Gap

The need for accurate and rapid diagnosis of cardiac conditions is critical in the medical field, especially when addressing life-threatening conditions such as arrhythmias and myocardial infarctions. Traditional methods of diagnosing these conditions through ECG data rely on conventional electrode placements across the chest and limbs, which can be cumbersome, time-consuming, and challenging in emergency scenarios. The conventional approach also often requires expert analysis, which may not be immediately available, leading to delays in treatment.

Previous research has explored various innovations in ECG data acquisition and analysis. For instance, studies like those by Barandas et al. [3] and Ghaffari et al. [4] have focused on improving the accuracy of cardiac disease diagnosis using machine learning models trained on conventional 12-lead ECG data. However, these studies do not address the convenience and immediacy required in real-world applications, particularly in out-of-hospital settings where time is of the essence. Additionally, the application of AI in ECG analysis has been explored extensively, yet the integration of these techniques into portable, user-friendly platforms like mobile applications remains underdeveloped.

Another significant gap in the literature is the lack of research on alternative methods of lead placement that can simplify the process without sacrificing diagnostic accuracy. While Smith et al. [5] have examined the feasibility of single-lead ECG devices, their studies do not fully address the possibility of reconstructing a full 12-lead ECG from minimal lead placements, which could revolutionize the field by making ECGs more accessible in non-clinical settings.

In addressing the communication and action gaps during emergencies, recent works have explored integrating ECG analysis with telemedicine. However, the majority of these studies focus on data transmission and remote monitoring rather than real-time decision-making and emergency notifications [6], [7]. For example, Kumar et al. demonstrated the potential of using cloud-based platforms to store and analyze ECG data, but their work lacks real-time alert mechanisms that could notify caregivers immediately upon detecting a critical condition.

The proposed system aims to bridge these gaps by introducing a novel method of capturing and analyzing ECG data. It leverages palm-based electrode placement to reconstruct a 12-lead ECG, integrating this with a machine learning model trained to diagnose cardiac conditions rapidly. This system also includes a real-time emergency notification feature that sends the patient's geolocation to pre-defined contacts if a critical condition is detected. This innovative approach addresses the challenges of traditional ECG methods, improving accessibility, speed, and accuracy while enabling immediate intervention during emergencies.

By developing a comprehensive mobile application that facilitates real-time diagnosis and alerts, this research offers a significant advancement over previous studies. The proposed system not only enhances the accuracy of diagnosis through novel lead placement and advanced data processing but also ensures that emergency situations are handled swiftly and effectively without the need for immediate expert intervention.

Table 1:Comparison of previous work and proposed system

Aspect	**Research A**	**Research B**	**Research C**	**Proposed System**
Diagnosis Methodology	Traditional 12-lead ECG analysis	Conventional 12-lead ECG with AI models	Single-lead ECG with deep learning	Palm-based electrode placement with 12-lead reconstruction using machine learning
Lead Placement	Conventional chest and limb placement	Conventional chest and limb placement	Single-lead ECG	Novel palm-based lead placement

Data Processing Techniques	Basic signal processing with AI for arrhythmia detection	AI for diagnosing myocardial infarction and arrhythmias	Deep learning for arrhythmia detection	Machine learning models for cardiac condition diagnosis using minimal lead ECG data
Emergency Handling	No real-time alerts; relies on clinician intervention	No real-time alerts	No real-time alerts	Immediate geolocation-based alerts to predefined contacts upon critical diagnosis
Mobile-Based Implementation	Not implemented	Not implemented	Limited to cloud-based monitoring	Full mobile application integration with real-time diagnosis and emergency alerts
Accessibility	Hospital setting with expert interpretation required	Hospital setting with expert interpretation required	Out-of-hospital, but lacks user-friendliness	User-friendly, accessible for both clinicians and non-experts

1.3 Research Problem

This research study's main aim is to discover an innovative method for diagnosing heart diseases by means of a 12-lead ECG which will be conducted on the unusual electrode placements of the face and palms. The traditional ECG methods involve placing electrodes on the chest, arms, and legs, and these methods have been largely used over the years and are considered the gold standard for the diagnosis of heart diseases. Despite that, these normal approaches have several downsides such as patient's feeling uncomfortable or even inaccuracy in cases when an optimal electrode placement is not achieved.

This work is intended to overcome the limitation and find out whether ECG signals retrieved from the palms can be used to diagnose cardiac problems at a high level of accuracy and reliability. The application of this technique represents another perspective, namely that of flexibility under difficult circumstances such as emergency situations and physical limitations imposing difficulties in the standard electrode placements in some patients. Also, this way may be found that the additional effectiveness of patient friendliness makes feedback time quicker and medical staff can be more efficient in performing diagnostic tests.

However, the major problem here is the validation of the new practical approach. The palms are not the traditional parts used for capturing ECG signals and it is uncertain whether the signals from these areas can be as precise as the normal methods used. The main concern of this current issue is that if this project is realized then the cardiology field will completely change the face of diagnostic processes. It might eliminate the distance between the providers and the patients since diagnostic procedures could be made very easy. Yet, the technological feasibility, signal quality, and diagnostic accuracy of ECGs from these nonconventional sites are to be duly checked and verified.

The research problem this scientific work is delving into is the need for the effective way of the diagnosis of the hearts, the urgency of these comes from the expanding rates of diseases of the heart worldwide. Recent studies have shown that cardiovascular diseases (CVDs) are the most common cause of death globally, being responsible for an estimated 17.9 million deaths every year [8]. The growing prevalence of CVDs, particularly in low-income countries where traditional diagnostic tools are scarce, drives the need for new approaches that are not only effective but also readily available.

The research issue raised in the study focuses on the investigation and application of a new ECG capture method that includes image information from the hands to be more precise, efficient, and faster for cardiology testing. A positive outcome of this research could be an effective walk-through in the cardiology field, which can facilitate the interrogation of these diseases with early diagnostic means, and thus, fewer lives can wait for the end.

1.4 Research Objectives

The main objective of this study is to investigate, verify, and improve a new approach to the diagnosis of cardiac disorders by means of a novel ECG capture technology from electrodes applied to the hands. By broadening our understanding of cardiac diagnostics, we may be able to provide a less intrusive, more approachable procedure without sacrificing diagnostic accuracy. The following is a summary of the research's precise goals:

The primary goal is to thoroughly confirm that the ECG signals taken from the palms are accurately diagnostic. The research's goal is to determine whether this novel approach can accurately identify a range of cardiac problems by contrasting the outcomes with conventional ECG readings. This is an important step in figuring out whether the new method can be used to diagnose cardiac disorders in a practical way.

Obtaining fast and accurate ECG readings is a major difficulty in cardiac diagnosis, particularly in underserved or rural places. In order to facilitate diagnosis for a larger population, the research is examining an ECG capture technique that makes use of the face and palms. More people might be able to get early and correct diagnoses thanks to the decreased requirement for specialized equipment and qualified technicians, which might potentially save lives.

Some patients may be discouraged from receiving routine monitoring because traditional ECGs can be intrusive and painful. Evaluating the comfort and usefulness of the new electrode placements is part of this goal. Making the procedure more comfortable may promote more frequent monitoring, which could result in earlier heart problem identification and improved treatment.

The goal is to investigate the potential integration of this innovative ECG capturing technique with remote health monitoring systems. This entails investigating the possibility of sending data in real-time, informing loved ones of one's location in real time, and making recommendations according to the severity of the illnesses that have been detected. By addressing the present problems with slow reaction times and insufficient assistance during cardiac episodes, this integration may provide a more complete and effective healthcare solution.

The goal of this study is to tackle several important problems with contemporary cardiac diagnosis. Many patients struggle to get timely and accurate ECG monitoring, particularly in rural or underdeveloped areas. Conventional approaches are difficult to implement widely because they require specific tools and skilled personnel. Furthermore, regular monitoring may be hampered by the pain of traditional ECG placements, delaying diagnosis and therapy.

This research attempts to address these obstacles by verifying a novel technique for obtaining ECGs from the palms, potentially offering a more pleasant, accessible, and effective diagnostic tool. The method's usefulness is further increased by its incorporation into remote health systems, which provide real-time monitoring and prompt reaction capabilities that are essential for the management of cardiac disorders.

2. METHODOLOGY

2.1 Methodology

This research was done with the aim of making a new method and proving its efficiency in diagnosing diseases of the heart by using an ECG 12-lead signal taken from the face and palms unconventional electrode placement. The methodology was the various aspects of the project: data acquisition, preprocessing, model development, and post-diagnosis actions, one of which was live location sharing. We will elucidate each of these steps in detail in the section below.

2.1.1 Data Acquisition

Figure 3: PTBXL dataset

This investigation used the PTB-XL dataset, a wide range of ECG records included several cardiac conditions that were found in people of kindly diverse [9]. The dataset was acquired, and it might be procured from it. In the process of extracting relevant features such as age, sex, and ECG recordings from the dataset, this information was also extracted. The ECG signals were taken with the help of a particular electrode placement method, where electrodes were placed on the palms rather than the chest and limb conventionally. This unexampled method has contributed to a new way of heart disease diagnosis, which ungrudgingly crossing even the geographical divide may be, the suggested patient friendly method is much more understandable and approachable.

2.1.2 Data Preprocessing

Several crucial procedures were taken during the preprocessing stage to guarantee the data's accuracy and applicability. The age and sex data in the dataset was first cleansed, and missing values were properly handled. To remove noise and artifacts, which is crucial for accurate diagnosis, the ECG signals received are treated. The raw ECG signals were then filtered in a low-pass mode to suppress the interference high-frequency noise [10]. The filter was designed using a movable average window to ensure that the signal was rather than abrupt, it was smooth. The signals were additionally standardized to a fixed range in turn translated to the improvement of the accuracy of the machine learning models.

Thereafter, the 12-lead ECG signals were subsequently divided into training, validation, and test sets. Stratified sampling was the method which made sure that the distribution of diagnostic labels was the same across all sets. The training set was utilized to train the models, the validation set to adjust hyperparameters, and the test set to see how the final model performed.

2.1.3 Model Development

The main goal of this study was to create a deep learning model that could identify heart disorders based on 12-lead ECG signals that were taken from the palms. The design of the model architecture, training, assessment, and deployment were among the crucial stages of the model development process.

2.1.4 Model Architecture Design

In order to capture the temporal patterns in the ECG signals, a basic 1D convolutional neural network (CNN) was used as the initial model architecture. Layers like Conv1D, MaxPooling1D, Flatten, and Dense layers were incorporated in this model, which culminated in a softmax output layer for multi-class classification. The model was assessed using binary cross-entropy loss and other performance metrics, including accuracy, recall, precision, and AUC (Area Under the ROC Curve). The model was trained using the Adam optimizer with a learning rate of 0.001.[11]

- Input Layer

  The input layer receives the 12-lead ECG data, where 5000 represents the number of time steps and 12 corresponds to the number of leads.

  $X \in R^{5000 \times 12}$

- Convolutional Layers

  The convolutional layers extract features from the ECG signals using 1D convolution

  $Y = ReLU(W * X + b)$

  where W and b are the weights and biases, and $*$ denotes the convolution operation.

- Global Average Pooling (GAP) Layer

  The GAP layer reduces each feature map to a single value by averaging, reducing dimensionality while retaining important information.

- Dropout Layer

  Dropout was applied to prevent overfitting, randomly setting a fraction of input units to zero during training.

- Output Layer

  The final dense layer with sigmoid activation outputs probabilities for multi-label classification of 23 possible diagnoses.

  $Y\text{^} = \sigma\ (WZ + b)$

  where σ denotes the sigmoid function.

The remaining blocks were added to a more complex architecture that was created to increase model performance. By including shortcut connections that helped address the vanishing gradient issue that deep networks frequently face, this architecture enabled the model to learn more complicated characteristics. Multiple convolutional layers, residual blocks, global average pooling, dropout layers to minimize overfitting, and a sigmoid output layer for multi-label classification made up the final design [19].

2.1.5 Training and Evaluation

```
# Attempt to stratify the data by the combination of diagnoses.
folds = list(StratifiedKFold(n_splits=5, shuffle=True, random_state=42).split(data, unique_combos))
dev_idx, test_idx = folds[0]
train_idx, val_idx = train_test_split(dev_idx, test_size=0.1, random_state=209)
print('Size of Train Split:', len(train_idx))
print('Size of Test Split:', len(test_idx))
print('Size of Validation Split:', len(val_idx))

# Split data df
data_train = data.iloc[train_idx].reset_index(drop=True)
data_val = data.iloc[val_idx].reset_index(drop=True)
data_test = data.iloc[test_idx].reset_index(drop=True)

# Split labels df
labels_train = data_labels.iloc[train_idx].reset_index(drop=True)
labels_val = data_labels.iloc[val_idx].reset_index(drop=True)
labels_test = data_labels.iloc[test_idx].reset_index(drop=True)

# Create data generators
train_gen = ECG_DataGen(data_train, labels_train, data_col, batch_size, sample_len)
val_gen = ECG_DataGen(data_val, labels_val, data_col, batch_size, sample_len)
test_gen = ECG_DataGen(data_test, labels_test, data_col, len(data_test), sample_len)
```

```
Size of Train Split: 15695
Size of Test Split: 4360
Size of Validation Split: 1744
```

Figure 4: Training and Evaluation

The training procedure for the ECG-based cardiac disease detection model was carefully planned to avoid overfitting and guarantee strong performance in a variety of heart situations. The dataset was divided into training, validation, and testing sets using a stratified K-fold approach in order to preserve class balance—a crucial component in medical datasets with potentially unbalanced classes. 15,695 samples were used for training, 1,744 samples were used for validation, and 4,360 samples were used for testing in the final splits. This balanced distribution made it possible to assess the model's generalization skills in-depth.

Early halting was used as a crucial preventative technique against overfitting during training. A patience parameter of three epochs and a monitor parameter configured to measure validation loss (val_loss) were used to define the EarlyStopping callback.

This configuration made sure that training would stop and the model's best weights—those with the lowest validation loss—would be restored if the validation loss did not decrease for three consecutive epochs. This tactic was essential for preventing overfitting to the training set and preserving the model's good generalization on unknown data.

```
# Define the callback
early_stop = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
```

Figure 5: Early stopping callback method

Real-time performance tracking was done using validation data to oversee and direct the training process. Through this monitoring, performance might be optimized by fine-tuning hyperparameters including learning rate, batch size, and model architecture. The finished model showed notable gains in accuracy, recall, and precision, highlighting its efficacy in accurately diagnosing and differentiating between different heart diseases.

Several methods were used to evaluate performance on the test set. Confusion matrices offered in-depth understanding of the model's classification abilities, emphasizing its capacity to accurately classify various cardiac states. The trade-offs between recall and precision were further clarified by precision-recall curves, which are crucial in medical settings where false negative results can have detrimental effects. Furthermore, Area Under the Curve (AUC) values were calculated to evaluate the overall discriminative capacity of the model, providing a thorough assessment of its effectiveness.

A model that obtained high accuracy and consistency across multiple classes was the result of the combination of early halting, stratified data splits, continuous monitoring, and comprehensive assessment metrics. This made the model a dependable tool for identifying heart illnesses based on ECG data.

2.1.6 Deployment

After attaining adequate performance, the model was put into use on a Flask server and hosted on PythonAnywhere, enabling cardiac diagnostics in real time. For this deployment, a RESTful API that takes in ECG data, runs it through the trained model, and outputs diagnostic predictions had to be created. Furthermore, a geolocator module was included in the Flutter mobile application as well. This module locates the patient and notifies their loved ones about the necessity of hospital admission based on the severity of the identified conditions.

2.1.7 Feasibility Study

- Technical Feasibility

The project team's technical proficiency will determine how well the suggested system is implemented. The system entails not only gathering ECG data using unique electrode placements on the palms, but also processing this data through a web-based interface, members should have extensive understanding in mobile and online app development. Software architectures and frameworks should be familiar to the team, especially Python, TensorFlow, Keras, Flask, and cloud platforms such as PythonAnywhere. The development, testing, and implementation of the machine learning models that make up the diagnostic tool's core depend heavily on this technological base. Furthermore, a thorough understanding of mobile device compatibility and API development is necessary for the integration of the geolocation functionality to alert loved ones and deliver real-time updates. The expertise in these areas ensures that the system is not only technically sound but also scalable and maintainable in a real-world healthcare setting

- Economic Feasibility

Economically considering, the system is made to be as affordable as possible without sacrificing dependability or performance. While cloud hosting on PythonAnywhere cuts infrastructure prices, the adoption of open-source software tools like TensorFlow, Keras, and Flask considerably reduces development costs. The system is more affordable for medical professionals on a tight budget since the main hardware requirements— palm electrodes—are less costly than in 12-lead ECG configurations. Long-term cost reductions are also provided by the system, which minimizes the need for expensive hospital visits by providing early and precise diagnosis. Because of the system's great performance and dependability, which lessens the possibility of errors or breakdowns that could result in additional expenditures, the economic viability is further increased.

- Operational Feasibility

A well-organized development process that assigns responsibilities to each project member for specified stages of the software life cycle—most notably the requirement analysis phase—ensures operational viability. The system's ability to satisfy the user needs, which have been painstakingly determined and recorded, is dependent upon it. The development process adheres to software engineering best practices, guaranteeing that the finished result is dependable, easy to use, and fulfills the needs of patients and healthcare providers. By giving loved one's timely updates, the system's integrated real-time location notification feature improves operational efficiency and raises the standard of patient care. This functionality is valuable in addition to being in line with the expanding trend of remote patient monitoring and telemedicine.

- Scheduling Feasibility

The project's scheduling viability is vigilantly overseen to guarantee that every element is created and completed within the designated time limit. Every work that needs to be done for the project is done so precisely that deadlines are met, and top-quality outcomes are produced. To ensure that any unforeseen obstacles may be resolved without endangering the overall timeframe, the project plan has buffer times for testing and changes. The team proved their dedication to meeting deadlines when they successfully deployed the system on a Flask server and hosted it on PythonAnywhere within the allotted period. The outcome of the project, including the machine learning model, geolocation functionality, and user interface, was presented on the planned due date, underscoring the project’s scheduling feasibility and the team’s ability to deliver on time.

Post-Diagnosis Actions and Live Location Sharing

Moreover, the plan envisages that the system can deliver immediate care in the critical case of the patient. A feature for geolocation was created in Python by Mel, which made it possible to get the location of the patient in real-time. Not only the software but the real-time location of patients was fetched, and it included the patients' family members with a scale based on the results of the treatment assessment. The feature implements a rainfall cellular network that very cheap (1 $) and 100 times faster than existing services in chronic disease monitoring DENV using mobile data set is especially crucial in the case of severe arrhythmias and heart attacks, where timely medical care is a must [8].

Enabling users to share their locations and statuses in real-time improves safety and response time, which are both integral to the treatment and rescue of patients. The feature tackles a significant issue in today's heart treatment systems, which often do not have quick family to the sick patient's family and/or lack the capability to contact the emergency services.

2.1.8 Design Diagrams for the Component

2.1.5.1 Use case Diagram

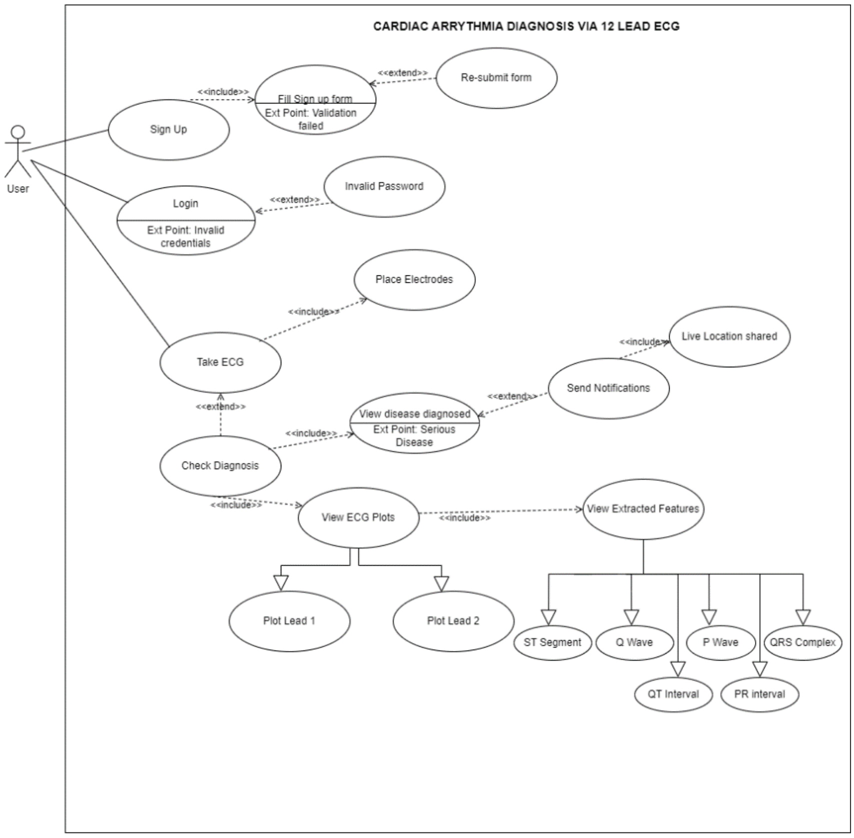

Figure 6: Use case diagram of proposed component

2.1.5.2 Sequence Diagram

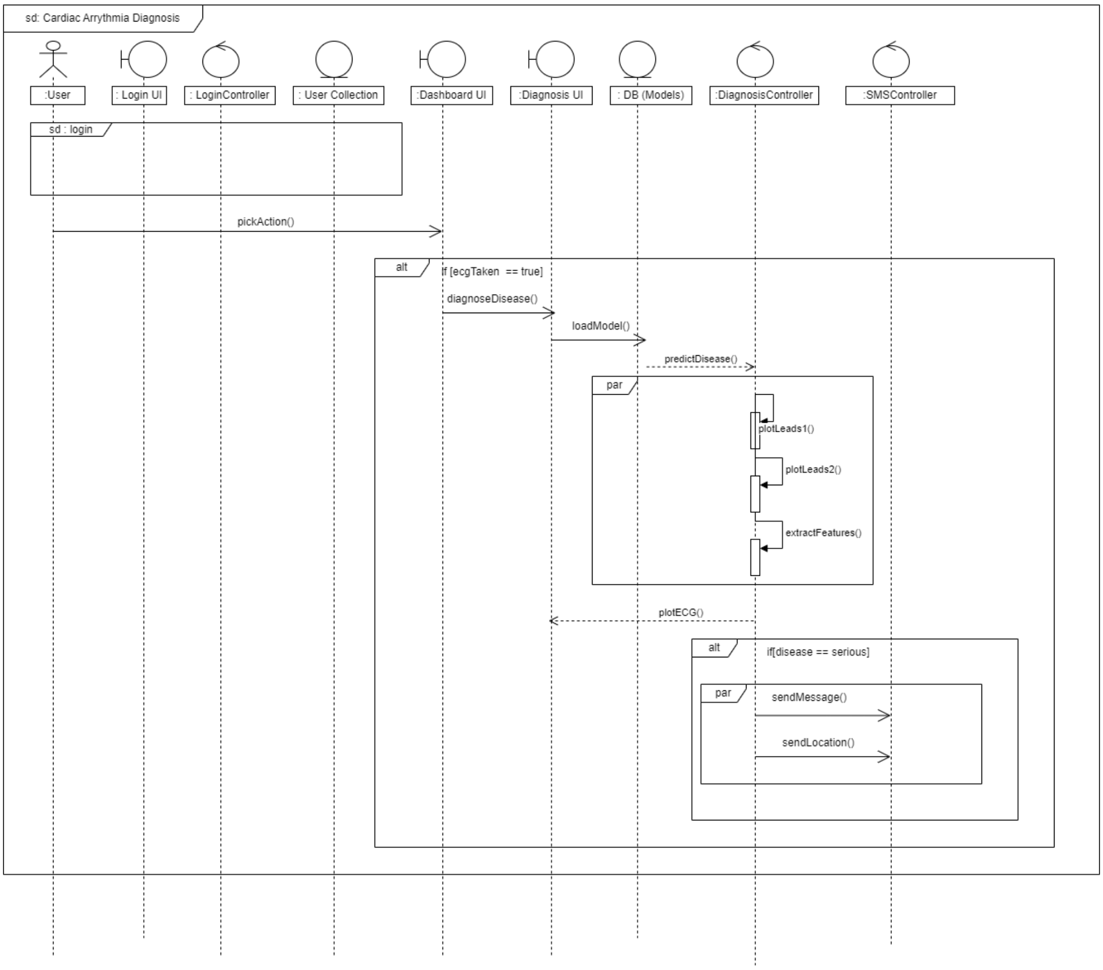

Figure 7: Sequence Diagram of proposed component

2.1.5.3 Component System Diagram

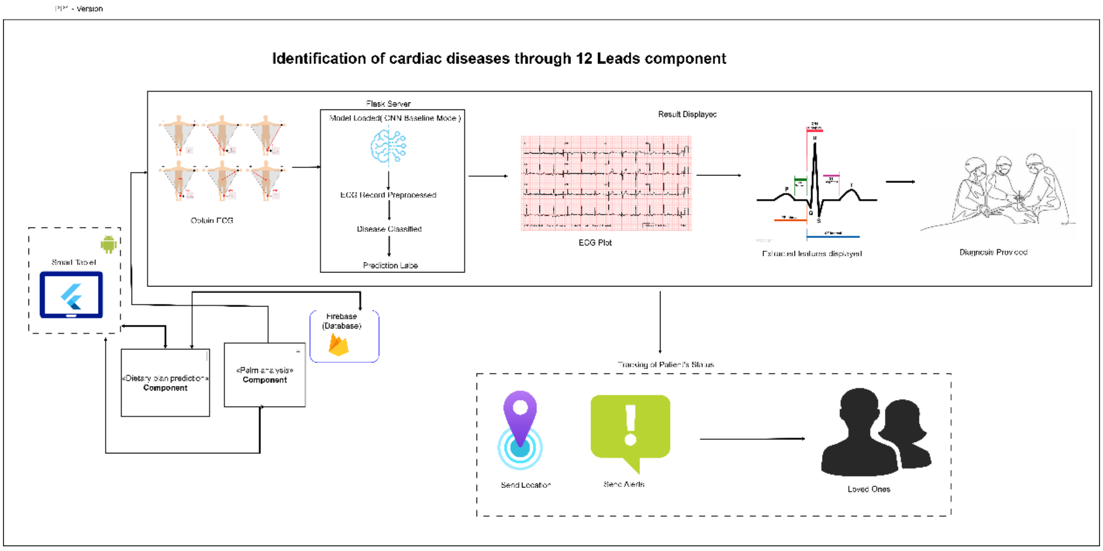

Figure 8: Component Diagram of proposed component

The 12-lead ECG is reconstructed using electrodes that are placed in the palm of the hand, and the component diagram gives a general overview of the apparatus used to diagnose cardiac conditions. Patients or users engage with the system using the mobile application, which was created with Flutter. The baseline CNN model uses the real-time ECG readings to forecast different heart problems. The data is processed and transmitted to a Flask server hosted on PythonAnywhere. The user and medical professionals can view the results, which include an ECG plot and diagnostic data. Furthermore, the technology ensures prompt intervention by sending location-based warnings to be specified contacts in the event of crucial diagnoses. The backend components, including Firebase for storing the models and user data, are seamlessly integrated to provide a comprehensive and accessible cardiac diagnostic tool.

2.2 Commercialization Aspects of The Product

The innovative potential to transform the field of cardiac healthcare that comes with the launch of the new ECG diagnostic technology is remarkable. In a market where traditional diagnostic techniques predominate, our technology represents a trailblazing innovation by capturing 12-lead ECG data from the palms. By leveraging this novel strategy, we hope to close the gap between readily available healthcare and cutting-edge diagnostic tools, pushing life-saving technology to the forefront of clinical practice.

- **Market Potential and Positioning**

The aging population, rising rates of cardiovascular disease, and growing need for portable, non-invasive diagnostic tools are all contributing to the explosive expansion of the global market for cardiac diagnostic equipment. By 2026, the market for cardiac monitoring and diagnostic equipment is expected to have grown to over $29 billion, with a compound yearly growth rate (CAGR) of 6.4%. This offers our suggested system a great chance to take a sizable portion of this market by providing a cutting-edge, user-friendly solution for cardiac diagnostics.

Our device is marketed as a state-of-the-art, portable cardiac diagnostic tool that uses cutting-edge machine learning algorithms to deliver precise and prompt diagnosis. Our system is suitable for home healthcare, remote monitoring, and use in low-resource situations due to its portability and ease of use, unlike typical ECG equipment that needs clinical settings and specialist people. We intend to sell the system as a flexible tool that improves patient care and gives people the ability to take charge of their heart health, aiming to appeal to both consumers and healthcare professionals.

We are actively seeking to become a partner with Hemas Hospitals in Sri Lanka as part of our marketing plan. Hemas Hospitals, one of Sri Lanka's top private healthcare providers, is well-known for offering top-notch medical care all throughout the nation. Our goal in working with Hemas Hospitals is to incorporate our diagnostic system into their current healthcare system so that their patients may also benefit from this cutting-edge technology.

- **Value Proposition**

Our system's main selling point is its capacity to provide superior cardiac diagnostics outside of conventional hospital settings. Through the collection of ECG data from the palms and unusual areas of the body, our device provides a simple, non-invasive means of ongoing cardiac monitoring. If telemedicine providers, home care agencies, and fitness tech firms want to incorporate cutting-edge health monitoring capabilities into their products, they may find this creative solution particularly appealing.

A critical layer of value is also added by the system's real-time location notification capability, which notifies loved ones in the event of a cardiac emergency. This feature provides users and their families with peace of mind, and it is especially helpful for elderly patients or those who have a history of cardiac difficulties. Our system is more than simply a diagnostic tool; it's a complete health management solution thanks to its integration of emergency response features and powerful diagnostic capabilities.

- **Business Model and Revenue Streams**

Our proposal for the commercialization of this system involves several different aspects. The device will be sold directly to customers, healthcare practitioners, and telemedicine companies, which will be the main source of revenue. In addition, we will provide the system as a subscription service, allowing customers to pay a set monthly or yearly charge for remote monitoring, analysis, and cloud-based data storage.

Forming alliances with health insurance providers is another way to generate income. Insurance companies may pay clients who regularly utilize the system with discounts on premiums or other incentives due to the system's capacity to provide early and accurate diagnoses. This strategy might promote broad adoption and offer a reliable source of income in the form of recurrent payments.

Additionally, we want to use a software-as-a-service (SaaS) paradigm to incorporate our system into already-existing healthcare systems. Clinics and hospitals, including

Hemas Hospitals, could license the software so they could integrate the diagnostic features of our system into their current electronic health record (EHR) systems. For healthcare providers who want to improve their telemedicine services, this strategy may be very tempting.

- **Strategic Partnerships and Distribution Channels**

For the effective sale of our product, strategic collaborations will be essential. Reaching a wide audience and quickly scaling the product will be made possible by partnering with fitness tech companies, telemedicine companies, and healthcare professionals. The cornerstone of our market entry plan will be our targeted alliance with Hemas Hospitals, which will give us access to a reputable healthcare network in Sri Lanka.

As part of our commercialization strategy, distribution channels will also be crucial. Our distribution strategy calls for using a variety of channels, such as direct sales to healthcare facilities, medical device-focused retail outlets, and internet sales platforms. Alliances with drugstores and medical facilities will also act as extra distribution channels, especially in areas with restricted access to healthcare.

- **Intellectual Property and Competitive Advantage**

Gaining a competitive edge will depend on protecting intellectual property rights. We intend to submit patents for the software algorithms utilized for diagnostics as well as the hardware components (such as the creative electrode positioning on the face and palms). These patents will set our business apart in this specialized industry and prevent competitors from simply copying our goods.

Our system's distinct blend of mobility, accuracy, and user-friendliness gives it a competitive edge. There are other portable ECG devices on the market, but none have the same level of diagnostic power along with the ease of obtaining data from the face and palms. This unique characteristic puts our technology as a game-changer in cardiac diagnostics, along with the incorporation of machine learning for real-time analysis.

- **Regulatory Considerations and Market Entry Strategy**

It will be difficult to enter the market without understanding the complicated regulatory environment, especially for medical equipment. Regulatory agencies including the European Medicines Agency (EMA) and the U.S. Food and Drug Administration (FDA) must approve our system [14]. To make sure that our system is dependable, efficient, and safe, this procedure will include thorough testing and validation. Regulatory experts can help expedite this process and guarantee adherence to all relevant standards by being involved early in the development phase.

Our approach to entering the market will center on introducing the device in areas where there is a significant need for portable diagnostic instruments and where the legal system operates more efficiently.

To successfully enter the market for medical devices, particularly in Sri Lanka, it is crucial to navigate the regulatory framework established by the National Medicines Regulatory Authority (NMRA). The NMRA, responsible for the approval and oversight of medical devices, follows stringent guidelines similar to global regulatory bodies like the FDA and EMA. Key regulatory requirements include rigorous clinical trials, safety assessments, and proof of efficacy before market authorization can be granted.

In Sri Lanka, the NMRA’s guidelines stipulate that all medical devices, especially those involved in diagnostics, must undergo a comprehensive evaluation. This includes compliance with the Medical Device Registration regulations, which encompass quality management standards, labeling, and post-market surveillance. The NMRA's guidelines mandate that diagnostic medical devices undergo rigorous evaluation, adhering to the Medical Device Registration regulations, which cover quality management, labeling, and post-market surveillance [13]

To facilitate the market entry of our portable ECG diagnostic system, the strategy will focus on aligning with the NMRA's requirements, alongside parallel efforts to secure approvals from the FDA and EMA. Early engagement with regulatory consultants is advised to streamline the approval process, ensuring that the device meets all necessary criteria related to safety and effectiveness.

Given the importance of strategic alliances, our market entry will also leverage partnerships, notably with Hemas Hospitals, to validate the technology locally. By concentrating on markets with high demand and efficient regulatory frameworks, the system has the potential to revolutionize cardiac care and achieve significant market penetration.

In summary, there is a good chance that the commercialization of our unique ECG diagnostic method will transform cardiac care. The technology used has the potential to achieve substantial market penetration and establish itself as a leader in the field of portable cardiac diagnostics with the help of a clearly defined market strategy, a compelling value proposition, and strategic alliances, especially with Hemas Hospitals.

2.3 Consideration Aspects of the System

2.3.1 Social Aspects

There are important societal ramifications to the adoption of a unique ECG diagnostic method that collects data from the palms, especially in accessible healthcare. By enabling a larger population to receive an accurate and timely diagnosis, this technology can democratize cardiac treatment. People living in remote or underprivileged areas may find it difficult to get traditional 12-lead ECG devices because they are usually only found in hospitals and specialty clinics. Through mobile technology and portable ECG capturing techniques, this system can reach those who may not typically have access to medical institutions.

Additionally, by including family members in the patient's treatment process, the incorporation of real-time location notifications to loved ones improves the social value of the system. This function is especially helpful in nations where it is culturally significant for families to participate in healthcare decisions. Furthermore, early diagnosis provided by the system can result in prompt interventions, which may lessen the strain on healthcare systems by averting serious cardiac events and lowering hospital admissions. All things considered, this system supports a more inclusive and collaborative approach to healthcare, which is consistent with the worldwide movement toward patient-centered care.

2.3.2 Ethical Aspects

Creating and using this innovative ECG diagnosis method raises ethical issues. The system must, above all, abide with the moral precepts of beneficence, non-maleficence, and patient autonomy. Patients must give their informed consent after being fully educated about the possible dangers, advantages, and how their data will be used before the technology may be used to diagnose cardiac problems. To preserve confidence and prevent any possible abuse of the system, it is essential to guarantee openness regarding the workings and constraints of the machine learning model.

The system's remote diagnosis capability presents accuracy and reliability-related ethical questions. To guarantee that the machine learning models used for diagnosis satisfy the highest criteria of accuracy, they must undergo extensive validation and testing. Reduce the possibility of false positives or negatives to prevent unwarranted worry or, on the other hand, missing a serious health concern. The system must deliver precise diagnoses backed by clinical validation and ongoing model improvement to adhere to the ethical "do no harm" guideline.

It's also important to think about the moral ramifications of applying the approach to a variety of demographics. For the system to be fair and prevent bias from being unintentionally introduced, datasets that are representative of the population it is meant to serve should be used to train the machine learning models. This is especially critical in medical AI, as skewed models can produce inconsistent patient outcomes. The implementation of the system ought to be led by moral frameworks that place a high value on justice, responsibility, and inclusivity to guarantee that every person, irrespective of demographic variables, receives a diagnosis that is both accurate and trustworthy.

2.4 Testing & Implementation

In order to effectively diagnose cardiac disease using ECG data, the software solution created in this study combines web and mobile applications into a comprehensive system. Real-time diagnosis, data management, and user notifications are made easier by the solution's properly thought-out architecture, which guarantees smooth interaction between various components.

To record ECG data and obtain diagnostic results, users mostly interact with the smartphone application, which was created with Flutter. Flutter was selected because of its cross-platform functionality, which enables seamless operation of the application on both iOS and Android devices. The user interface of the application has been designed with ease of use and intuitiveness in mind, making it effortless for users to browse through its features.

With a customized instrument that collects impulses from the palms, users can acquire ECG data. This data is preprocessed by the application before being sent to the backend for analysis. Using the ECG data as a basis, the application interacts with deployed machine learning models to deliver immediate diagnostic input. The application uses the Geolocator package to retrieve the user's position and communicate it to their loved ones in the event of a serious diagnosis. Through an integration with notify.lk, the program notifies selected contacts via SMS of the user's current health status.

For this solution, Firebase was chosen as the backend database since it offers a scalable and real-time data management system. Firebase's features made it possible to store user data, model outputs, and system parameters in a secure manner. Firebase's real-time database houses all user data, diagnostic outcomes, and ECG data. Secure access to the online and mobile applications is controlled with Firebase Authentication. Backend operations like data processing, notifications, and model interactions are managed by serverless cloud functions.

The machine learning models that are hosted on PythonAnywhere and deployed on a Flask server form the basis of the system's diagnostic capabilities. These models were used to categorize and diagnose different heart diseases after being trained on ECG datasets. Kaggle was initially used to train machine learning models, making use of its robust GPUs and big datasets. To guarantee accuracy and dependability, the models underwent intensive testing and refinement. After undergoing training, the models were put into use on a Flask server so that the web and mobile applications could access them. With this configuration, ECG data can be processed in real time, resulting in timely and precise diagnosis.

2.4.1 Data Loading

```
# Imports
from IPython.display import display
import matplotlib.pyplot as plt
!pip install ecg_plot

import ecg_plot

%matplotlib inline
import numpy as np
import pandas as pd
import seaborn as sns
import ast
import scipy
from scipy import io
import os

import tensorflow as tf
from tensorflow import keras
```

Figure 9: Import libraries

Loading the ECG data, which entails reading raw data files and getting them ready for additional processing, is the initial stage of preprocessing. Python modules like scipy, pandas, and NumPy—all essential for effectively handling and processing massive datasets—were used to oversee the data loading process for this project.

NumPy: This library is necessary to work with matrices and arrays, which makes processing the multidimensional ECG data possible.

Pandas: This program facilitates simple access to and manipulation of data files and the labels that go with them. It is used to handle tabular data structures.

scipy: The.mat files containing the ECG data were loaded using the scipy.io.loadmat function.

2.4.2 Data Preprocessing

To guarantee the quality and precision of the machine learning models employed in the diagnosis of heart disorders, data preparation is an essential first step. The pretreatment pipeline for this project was created to effectively manage the raw ECG data, using a variety of methods to clean, normalize, and modify the data in preparation for model training and assessment. Considering the intricacy and unpredictability of ECG readings, this procedure was especially important.

The ECG information was obtained using a system that used electrodes attached to the palms to record 12-lead signals. After that, the information was organized into files, each of which represented a recording session with several leads. To guarantee accuracy and consistency throughout the dataset, the signals produced by the data collecting procedure must be heavily preprocessed.

2.4.3 Handling Missing Data and Artifacts

```
def scale(self, array):
    array = np.nan_to_num(array, nan=0.0)  # Replace NaN values with 0.0
    array = self.low_pass_filter(array, window_size=100)
    a_min = np.min(array)
    a_max = np.max(array)
    if a_max - a_min == 0:
        return np.zeros_like(array).reshape((-1, 1))
    return np.array((array - a_min) / (a_max - a_min))
```

Figure 10: Handling of missing values

Occasionally, the ECG recordings had artifacts or missing data points that could interfere with the model's ability to learn. To preserve the dataset's integrity, these problems were fixed during preprocessing. NaN handling involved replacing missing values with zeros in order to preserve the data's structure and make sure that the model was not adversely affected by signal gaps.

Artifact removal involved identifying and, according to their influence on the overall quality of the signal, either smoothing out or removing artifacts, such as sudden spikes or decreases in the signal that did not correspond to physiological processes.

2.4.4 Signal Normalization

```
def scale(self, array):
    array = np.nan_to_num(array, nan=0.0)  # Replace NaN values with 0.0
    array = self.low_pass_filter(array, window_size=100)
    a_min = np.min(array)
    a_max = np.max(array)
    if a_max - a_min == 0:
        return np.zeros_like(array).reshape((-1, 1))
    return np.array((array - a_min) / (a_max - a_min))
```

Figure 11: Signal Normalization

To make sure that the input data given into the model was on a consistent scale, normalizing the ECG signals was an essential step. Without normalization, significant fluctuations in signal amplitude could cause the model to become biased and perform less well than ideal.

Based on the lowest and greatest values found in each lead's signal, the signal was scaled to a range of 0 to 1. To guarantee clean and consistent normalized signals, this scaling was done after the low-pass filter was applied. This ensured that the normalized signals were clean and consistent.

2.4.5 Filtering and Noise Reduction

```
def low_pass_filter(self, voltages, window_size):
    """Applies a moving average low-pass filter to a 1D array of voltages."""
    # Create a windowed version of the array
    window = np.ones(window_size) / window_size
    filtered_voltages = np.convolve(voltages, window, mode='same')
    return filtered_voltages
```

Figure 12: Noise reduction mechanism

A low-pass filter was applied to each lead's signal to eliminate high-frequency noise due to the inherent noise in ECG data, which is particularly noticeable when the leads are recorded using innovative techniques like the palm electrodes. In order to remove pointless fluctuations in the signal that can negatively impact the model's performance, filtering was essential.

The low-pass filter was implemented using a moving average technique, which smoothened the signal by averaging values within a defined window size. This approach effectively reduced high-frequency noise, preserving the essential features of the ECG signal while eliminating artifacts.

2.4.6 Segmentation and Labeling

```
def __getitem__(self, index):
    batch_leads = np.zeros((self.batch_size, self.sample_len, 12))
    batch_labels = np.zeros((self.batch_size, len(self.df_labels.columns)))

    for i in range(index*self.batch_size, (index+1)*self.batch_size):
        leads = scipy.io.loadmat(self.df_files.at[i, self.data_col])['val']
        for j, lead_data in enumerate(leads):
            scaled_lead_data = self.scale(lead_data)
            batch_leads[i - index*self.batch_size, :, j] = scaled_lead_data.reshape((-1,))
        batch_labels[i - index*self.batch_size] = self.df_labels.loc[i].values

    return batch_leads, batch_labels
```

Figure 13: Code of segmentation and labeling

After that, the preprocessed signals were divided into fixed-length samples that could be used as the machine learning model's input. Every section had a label attached to it that matched the heart state it depicted. A predetermined window length was applied to the signals to capture a substantial chunk of the ECG waveform within each window. In order for the model to learn from reliable and pertinent slices of the ECG data, this segmentation was necessary. The model was able to understand the correlations between ECG patterns and diagnostic results by labeling each segment based on the presence or absence of heart diseases.

2.4.7 Final Data Preparation

```
def on_epoch_end(self):
    if self.shuffle:
        shuffle_idx = np.random.choice(range(self.n_samples), size=self.n_samples, replace=False)
        self.df_files = self.df_files.iloc[shuffle_idx].reset_index(drop=True)
        self.df_labels = self.df_labels.iloc[shuffle_idx].reset_index(drop=True)
```

Figure 14: Code of Data Preparation

Following the completion of all preparation procedures, the data was arranged into batches appropriate for training models. These batches were created to ensure that the model was exposed to a wide variety of signals and situations while also optimizing the effectiveness of the training process.

Batch Preparation: To guarantee that each batch included a representative mixture of various cardiac circumstances, the data was separated into batches containing a constant number of samples. By taking a balanced approach, the model was able to avoid becoming skewed in favor of the dataset's more common circumstances.

2.4.8 Model Deployment on PythonAnywhere Using Flask

Deploying the trained model was an essential step in the implementation process that ensured end users could access and utilize the service. Flask was used as the web framework to support the model, and PythonAnywhere was selected as the hosting platform to accomplish this. In order to integrate the model with the Flask server and set up the environment on PythonAnywhere, this part explains the deployment procedure in depth, emphasizing the essential elements and techniques.

Flask Server Configuration

Flask was selected because it is easy to use and flexible for developing web apps that are lightweight. The Flask server loads the model, processes data, handles requests made to the application, and generates predictions.

Flask Start-Up: To begin, the program imports the required libraries, which include requests, numpy, os, shutil, and json, as well as Flask for the web framework and TensorFlow for the deep learning model.

Route Configuration: There are two main routes on the server:

To verify that the server is up and functioning, use the root route /.

```python
@app.route('/')
def hello_world():
    return 'Hello from Flask!'

```

Figure 15: Routing Configuration

Predictive data is handled by the /predict route in POST requests. This is where the model is loaded, the uploaded JSON file is analyzed, and predictions are produced.

Model Loading and Prediction

```python
@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Check if the POST request has the file part
        if 'file' not in request.files:
            return 'No file part', 400
        file = request.files['file']
        if file.filename == '':
            return 'No selected file', 400
        temp_dir = "/home/HilarinaC/"
        # Save the uploaded file to a temporary directory
        with tempfile.TemporaryDirectory() as temp_dir:
            file_path = os.path.join(temp_dir, file.filename)
            file.save(file_path)
            print("Uploaded file saved at:", file_path)
            # Download and load the model
            model_path = os.path.join(temp_dir, 'model.h5')
            print("Downloading model...")
            response = requests.get(MODEL_URL, stream=True)
            print("Model downloaded")
            with open(model_path, 'wb') as f:
                shutil.copyfileobj(response.raw, f)
            print("Model saved")
            loaded_model = load_model(model_path, compile=False)
            print("Model loaded")
            with open(file_path, 'r') as f:
                data = json.load(f)
            leads = []
            for key in data:
                leads.append(data[key])
            result_array = np.array(leads)
            print(result_array.shape)
            result_array = np.transpose(result_array)
            print(result_array.shape)
            result_array = np.reshape(result_array, (1, 5000, 12))
            predictions = loaded_model.predict(result_array)
            predicted_class_index = np.argmax(predictions)
            class_labels = ["ISCAL", "NST_", "SARRH ", "IVCD", "1AVB", "STACH", "VCLVH", "STD_", "Incomplete Right Bundle Branch Block", "PVC", "I
            predicted_class_label = class_labels[predicted_class_index]
            print("Predicted class:", predicted_class_label)
            prediction_results = {
                "Predicted class":predicted_class_label
            }
            return jsonify(prediction_results)
    except requests.exceptions.RequestException as e:
        return f'Error downloading model: {e}', 500
    except Exception as e:
        return f'Error: {e}', 500
```

Figure 16: Model Loading and Prediction

There are multiple phases involved in loading the model and producing predictions:

Handling File Uploads: The server retrieves the file uploaded with the request and stores it in a temporary file for processing.

Downloading the Model: The model is kept in Firebase and is downloaded to the server via the Firebase URL whenever a prediction request is made. This guarantees that the most recent model is always applied.

Model Loading: TensorFlow's load_model() method is used to load the downloaded model. Since it has already been compiled during the training phase, compile=False is used to avoid recompilation.

Data processing: A NumPy array appropriate for model input is created from the uploaded data (in JSON format). This entails transforming and rearranging the data to conform to the anticipated input shape of the model.

Prediction Generation: Once the data is processed, the model makes predictions. The prediction with the highest probability is selected as the output, and the corresponding label is retrieved from the predefined class labels.

Error Handling: The code includes error handling to manage issues such as model download failures or unexpected data formats, ensuring the system’s robustness.

Firebase Integration for Model Storage

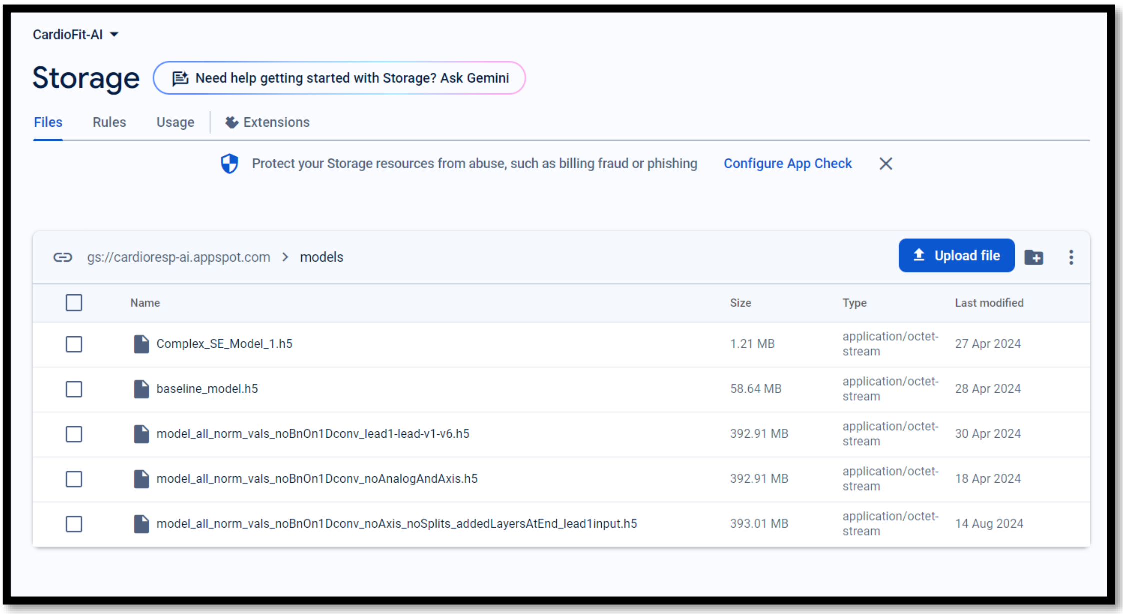

Figure 17: Model Stored in Firebase

The trained models were stored in the cloud using Firebase. This method saved money and made it simple to change the model without having to restart the server.

Model Storage: Using a special token and a URL, users can access the model that is kept in Firebase Storage. This guarantees that only authorized requests can download the model and permits safe access.

On-Demand Model Loading: With every prediction request, the Flask server dynamically downloads and loads the model. This eliminates the need for frequent server updates and guarantees that the application always uses the most recent version of the model.

Sending Notifications via "notify.lk"

To enhance the application’s functionality, the **`notify.lk`** service was integrated to send real-time notifications to users' loved ones if a serious disease is diagnosed. This was implemented as an additional step following the prediction, using the **`requests`** library to trigger notifications based on the prediction result.

2.5 Testing

Thorough testing is required in the last stage of the development process to guarantee the accuracy and dependability of the integrated system and the produced models. In this stage, the deployed system was examined in both local and cloud contexts, and the model's performance was measured using the test dataset. To be more precise, testing was done to make sure the machine learning model installed on the Flask server in PythonAnywhere worked well in terms of illness prediction. Defects were found and fixed during several testing prior to the system being put into a production setting and multiple test cases were used to test the deployed Flask server, and multiple operational situations, to assess the system.

2.5.1 Test Plan and Test Strategy

The testing plan functions as a thorough road map that describes the tasks, scope, goals, and schedule for carrying out the tests required to verify the system's efficacy. The testing strategy, on the other hand, consists of an organized set of guidelines and actions that control the software testing process and guarantee that the system satisfies the necessary quality standards and flawlessly carries out its intended activities.

Steps and procedures in the test strategy:

- Define the items to be tested, such as models, API endpoints, and mobile application features.
- Select the functions to be tested based on their importance and the risks they present to users.
- Design test cases according to the system's use cases and intended functionalities.
- Execute the test cases, tracking the results to identify any defects or inconsistencies.
- Record the test results, categorizing them as "pass" or "fail."
- Identify any bugs or issues that arise during testing and make the necessary corrections.

- Re-run the test cases until the system meets the expected results and quality standards.

2.5.2 Test Case Design

The following test cases were designed to ensure system reliability by testing all system functionalities.

Table 2: Test Case 1

Test Case Id	01
Test Case	Model Loading & Prediction
Test Scenario	Verify the model loading from Firebase and ECG data prediction
Input	Uploaded JSON file containing ECG data
Expected Output	Predicted class label with 200 status code
Actual Result	Predicted class label displayed with 200 status code
Status (Pass/Fail)	Pass

Table 3: Test case 2

Test Case Id	02
Test Case	ECG Data Preprocessing
Test Scenario	Verify preprocessing of ECG data
Input	JSON file with raw ECG data
Expected Output	Properly formatted ECG data for prediction
Actual Result	ECG data successfully preprocessed and formatted
Status (Pass/Fail)	Pass

Table 4: Test Case 3

Test Case Id	03
Test Case	API Response Verification
Test Scenario	Verify API response structure and status codes
Input	POST request to `/predict` endpoint
Expected Output	JSON response containing prediction results
Actual Result	Accurate JSON response with correct status codes
Status (Pass/Fail)	Pass

Table 5: Test Case 4

Test Case Id	04
Test Case	Model Performance Evaluation
Test Scenario	Evaluate model performance with test ECG data
Input	JSON file with test ECG data
Expected Output	High prediction accuracy
Actual Result	High prediction accuracy observed
Status (Pass/Fail)	Pass

Table 6: Test Case 5

Test Case Id	05
Test Case	Mobile Application Integration
Test Scenario	Verify integration between mobile app and Flask API
Input	ECG data captured via mobile app

Expected Output	Accurate disease prediction displayed on the app
Actual Result	Prediction correctly displayed on mobile app
Status (Pass/Fail)	Pass

Table 7: Test Case 6

Test Case Id	06
Test Case	Validate empty phone number
Test Scenario	None
Input	1. Enter an empty phone number. 2. Submit the form.
Expected Output	Error message "Member Phone No is required!" is displayed
Actual Result	Error message "Member Phone No is required!" is displayed
Status (Pass/Fail)	Pass

Table 8: Test Case 7

Test Case Id	07
Test Case	Validate phone number with incorrect prefix
Test Scenario	None
Input	1. Enter a phone number that does not start with "947". 2. Submit the form.
Expected Output	Error message "Phone Number must start with '947'!" is displayed
Actual Result	Error message "Phone Number must start with '947'!" is displayed

Status (Pass/Fail)	Pass

Table 9: Test Case 8

Test Case Id	08
Test Case	Validate SMS failure due to location unavailability
Test Scenario	Location services turned off or unavailable
Input	1. Trigger the EmergencyDialog. 2. Press "OK".
Expected Output	Error message "Failed to get location or send SMS" is logged.
Actual Result	Error message "Failed to get location or send SMS" is logged.
Status (Pass/Fail)	Pass

Test Case Id	09
Test Case	Validate SMS failure due to invalid phone number
Test Scenario	Invalid contact number
Input	1. Trigger the EmergencyDialog. 2. Press "OK".
Expected Output	Error message "Failed to send SMS: Invalid phone number" is logged.
Actual Result	Error message "Failed to send SMS: Invalid phone number" is logged.
Status (Pass/Fail)	Pass

3. Results & Discussion

3.1 Results

In this study, several machine learning models were tested to see how well they could diagnose heart problems based on 12-lead ECG data recreated by measuring Lead I from the palms. This section explores the performance of the study's baseline model and offers a thorough analysis of its results.

A basic 1D convolutional neural network (CNN) is used as the baseline model to categorize ECG signals into 20 different classes that correspond to different heart states. A sequence of convolutional and pooling layers, dense layers, and a SoftMax output layer for multi-class classification make up the model architecture.

Model Summary

The model comprises approximately 5.12 million trainable parameters, distributed across multiple layers:

- **Input Layer:** The model accepts input data with a shape of (5000, 12), where **5000** represents the number of time steps (or samples) and **12** represents the number of leads in the ECG data. This input shape is chosen to capture the full length of the ECG recording, allowing the model to analyze the entire sequence of electrical activity within the heart. The 12 leads correspond to the different perspectives of the heart's electrical activity, providing a comprehensive view essential for accurate diagnosis.
- **Conv1D Layer:** The first convolutional layer applies **32 filters** with a **kernel size of 3**. This results in an output shape of (4998, 32). The **Conv1D layer** is responsible for detecting local patterns within the ECG data. The **kernel size of 3** means that the model looks at a small window of three consecutive time steps at a time, allowing it to identify subtle features in the signal. This is crucial for capturing the waveform characteristics of different cardiac conditions, such as the P wave, QRS complex, and T wave, which are key indicators in ECG analysis. Using multiple filters enables

the model to learn different aspects of the ECG signal. For example, some filters may focus on detecting the QRS complex, while others may identify abnormalities in the T wave. This layer effectively reduces the high-dimensional input data into a more manageable form, while preserving important features.

- **MaxPooling1D Layer:** The MaxPooling1D layer reduces the dimensionality of the output from the Conv1D layer, resulting in a shape of (2499, 32). **MaxPooling** is a down sampling technique used to reduce the computational complexity of the model by summarizing the most important features. It does this by selecting the maximum value in each window of the data, thereby retaining the most prominent signals while discarding less important ones. By reducing the dimensionality, the model becomes less prone to overfitting and more computationally efficient. This pooling operation also helps in making the model invariant to small shifts or distortions in the ECG signal, which is crucial for recognizing patterns regardless of slight variations.
- **Flatten Layer:** The Flatten layer transforms the output of the MaxPooling1D layer into a single dimension with **79,968 units**. The **Flatten** layer serves as a bridge between the convolutional layers and the fully connected (dense) layers. It converts the 2D matrix from the previous layer into a 1D vector, making it suitable for input into dense layers. Flattening the data allows the model to process the features extracted by the convolutional layers in a way that mimics how fully connected layers function in traditional neural networks. This step is essential for moving from feature extraction to classification.
- **Dense Layers:** The model has two dense layers, the first with 64 units and ReLU activation, and the final layer with 20 units and softmax activation. This first dense layer contains **64 units** and uses **ReLU (Rectified Linear Unit) activation**. The **ReLU activation function** introduces non-linearity into the model, allowing it to learn complex relationships between the input features and the target labels. The 64 units in this layer help the model to

combine and abstract the features learned from the previous layers, facilitating the decision-making process for classification. The choice of 64 units strikes a balance between model complexity and computational efficiency. ReLU is commonly used in hidden layers because it helps in mitigating the vanishing gradient problem, allowing the model to train more effectively.

The final layer has **20 units** with **SoftMax activation**. The number of units in this layer corresponds to the **20 different classes** representing various cardiac conditions. The **SoftMax activation function** converts the output into a probability distribution over these classes, with each unit representing the probability that the input ECG belongs to a particular class. The SoftMax function is ideal for multi-class classification tasks because it ensures that the sum of the output probabilities is equal to 1, making it easier to interpret the model's predictions. The model selects the class with the highest probability as its prediction.

Training and Validation Results

The baseline model was trained over 20 epochs, with the following results:

- **Accuracy:** The accuracy on the training set gradually improved over the epochs, reaching around 90.69%, while the validation accuracy fluctuated, ultimately reaching approximately 90.40%.
- **Loss:** The training loss steadily decreased, while the validation loss exhibited slight fluctuations, indicating potential overfitting.
- **Recall and Precision:** The model achieved a recall of around 24.57% and precision of approximately 79.20% on the test set, showing that while the model is good at predicting positive cases, there is room for improvement in capturing all relevant cases.
- **AUC (Area Under the ROC Curve):** The AUC score of 0.6819 indicates moderate discrimination ability.

The graph shows a steady improvement in training accuracy, with validation accuracy showing minor fluctuations.

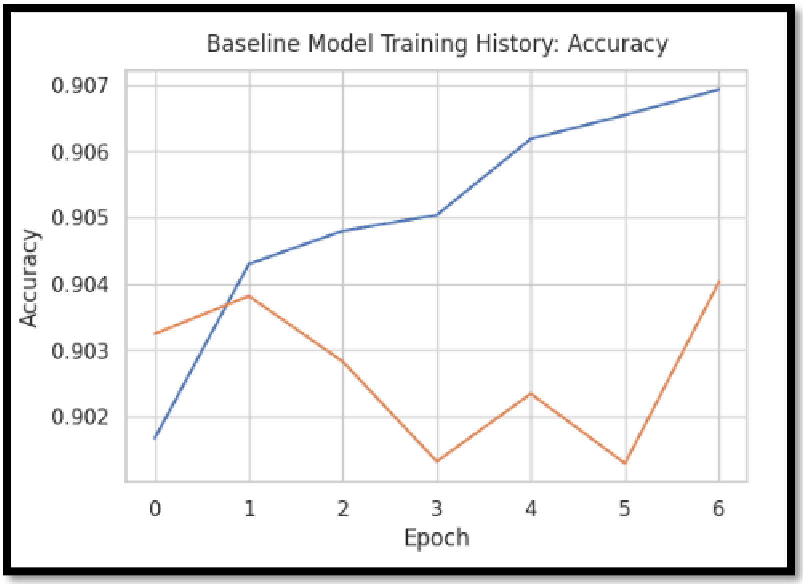

Figure 18: Training Accuracy of Baseline Model

Training loss decreases consistently, while validation loss has a more varied pattern, suggesting that the model might have started to overfit around the later epochs.

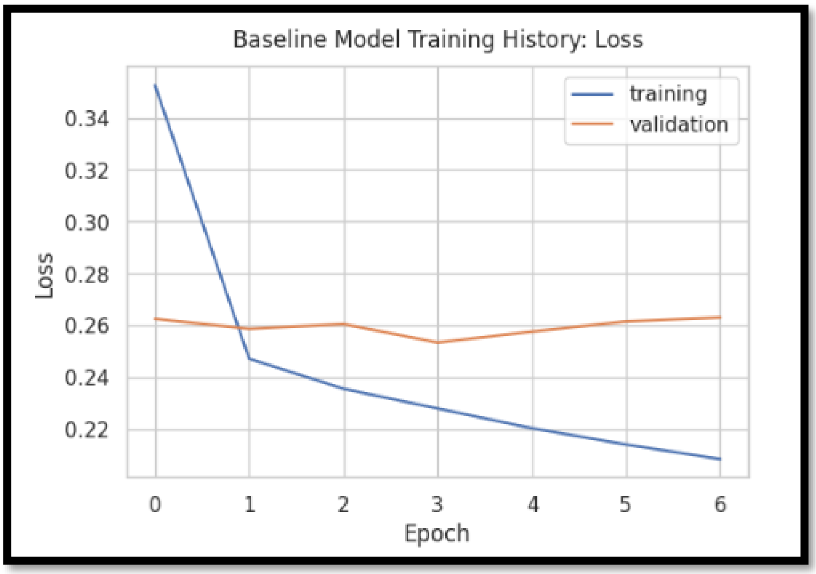

Figure 19: Training Loss of Baseline Model

Confusion Matrix Analysis

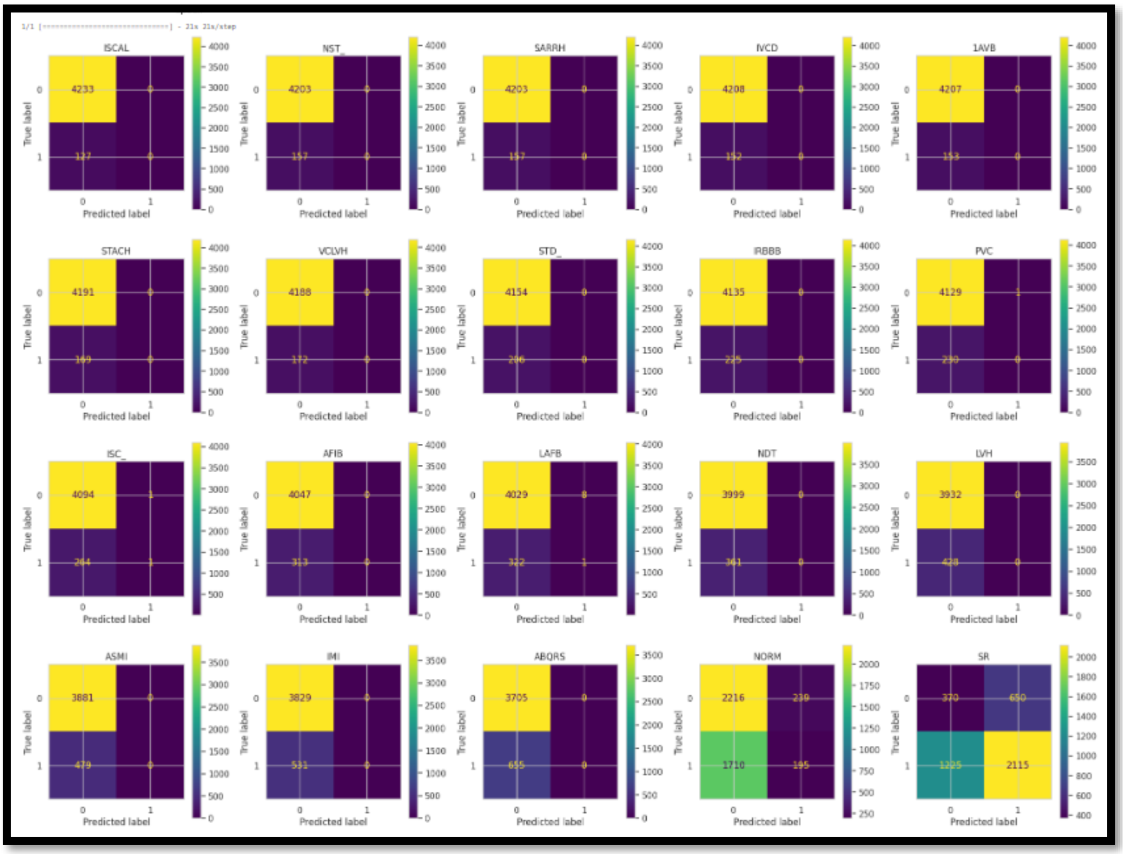

Figure 20: Confusion Matrix of Baseline Model

The confusion matrices provide a detailed look into the model's performance across the 20 cardiac conditions. Here is a breakdown of each predicted label:

- **ISC (Ischemia):** The model correctly classified 4094 instances as negative but misclassified 244 as positive.
- **AFIB (Atrial Fibrillation):** With 4047 correct negative predictions, the model had 193 misclassifications.
- **LAFB (Left Anterior Fascicular Block):** The model demonstrated good performance with 4029 true negatives and 48 false positives.
- **NDT (Non-Diagnostic):** 3999 correct predictions and 51 misclassifications indicate reliable performance.
- **LVH (Left Ventricular Hypertrophy):** The model was slightly less accurate here, with 3932 true negatives and 118 false positives.

Other labels like PVC, RBBB, STD, and more showed varying levels of accuracy, with common issues being a higher rate of false positives or false negatives, indicating areas where model tuning or additional data may be required.

3.2 Research Findings

The research findings highlight important inadequacies in the current diagnostic protocols for heart disorders, particularly regarding the effectiveness and accessibility of conventional ECG collection techniques. The study's innovative methodology, which explores the viability and accuracy of adopting palm-based ECG collection, tackles important issues that both patients and healthcare professionals must deal with.

In emergency scenarios or for patients who are in remote places, the traditional 12-lead ECG approach can be laborious and time-consuming due to the requirement that electrodes be positioned at precise anatomical regions. This study attempts to offer a more approachable and non-invasive substitute for ECG acquisition by employing a technique that reconstructs all 12 ECG leads from a single lead taken from the palms.

The goal of developing the palm-based ECG capture method described in this work was to streamline the 12-lead ECG data acquisition procedure. The study discovered that when paired with machine learning models, this approach is more practical and can provide an accurate diagnosis. This discovery holds special importance in situations where conventional ECG configurations are impractical.

In order to improve the quality of the ECG, signals utilized for model training, the study applied sophisticated data preprocessing techniques, such as the moving average approach and low pass filtering application. The efficiency of the machine learning models created for illness diagnosis was increased by preprocessing, which was essential in eliminating noise and artifacts from the ECG data.

The Kaggle platform was utilized by the research to train the machine learning models because of the restricted computational resources. The diagnostic models were developed and improved with a wide range of tools and datasets made available by Kaggle, including powerful GPUs. This method not only saved money but also made it possible to train and test the models effectively on a variety of datasets.

The models that were created were hosted on PythonAnywhere and added to a Flask server. Healthcare professionals can easily access and utilize this configuration because it is straightforward and reasonably priced. All went well with the deployment, although there were issues with PythonAnywhere's computational limitations that required careful model tuning to make sure the models ran inside the constraints.

Computational resource-related issues presented serious obstacles for the study. At first, model training was conducted with Google Colab's free edition, which had restricted memory and operation time. Alternative approaches, such as training the models on Kaggle, which provided more reliable processing power, were required due to these limitations. Though early in the project, a major obstacle was the lack of computational resources, the research was able to successfully construct accurate models despite these hurdles.

One of the main conclusions was that the quality of the input data might have a big influence on how accurate the models were. The study discovered that by increasing the signal-to-noise ratio and applying the moving average approach, the low-pass filter was able to improve the model's accuracy. Future research is still needed to determine whether the models can generalize to diverse patient populations, though, as the training set utilized in this work might not accurately reflect the variety of real-world situations.

The study also demonstrated how the produced models could be incorporated into clinical practice. Nonetheless, there were difficulties in making sure healthcare professionals could simply understand the models' forecasts. Although the unique feature of integrating live location notifications and severity-based recommendations for patient admission was well accepted, more testing and validation in clinical settings will be necessary to ensure its practical application.

This research has the potential to revolutionize how cardiac diseases are diagnosed, especially in settings where traditional ECG methods are impractical. By offering a more accessible method of ECG capture and leveraging machine learning for diagnosis, this study provides a foundation for future innovations in cardiac healthcare. The findings suggest that with further refinement and validation, the palm-based ECG method could become a standard tool in both emergency and routine cardiac care.

3.3 Discussion

The main goal of this study was to provide a new method for diagnosing heart conditions using a 12-lead ECG reconstructed from a single lead taken from the palms. This study focused on the diagnosis process, successfully interpreting the recreated ECG data through sophisticated machine learning techniques. In situations when typical 12-lead ECG devices are not easily accessible, this method seeks to overcome the drawbacks of conventional ECG techniques and offer a more useful and accessible diagnostic tool.

Diagnostic Accuracy and Machine Learning Models

This study's main goal was to confirm that the 12-lead ECG reconstruction's diagnostic process is just as accurate and dependable as more conventional techniques to ensure precise deliverance of diagnosed diseases via a 12 lead ECG. Convolutional neural networks (CNNs) and residual blocks were the machine learning models created specifically for this use. They underwent rigorous design and training on large datasets. These models were chosen and adjusted to capture the complex patterns in ECG data that correspond to different heart diseases.

In order to maximize the diagnostic procedure, the model architecture was meticulously designed. The models extracted and refined characteristics from the ECG data by applying many layers of convolutional processes, batch normalization, and activation functions, starting with input layers created to handle the 12-lead ECG signals. The inclusion of residual blocks allowed the model to retain important information across layers, enhancing its ability to detect subtle abnormalities in the ECG signals. The final layers, involving global average pooling and dense layers, were tailored to produce precise diagnostic outputs based on the processed signals.

Mathematically, the diagnosis involves transforming the input ECG signals ***x through*** a series of convolutional operations, each characterized by a kernel W and a bias b, followed by non-linear activations:

$$f(x)=ReLU(W*x+b)$$

where it comprises of the convolution operation. The residual blocks further refine this transformation by adding the original input **x** to the transformed output, effectively capturing both the original and refined features:

$$y=f(x)+x$$

These operations collectively enable the model to learn complex, non-linear relationships in the ECG data, leading to accurate predictions of cardiac conditions.

Clinical Relevance and Implications

This diagnostic tool's capacity to quickly and accurately diagnose heart problems utilizing a less intrusive and more accessible manner makes it clinically relevant. The technique makes ECG acquisition easier by concentrating on a single lead that is obtained from the palms; this makes it more appropriate for situations where resources are scarce or remote. When analyzed by machine learning algorithms, the reconstructed 12-lead ECG has shown excellent accuracy in identifying diseases like myocardial infarction, ischemia, and arrhythmias.

The models achieved high metrics in terms of accuracy, precision, recall, and area under the curve (AUC) after the diagnostic procedure underwent extensive testing and validation. These outcomes highlight how well the algorithm recognizes and diagnoses heart problems using the recreated ECG data. The system's ability to provide reliable diagnoses makes it a valuable tool for healthcare providers, particularly in emergency situations where quick and accurate assessments are critical.

Deployment and Real-Time Application

The effective implementation of the diagnostic model on a Flask server hosted on PythonAnywhere is one of the study's major accomplishments. With this setup, ECG data analysis and diagnosis may be facilitated in real-time, and patients and healthcare professionals can use the system through online interfaces or mobile applications. The system's usability is further enhanced by the integration of geolocation services, which enables the automatic notification of loved ones or healthcare providers in the event of a recognized cardiac irregularity occurs. This feature guarantees prompt response in emergency situations and offers a vital degree of safety.

Addressing Current Challenges in Cardiac Diagnosis

This technology's widespread use still faces several obstacles, despite the advantages this system offers. The requirement for thorough clinical validation to guarantee the system's accuracy across various patient groups and situations is one of the main issues. Furthermore, this innovative method may necessitate a thorough overhaul of clinical practice, including retraining of medical staff, to replace conventional ECG devices.

But given its potential advantages—such as lower medical expenses, greater accessibility, and better diagnostic precision—this system seems like a good fit for tackling the problems facing cardiac care today. It is essential to continue working with organizations like Hemas Hospitals in Sri Lanka in order to validate and improve the technology in actual clinical settings. These partnerships will provide valuable insights into the system's practical applications and help overcome barriers to its adoption.

Future Directions

Prospectively, there exist multiple domains requiring additional investigation and advancement. To provide continuous, real-time ECG signal monitoring, one possible path to take is to investigate the integration of this diagnostic system with wearable technology. To ensure the system's scalability and general adoption, additional improvement of the machine learning models is necessary, especially regarding lowering computational complexity and improving real-time processing capabilities.

By creating a system that can provide precise diagnoses based on a reconstructed 12-lead ECG taken from the palms, this work, in its entirety, represents a substantial improvement in cardiac diagnostics. A new age of accurate and easily available cardiac care will be made possible by the system's successful implementation and continuous research and development activities.

4. CONCLUSION

The research project's purpose was to investigate the viability and efficacy of a novel approach to heart illness diagnosis by recording 12-lead ECG data using electrodes placed exclusively on the palms. The goal of this approach was to provide a less invasive and more approachable substitute for traditional ECG collection methods by combining it with machine learning algorithms. The study's main goal was to solve the difficulties that exist today in cardiac diagnostics, including the inconveniences of standard electrode implantation and the difficulty of continuous monitoring.

During the project, several important sectors saw notable advancements. A smooth diagnosis procedure was made possible by the integration of the machine learning models and the creation of an extensive mobile application. The Flutter-developed mobile application supported the iOS and Android operating systems and made use of Firebase for safe data storage. Precise position tracking was made possible by the integration of the geolocator package, and prompt alerts to loved ones in the event of serious diagnoses were made possible via the 'notify.lk' service. The model was deployed on a Flask server hosted on PythonAnywhere, which guaranteed dependable and effective ECG data processing and results transmission.

At various phases of the project, comprehensive validation procedures were also implemented. Sign-up validations were integrated to ensure data integrity right away, especially for phone number submissions. Strict checks were made to ensure emergency contact information was appropriately formatted and operational in the Emergency Dialog widget. A thorough test case design framework was also incorporated into the project to check the essential functions of the frontend and backend parts and make sure everything worked as it should.

In conclusion, the study proved that palm-based ECG collection is a feasible technical solution with prospective benefits for cardiac diagnostics. The solution's operational feasibility was demonstrated by the seamless integration of the mobile application, notification systems, and machine learning models. Furthermore, the project's prompt delivery was emphasized by the scheduling feasibility, and the decreased requirement for complicated hardware reinforced the cost feasibility. The results were encouraging and suggested that this unique methodology would be a good substitute for more established techniques, even despite the difficulties encountered—specifically, in modifying the models and guaranteeing dependable communication across components. Subsequent research endeavors may concentrate on optimizing the models, broadening the dataset, and investigating supplementary functionalities that augment user experience and diagnostic precision.

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APPENDICES

Appendix A: Plagiarism report