NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF COMPUTER INFORMATION SYSTEMS

ECG DIAGNOSIS, ANALYSIS, AND INTERPRETATION IN CARDIOLOGY USING DEEP LEARNING MODELS FOR CLASSIFICATION AND PREDICTION

PhD THESIS

Oluwafemi Ayotunde OKE

Nicosia

December, 2024

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December, 2024

APPROVAL

We certify that we have read the thesis submitted by Oke Oluwafemi Ayotunde titled **"ECG Diagnosis, Analysis, And Interpretation in Cardiology Using Deep Learning Models for Classification and Prediction"**. After careful scrutiny of the thesis, it has met the unanimous consensus and in our combined opinion, it is fully adequate in scope and in quality as a thesis for the award of degree of Doctor of Philosophy (PhD) degree in Computer Information Systems, and hereby recommended for approval and acceptance.

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I hereby declare that all information in this document has been obtained and presented according to academic rules and ethical conduct. I also declare that as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

Oke Oluwafemi AYOTUNDE
20/12/2024

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ABSTRACT

ECG DIAGNOSIS, ANALYSIS, AND INTERPRETATION IN CARDIOLOGY USING DEEP LEARNING MODELS FOR CLASSIFICATION AND PREDICTION

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The integration of artificial intelligence across industries has significantly enhanced efficiency, performance, and scalability. In clinical settings, AI advancements have demonstrated potential in improving patient outcomes and optimizing healthcare processes. However, while hybrid AI models—combining multiple AI techniques—show promise, there is limited research specifically addressing their application in cardiology, particularly in real-time diagnostic and decision-making tools. This study aims to fill this gap by leveraging innovative AI frameworks to develop scalable, hybrid AI models tailored to the health sector, with a specific focus on cardiology. This involves the analysis of electrocardiogram (ECG) image results using the proposed methodology comprising of a combination of 2 standalone deep learning models (Inception V3 and VGG16) integrated together to create a hybrid model for the prediction-classification analysis of 6 different heart conditions (abnormal heart condition, atrial fibrillation, ischemic heart disease, myocardial infarction, normal heart condition, and sinus bradycardia). Hybrid datasets consisting of datasets from Near East University (NEU) cardiac center and Kaggle online database were implemented in the study. 80% of the Kaggle online datasets were used for training and 20% for validation while 100% of the NEU datasets was used testing. The hybrid AI model has demonstrated exceptional performance in the classification of ECG images, achieving high accuracy, sensitivity, specificity, precision, and F1-score. With an achieved accuracy of 99%, 99% sensitivity (recall), 99%

specificity, 99% precision, and 99% F1-Score, the model holds significant benefits and potential for improving the diagnosis and management of heart diseases, ultimately enhancing patient outcomes. In addition to the classification performance metrics scores of the hybrid AI model, the research also integrates AI-driven cardiac care through the development of a web ECG classifier application for clinical integration. All of which play significant importance to patients, cardiologists and the field of cardiology at large towards a faster, precise, efficient, and patient-centered approach to heart disease diagnosis, analysis, interpretation and treatment, leading to an overall patient well-being.

Keywords: Artificial intelligence, hybrid AI model, classification, cardiology, clinical implementation

ÖZET

SINIFLANDIRMA VE TAHMİN İÇİN DERİN ÖĞRENME MODELLERİ KULLANILARAK KARDİYOLOJİDE EKG TEŞHİSİ, ANALİZİ VE YORUMLANMASI

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Yapay zekanın endüstriler arasında entegrasyonu, verimliliği, performansı ve ölçeklenebilirliği önemli ölçüde artırmıştır. Klinik ortamlarda, AI gelişmeleri hasta sonuçlarını iyileştirme ve sağlık hizmetleri süreçlerini optimize etme konusunda potansiyel göstermiştir. Bununla birlikte, birden fazla AI tekniğini birleştiren hibrit AI modelleri umut vaat ederken, özellikle gerçek zamanlı tanı ve karar alma araçlarında kardiyolojideki uygulamalarını ele alan sınırlı araştırma vardır. Bu çalışma, özellikle kardiyolojiye odaklanarak sağlık sektörüne göre uyarlanmış ölçeklenebilir, hibrit AI modelleri geliştirmek için yenilikçi AI çerçevelerinden yararlanarak bu boşluğu doldurmayı amaçlamaktadır. Bu, 6 farklı kalp rahatsızlığının (anormal kalp rahatsızlığı, atriyal fibrilasyon, iskemik kalp hastalığı, miyokard enfarktüsü, normal kalp rahatsızlığı ve sinüs bradikardisi) tahmin-sınıflandırma analizi için bir hibrit model oluşturmak üzere bir araya getirilmiş 2 bağımsız derin öğrenme modelinin (Inception V3 ve VGG16) bir kombinasyonundan oluşan önerilen metodolojiyi kullanarak elektrokardiyogram (EKG) görüntü sonuçlarının analizini içerir. Çalışmada Yakın Doğu Üniversitesi (YDÜ) kalp merkezi ve Kaggle çevrimiçi veritabanından alınan veri kümelerinden oluşan hibrit veri kümeleri uygulandı. Kaggle çevrimiçi veri kümelerinin %80'i eğitim için, %20'si doğrulama için kullanılırken, YDÜ veri kümelerinin %100'ü test için kullanıldı. Hibrit AI modeli, yüksek doğruluk, duyarlılık, özgüllük, kesinlik ve F1 puanı elde ederek EKG görüntülerinin sınıflandırılmasında olağanüstü bir performans göstermiştir. Elde edilen

%99 doğruluk, %99 duyarlılık (geri çağırma), %99 özgüllük, %99 kesinlik ve %99 F1 puanı ile model, kalp hastalıklarının teşhisini ve yönetimini iyileştirmek ve nihayetinde hasta sonuçlarını iyileştirmek için önemli faydalar ve potansiyel taşımaktadır. Araştırma, hibrit AI modelinin sınıflandırma performans ölçütleri puanlarına ek olarak, klinik entegrasyon için bir web EKG sınıflandırıcı uygulamasının geliştirilmesi yoluyla AI odaklı kardiyak bakımı da entegre etmektedir. Bunların hepsi, kalp hastalığının teşhisi, analizi, yorumlanması ve tedavisine yönelik daha hızlı, kesin, etkili ve hasta merkezli bir yaklaşıma doğru hastalar, kardiyologlar ve genel olarak kardiyoloji alanı için önemli bir öneme sahiptir ve bu da genel hasta refahına yol açar.

Anahtar Kelimeler: Yapay zeka, hibrit model, sınıflandırma, kardiyoloji, klinik uygulama

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ABBREVIATIONS

AI:	Artificial Intelligence
ML:	Machine Learning
DL:	Deep Learning
CVDs:	Cardiovascular Diseases
ECG:	Electrocardiogram
F1-Score:	F1 Score (Harmonic Mean of Precision and Recall)
IDE:	Integrated Development Environment
PWA:	Progressive Web Application
SDLC:	Software Development Life Cycle
SGD:	Stochastic Gradient Descent
CSS:	Cascading Style Sheets
HTML:	Hypertext Markup Language
API:	Application Programming Interface
VGG16:	Visual Geometry Group 16
Inception V3:	Inception Version 3
Keras:	Open-source Neural Network Library in Python
CMD:	Command Line Interface
EHR:	Electronic Health Record
Adam:	Adaptive Moment Estimation
WGSI:	Web Server Gateway Interface

CHAPTER ONE

INTRODUCTION

The first chapter of this research provides a comprehensive overview of the background of the study, the problem, aim and objectives, the significance and contribution to the field of the study, the limitations, definition of terminologies, and finally, the thesis overview.

1.1.Background of the Study

The prevalence of cardiovascular diseases (CVDs) has been increasing globally, making heart disease one of the leading causes of morbidity and mortality (Amini et al. 2021), and the early and accurate diagnosis is critical for effective management and treatment of these conditions (Ahsan & Siddique, 2022). Cardiology is the branch of medicine that deals with the study of the heart as well as the disorders of the heart, cardiovascular system and part of the circulatory system (Tiwari et al. 2021). The field include medical diagnosis and treatment of congenital heart defects (Liu et al. 2022). Physicians who specialized in cardiology are referred to as cardiologist (Nezamabadi et al. 2023). Electrocardiograms (ECGs) are widely used diagnostic tools that record the electrical activity of the heart, providing essential information for diagnosing various heart conditions (Saini & Gupta, 2021). However, interpreting ECGs can be complex and time-consuming, often requiring the expertise of trained cardiologists (Hong et al. 2022). In recent years, artificial intelligence (AI) has shown tremendous potential in automating and enhancing medical diagnostics (Venigandla, 2022). This study explores the use of AI models and a hybrid approach in combining the AI models (Inception V3 and VGG16) models, for the automated diagnosis, interpretation, and analysis of ECG images. Furthermore, the motivation behind this research stems from the potential utilization of AI models in ECG image diagnosis, interpretation, and analysis as there is the increasing need for efficient and accurate cardiac health assessment (Ebadinezhad & Mobolade, 2024; Olawale & Ebadinezhad, 2023).

1.2.Problem Statement

Cardiovascular diseases are at the forefront; hence, there is a need for innovative technologies to aid diagnostics and improve diagnostics accuracy to ensure lives are not lost. Despite the emergence of advanced medical technologies, heart diseases are still being diagnosed inaccurately or late because traditional ECG interpretation methods are complex, not only mostly time-consuming-as identified by Kashou et al. (2020)-but also susceptible and prone to human error, as discussed by Faruk et al. (2021), many times labor-intensive-as stated by Thiagarajan et al. (2020)-and variable among clinicians, according to Hoang et al. (2021). More than that, among the different health problems common in Cyprus, the heart condition problems are the most prevalent health problems (Lambros & George, 2018). These gaps have therefore made the research of AI models necessary as a hybrid approach to address these challenges since there is a dire need for a system that is both reliable and efficient, which can assist in the correct classification of ECGs, so as to lighten the burden on healthcare professionals and improve patient outcomes.

1.3.The Aim of the Study

This research aims at combining of the strengths of Inception V3 and VGG16 AI models in clinical diagnosis and interpretation of ECG images for six different heart conditions. The specific objectives of the study are as follows:

a) To design a hybrid AI model that will integrate the architecture of Inception V3 and VGG16 for ECG image classification.

b) To evaluate the performance of the hybrid AI model regarding accuracy, sensitivity, specificity, precision, and F1-score.

c) To integrate the developed hybrid AI model into a web application named "ECG web classifier".

d) To find the probable impact of the hybrid AI model on the classification diagnosis and prediction analysis of heart diseases in the developed web ECG classifier application.

1.4.Significance of the Study

The impact and significance of this study can be considered in the light of the following aspects:

- Clinical Impact: A hybrid AI model can provide a fully automated, highly accurate tool for ECG classification to clinical practitioners to support clinicians in more efficient and effective diagnosis of heart diseases.

- Technological advancement: The integration of inception V3 and VGG16 models is a masterful AI model in the field of medical AI, showing the prospect of hybrid AI models to improve accuracy.
- Accessibility: The model will be deployed as a web ECG classifier application to ensure advanced diagnostic tools are available globally. It would facilitate areas where specialized cardiology services are not accessible.

1.5.Contribution to the Field of the Study

This work broadly contributes to the area of computer science, more so in fields such as artificial intelligence and analysis of medical images.

Development of a new hybrid AI model through the combination of two powerful architectures, namely, Inception V3 and VGG16, enhances the literature understanding on how different deep learning models can be combined with the aim of enhancing performance. The methodology and results of this study add to the growing literature related to hybrid AI models, thus adding insight to knowledge that may be used outside the domain of ECG analysis. From the departmental point of view, this research also shows the concrete application of theoretical computer science in practical health problems.

It highlights how AI can potentially improve diagnostic processes and patient outcomes, showcasing relevance and impact from computer science research in interdisciplinary areas. A web ECG classifier application was developed which provides throughput advantages in terms of overall time taken for drawing conclusions on the diagnosis, interpretation, and analysis of heart problems in patients. Similarly, the successful deployment of the model as a web ECG classifier application makes it important in terms of software engineering aspects and is going to serve students and faculty alike as an inspirational case study to be taken to the field in AI applications involving medicine. Moreover, this serves to extend advanced technical knowledge regarding the crucial involvement of computer science in pressing contemporary societal issues in line with commitment to innovation excellence in research outcomes.

1.6.Limitations

The study shall focus on the development and validation of the hybrid AI model in classifying ECG images into six conditions of the heart.

However, some of the limiting factors are the dependency on the quality and diversity of ECG datasets used for training, computational resource constraints, the fact that it focuses on only 6 heart problems, model choices, the use of only two standalone AI models to make the hybrid AI model, study up until this year-July 2024, this semester, ethical and regulatory issues that surround AI applications in the diagnosis of some cardiac centers, and further generalization in different clinical settings is still required.

1.7.Definition of Terminologies

For the purpose of this research, "variables" can be defined as different factors or parameters that have to do with the research study. They include:

• ECG: An electrocardiogram is a graphical record of the electrical activity of the heart over time (Fuior et al. 2021). It is used in various diagnoses of heart conditions, as it recognizes certain rhythms and structural abnormalities within the heart (Li & Boulanger, 2022). These ECG traces are created when electrodes placed on the skin measure electrical signals arising from the cardiac muscle at its contraction and relaxing phases (Zhu et al. 2021).

• Electrocardiograph: An electrocardiograph is a medical device used to record the electrical activity of the heart through capturing and amplifying the electrical signals that are generated by the heart, and displays it as a waveform on a screen or prints it on paper as stated by Aggarwal & Wei, 2021.

• Cardiologist: A cardiologist is a medical doctor specializing in diagnosing, treating, and preventing diseases of the heart and blood vessels (Batchelor et al. 2023). Cardiologists interpret ECGs and other diagnostic tests to assess heart health, develop treatment plans, and manage patients with cardiovascular conditions (Al-Zaiti et al. 2022).

• Artificial Intelligence: Intelligence developed in machines could be defined as those that think and perform like human beings, according to Dong et al. (2020). AI is a general subject that uses technology to try to give the possibility of capabilities in machines for reasoning, learning, problem-solving, perception, and language understanding. According to Chen et al. (2020), in health, AI has been applied to diagnosis and prediction, including interpretation of ECG data.

• Machine Learning: Machine Learning is a subset of AI that focuses on developing algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data (Sarker, 2021). Machine learning techniques are used to identify patterns in ECG image signals that may indicate specific heart conditions (Feeny et al. 2020).

• Deep Learning: Deep Learning is a branch of machine learning concerned with neural networks having many layers, also called deep neural networks. Dargan et al. (2020) present that such deep neural networks learn complex patterns and abstractions from huge data and are more effective, especially for image and signal analysis; therefore, ECG interpretation becomes an important modality for treatment.

• Transfer Learning: Narrowly, it refers to machine learning where a model developed for a particular task is reused as the starting point for models on a second task. Reference can be made to Niu et al. 2020.

This especially helps in situations where data on the new task are extremely limited. According to Zhu et al. 2021. These models, pre-trained on ImageNet, such as Inception V3 and VGG16, can be fine-tuned in the context of ECG analysis to improve their diagnostic accuracy using relatively small ECG datasets.

• Dataset: A dataset is a collection of data used for training and evaluating machine learning models (Paullada et al. 2021). In ECG analysis, datasets typically consist of ECG recordings, along with annotations or labels indicating the presence or absence of specific heart conditions (Nezamabadi et al. 2023).

• Preprocessing: Preprocessing refers to the various techniques and methods applied to raw data to prepare it for analysis (Fan et al. 2021). For ECG data, preprocessing steps may include noise reduction, normalization and segmentation of the ECG (Liu & Li, 2021).

• Feature Extraction: Feature Extraction involves identifying and isolating the most informative attributes or characteristics from raw data that will be used by machine learning algorithms (Hajji et al. 2021). For ECG data, features may include time-domain, frequency-domain, and morphological characteristics of the ECG waveform (Singh & Krishnan, 2023).

• Classification: Classification is a machine learning task where the goal is to assign input data to one of several predefined categories (Luo, 2021). In the context of ECG analysis, classification models aim to categorize ECG recordings into classes such as normal, arrhythmia, or other specific heart conditions.

• Prediction: In general, it is the process of inferring or estimating, from a previously trained model in machine learning, the outcome for new unseen data. Wiemken & Kelley, 2020. In ECG analysis, prediction simply means calculating the likelihood of the different conditions of the heart given an input ECG image.

• Performance Metrics: These are the quantitative measures taken to determine the effectiveness and accuracy of the performance of a machine learning model. General metrics for ECG classification models include accuracy, sensitivity, specificity, precision, recall, and the area under the receiver operating characteristic curve, AUC-ROC (Somani et al. 2021).

• Support: The number of actual occurrences of the class in the dataset (Sohn et al. 2020).

• Web Application: A web application is software that runs over the internet in a web browser and resides in a web server. Web-based applications for ECG analysis include remote access to diagnostic tools in which clinicians may upload, analyze, and interpret ECG data online (Berners-Lee et al. 2023; Xu, 2020).

• PWA stands for Progressive Web Application, which is an online application utilizing the latest web technology to create an application experience on the web. According to Fauzan et al. (2022), it was designed to work offline and load fast in order to enrich user experiences. These are what make the PWAs quite reliable and responsive for medical applications.

• Human-Computer Interaction (HCI): Human-Computer Interaction (HCI) is the study of how people interact with computers and software (Ramadoss et al. 2021). In the context of ECG analysis, HCI focuses on designing user interfaces that are intuitive and efficient for healthcare professionals, facilitating accurate and timely diagnosis.

1.8.Project Time Schedule

This section contains tabular and diagrammatic representation of the research process from inception till completion as shown in Table 1.1.

Table 1.1:

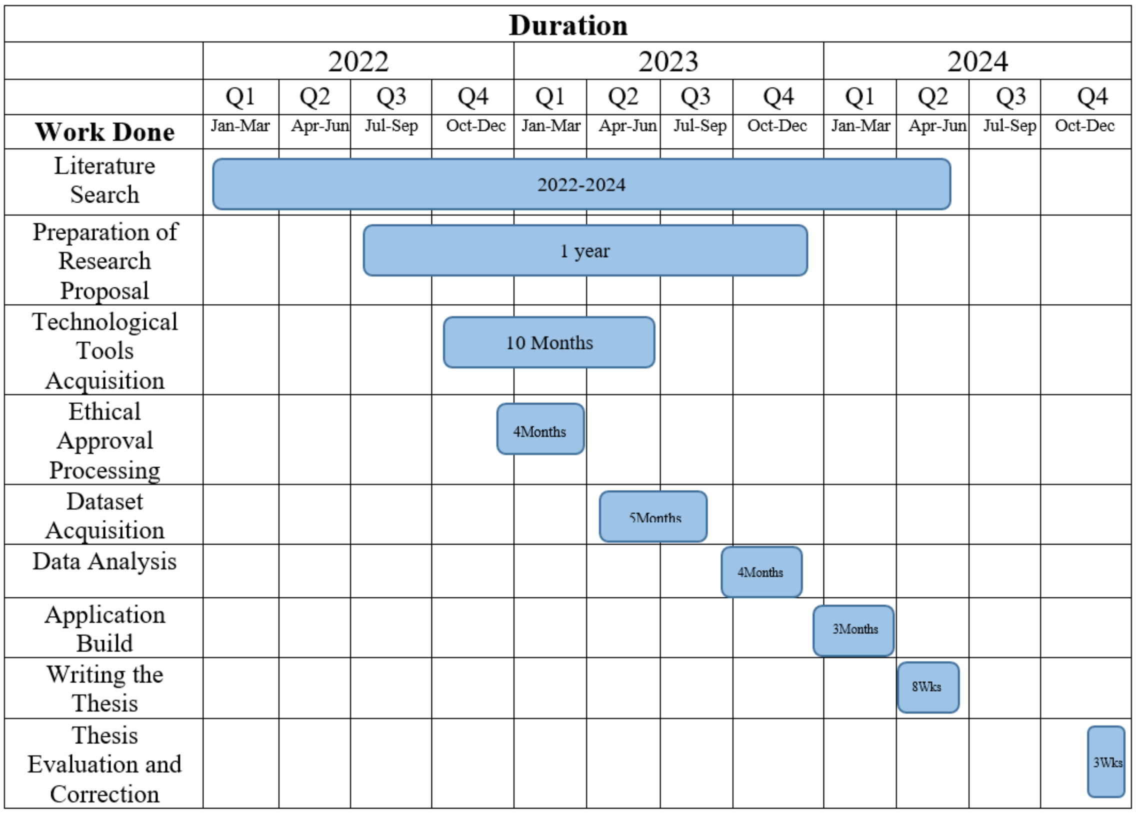
Project time schedule

Work Done	Duration
Literature Search	December 2022 until thesis defense
Preparation of Research Proposal	12 Months
Technological Tools Acquisition	10 Months
Ethical Approval Processing	4 Months
Dataset Acquisition	5 Months
Data Analysis	4 Months
Application Build	3 Months
Writing the Thesis	2 Months
Thesis evaluation and correction	3 Weeks

Diagrammatically it is represented using Gantt Chart which shows the start and finish dates of the different timelines, milestones, and dependencies of the project and thereby allow for effective planning and tracking of the progress of it as indicated by Grudzinskas et al. (2022) in Figure 1.1.

Figure 1.1:

Gantt chart diagram



1.9.Thesis Overview

This section provides in detail the structure of the thesis as a way to help a reader understand the line of logical disposition it has assumed and in what manner. It, therefore, highlights what is contained in successive chapters and their individual contributions towards the whole research study. In such a way, the thesis tries to increase comprehension and, therefore, provides a roadmap through which a reader shall navigate while studying the research. The structure of the thesis is the following:

Chapter One gives the background, problem statement, objectives, scope, and significance of the study, and the definition of variables. The second chapter has a review of related existing research in AI models on ECG analysis, including the systematic literature review, bibliometric analysis, comparative analysis, and theoretical frameworks used in the study. Chapter three focuses on the design, development, and implementation of the hybrid AI model by describing data pre-processing, model training, and evaluation. Chapter four outlines the performance metrics and comparative analysis from the findings. It goes on to chapter five which discusses the results interpretation, implications to clinical practice, strengths, limitations, and future directions. Chapter six summarizes key findings, implications, and recommendations for future research.

CHAPTER TWO
LITERATURE REVIEW

This chapter covers the theoretical framework and review of existing research on AI models in ECG analysis, together with the strengths and limitations of various approaches.

2.1.Theoretical Framework

2.1.1. Artificial Intelligence Models

Artificial intelligence (AI) is a broad range of computational techniques and algorithms that enable machines to mimic human intelligence. Key AI models include machine learning and deep learning, which have proven to be particularly good at pattern identification and the ability to make predictions based on large datasets (Zhu, 2020). Artificial intelligence models driven by machine learning models have huge potential for the automation and enhancement of several diagnosis processes in medical diagnosis, such as image analysis and disease prediction, as illustrated in Figure 2.1.

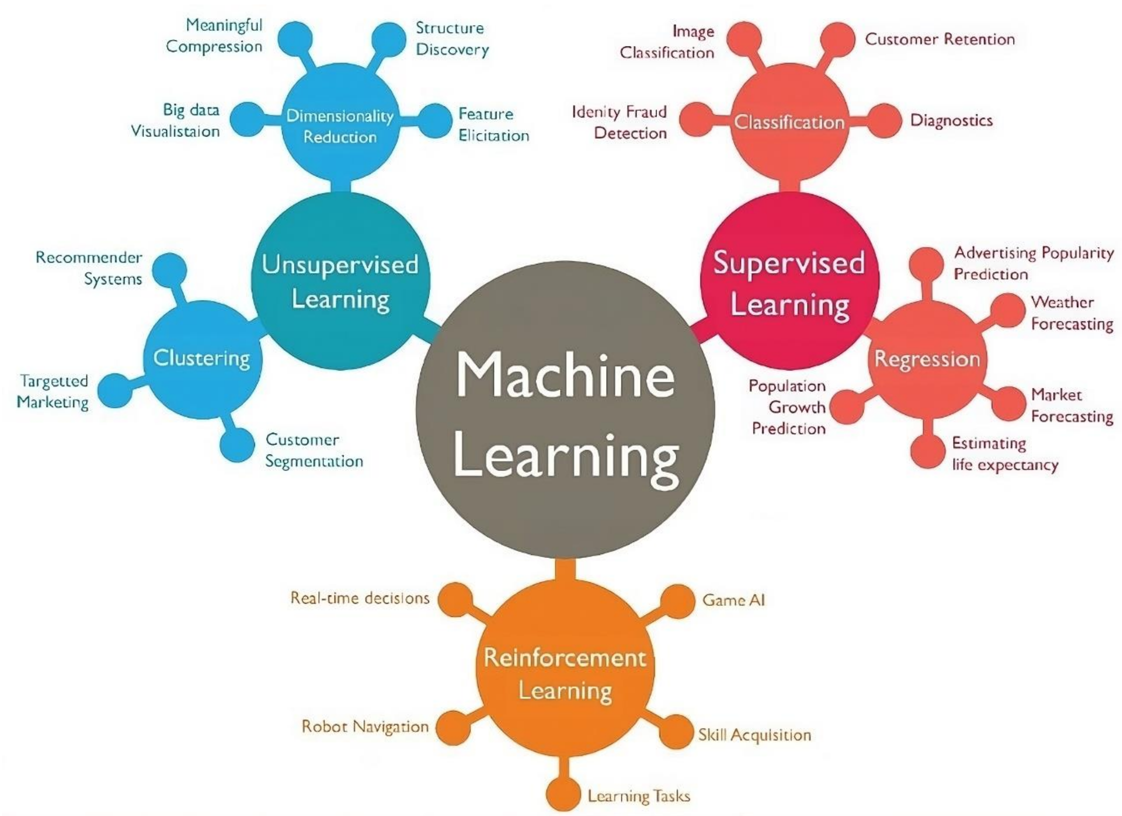
ML is a subcategory of artificial intelligence that involves the development of algorithms and statistical models that give computers the ability to perform tasks without explicit programming, while learning from past data to make predictions or decisions based on the data (Soori et al. 2023). From basic methods such as supervised and unsupervised learning to reinforcement learning that might be applied against various challenges, image recognition, natural language processing, and diagnostics- Machine learning is an exciting area (Habehh & Gohel, 2021).

Supervised Learning in machine learning is a form of training for an algorithm wherein the same is trained using a labeled dataset. In other words, each of the examples in the set is clearly matched with its correct output label (Al-Azzam & Shatnawi, 2021). The model learns to map inputs to the desired output by finding patterns in the data. Supervised learning is particularly useful in tasks where the objective is to predict or classify data based on past observations (Jiang et al. 2020). It finds wide usage in diagnostic applications where known outcomes, such as disease presence, are used to train models for the prediction of similar outcomes in new and unseen data (Caballé et al.

2020).

Figure 2.1:

Machine Learning Classification (Comlan & Alokpo, 2023)



This is a subcategory of supervised learning wherein one is interested in assigning input data to one of several pre-defined categories (Chen et al. 2020). In the context of machine learning, classification algorithms analyze training data and develop a model that can categorize new data points into one of the predefined classes (Seliya et al. 2021). Classification is crucial in diagnostic systems, where it can be used to categorize patients based on their medical images, symptoms, or other diagnostic criteria into various health conditions (Shu et al. 2021).

Image classification, in this respect, is a special form of classification whose inputs are images while the outputs are the classes that the image would fall into (Du et al. 2021). The process here will involve classifying an image through its visual contents to fall into a specific category, like distinguishing different heart conditions from ECG images. Advanced architectures such as VGG16 and Inception V3 have been designed to capture complex patterns in image data, hence making them suitable for medical diagnostics. These models are going to be trained on great datasets of labeled images to be able to accurately classify a new image that can help diagnose several medical conditions (Bhatt et al. 2021).

Medical diagnostics, concerning the machine learning aspects and classification techniques, could define the diagnosis to predict several ailments or diseases that might show signs from any medial data (Xie et al. 2021). Diagnostic analysis by various machine learning models, where supervising usually has been conducted properly, supports in diagnostics via their analysis in radiology images or patient records against accurate prediction of the class results. This approach will be able to facilitate more accuracy in medical diagnostics with better patient outcomes and personalized treatment plans (Shehroz Khan et al. 2024).

AI models for classification and prediction, particularly those based on deep learning architectures such as convolutional neural networks (CNNs), have revolutionized the field of medical imaging (Singh, 2021). These models are designed to classify images into predefined categories and predict outcomes based on input data (Wagner et al. 2021). Image analysis of ECGs has been one of the major tasks where models such as Inception V3 and VGG16 can be extensively used, because they are able to capture and explain almost all complex patterns in the data and yield perfect classification for heart conditions. Besides the use of VGG16 and Inception V3, there are many deeper learning models showing outstanding performance in the processing of ECG images:

• **ResNet (Residual Networks)**: ResNet is famous for its deep architecture, which could be effectively trained without a problem of vanishing gradient thanks to the use of residual blocks. This turns ResNet into an extremely effective means for complicated image recognition tasks, including the classification of ECG images (Xu et al. 2023).

• **Densenet**: It connects each layer to every other layer in a feed-forward manner, which promotes feature reuse and improves gradient flow. In the Dense Convolutional Network, very remarkable results have been achieved concerning medical image analysis, including ECG images (Li et al. 2020).

• **MobileNets**: The very name suggests that these models are targeted at mobile or edge devices with a view toward efficiency in their computation. Its lightweight nature and depthwise separable convolution make it good for real-time ECG image processing, specifically in portable health applications (Kumar et al. 2021).

• **AlexNet**: This is one of the pioneering deep learning models that show the potentials of CNN in image classification. While this model may be older, it laid the foundation for other models currently being used to date in medical image processing, including ECG, by Ba Mahel et al. in 2022.

2.1.1.1.Performance Evaluation Metrics

A number of performance evaluation metrics can be employed when assessing the efficacy and efficiency of such hybrid AI models for the diagnosis, interpretation, and analysis of ECG images. These metrics constitute a complete toolkit for assessing the performance of the hybrid AI model in ECG image diagnosis, with each offering a different look at the performance of the model. According to Pham et al. (2020), the metrics used in this study are explained as follows:

a) Accuracy: refers to the measure of the true results, or the true positive and true negative, ratio compared to the total number of test cases as illustrated in Equation 2.1 below. "This is the simplest overall index for general assessment of model's performance. Zhang et al. 2020.

(Eq. 1.1)

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{FN} + \text{TN})}$$

b) Precision: The ratio of positive identifications that were correct represented by Equation 2.2. It is only informative when the cost of a false positive is high (Powers & Ailab, 2020).

(Eq. 2.2)

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

c) Recall (Sensitivity): The ratio between actual positives-those that were found-is given by Equation 2.3. The measure is of considerable importance when the cost of a false negative rate is high (Chicco et al. 2021).

(Eq. 3.3)

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

d) F1-Score: The harmonic average of precision and recall provides a single measure to balance both considerations given in Equation 2.4. It is useful when you need to balance between precision and recall (Miao & Zhu, 2022).

(Eq. 4.4)

$$\text{F1} - \text{score} = \frac{2 * (\text{Sensitivity} * \text{Precision})}{(\text{Sensitivity} + \text{Precision})}$$

e) Specificity: The proportion of actual negatives that were correctly identified is referred to as specificity or true negative rate. This is expressed in Equation 2.5, where it is of practical use under circumstances when false positives are quite costly (Gray et al. 2020).

(Eq. 5.5)

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})}$$

Where:

TP = True Positives;

TN = True Negatives;

FP = False Positives;

FN = False Negatives

f) Area Under the ROC Curve (AUC-ROC): The ROC plots the true positive rate against the false positive rate. AUC-ROC basically gives a measure of how well the model is able to discriminate between classes. An AUC of 1 represents a perfect model, and an AUC of 0.5 shows a model that has no discriminative capability (Carrington et al. 2023).

g) Confusion Matrix: A tabular representation to describe a model's classification performance. This will be able to show some metrics such as true positives, false positives, true negatives, and false negatives of a model and will provide more in-depth information about how the model works. (De Diego et al. 2022).

2.1.2. Electrocardiogram (ECG)

Electrocardiogram (ECG) is a critical diagnostic tool in cardiology, used to detect and monitor various heart conditions by measuring the electrical activity of the heart. The interpretation of ECGs requires expertise, as it involves identifying subtle changes in wave patterns that indicate different cardiac abnormalities (Cook et al. 2020). AI models have been increasingly applied to automate ECG diagnosis, analysis, and interpretation, offering high accuracy and consistency which assist cardiologists in identifying conditions such as atrial fibrillation, myocardial infarction, and ischemic heart disease, thereby improving diagnostic efficiency and patient outcomes (Lopez-Jimenez et al. 2020).

There are many types of heart diseases identifiable through an ECG image data as Figure 2.2 shows the cardiovascular disease incidence rate in Cyprus and Figure 2.3 depicting the world cardiovascular disease incidence rate which all cause deaths globally, such that if the diseases are diagnosed through intelligent systems, the efficiency of the physician diagnosis and the patient's overall health can be improved (Romiti et al. 2020). Hence, theoretical discussions are carried out regarding the model hybridization process and its application in clinical implementation for target users, which include theoretical frameworks in terms of the datasets and the technological standpoints employed.

Figure 2.2:

Cardiovascular Disease Incidence Rate in Cyprus (Lambros & George, 2018)

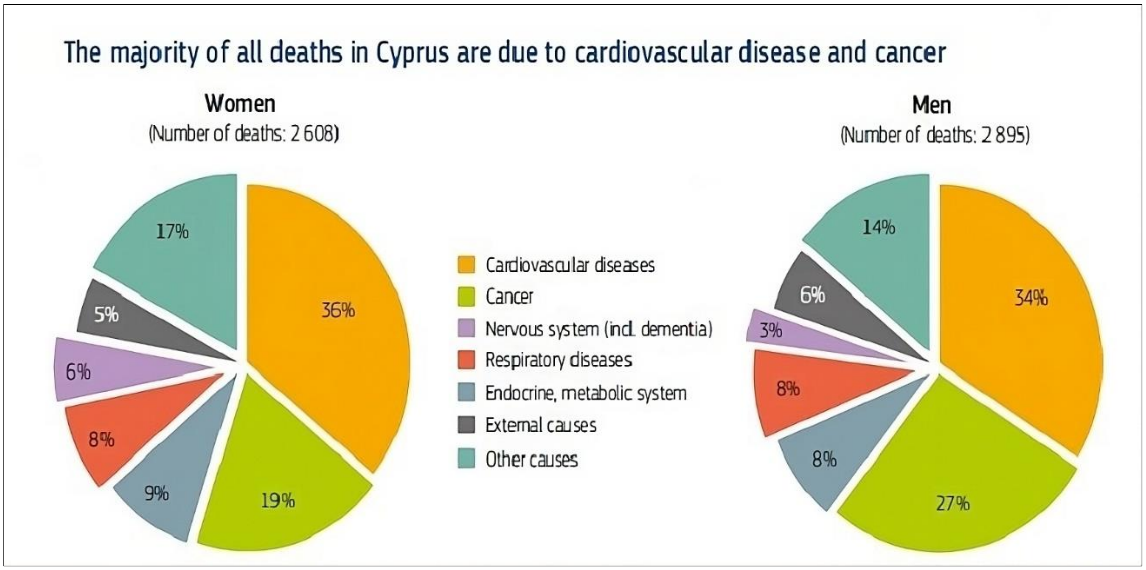
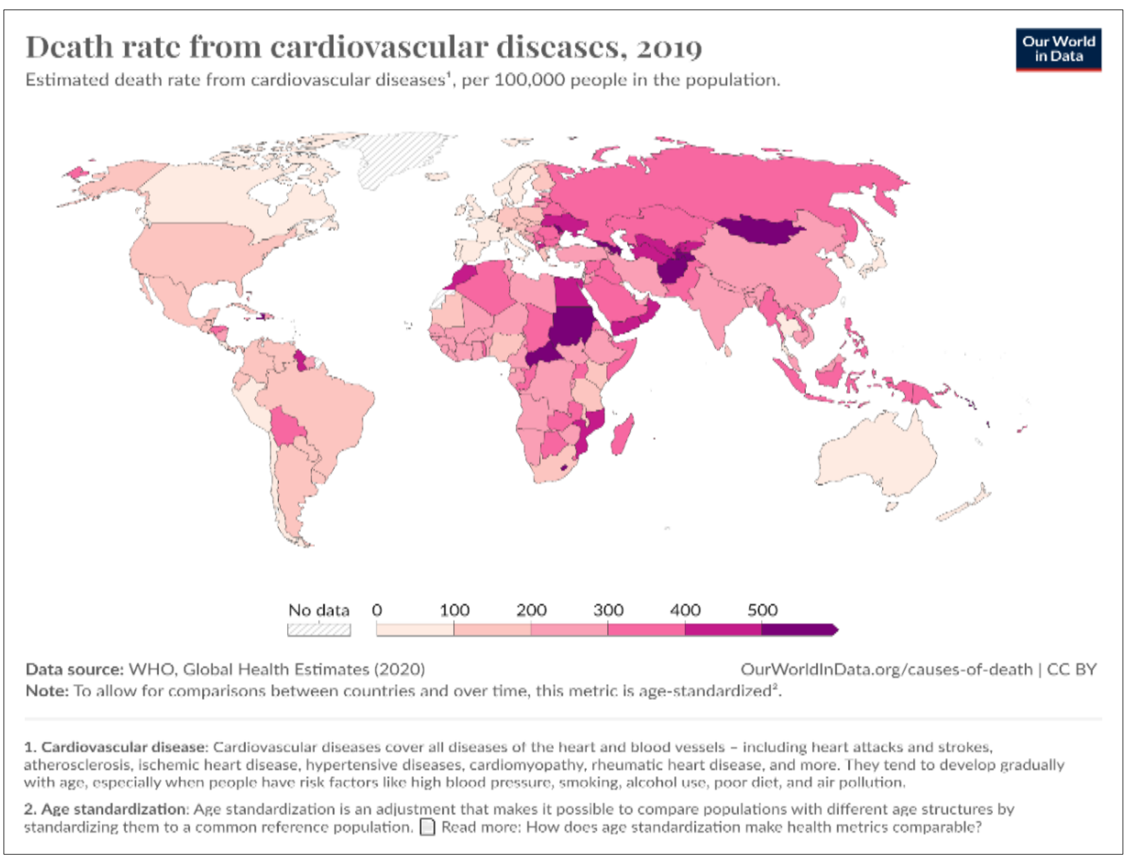


Figure 2.3:

World Cardiovascular Disease Incidence Rate (Jagannathan et al. 2019)



2.1.2.1.Hybrid Dataset Overview

The data used in this study is a combination of primary and secondary data from two sources: one from a cardiac center and the other from an online database. A combination of these two heterogeneous datasets from their respective sources makes up the hybrid data consisting of ECG images for six different classes of heart problems, namely abnormal heart condition, atrial fibrillation, ischemic heart disease, myocardial infarction, normal heart condition, and sinus bradycardia-all of which can be detected by the hybrid AI model.

a) Abnormal Heart Condition

Abnormal heart conditions encompass a variety of cardiac abnormalities that can affect the heart's structure or function, leading to impaired circulation and various clinical symptoms (Nicholson et al. 2022). These conditions can be congenital or acquired and may include arrhythmias, cardiomyopathies, and valve diseases.

b) Atrial Fibrillation

Atrial Fibrillation (AF) is the most common cardiac arrhythmia categorized by rapid and irregular beating of the atrial chambers of the heart. This condition leads to increased risks of stroke, heart failure, and other cardiovascular complications associated with the disease (Rafaqat et al. 2022).

c) Ischemic Heart Disease

Ischemic heart disease, also known as coronary artery disease, is a condition whereby the heart muscles are subjected to reduced blood flow because of narrowed or blocked coronary arteries, leading to chest pain commonly referred to as angina or myocardial infarction, popularly known as a heart attack (Hanafi et al. 2022).

d) Myocardial Infarction

The system is said to be in Myocardial Infarction-the common name 'heart attack,' which occurs by the block of blood flow at a part of the heart damaging or dying out due to insufficiency in blood flow and oxygen for the period of time. It may be caused mostly by blockages in one or more of these coronary arteries (Kumar Singh & Kumar Jat, 2021).

e) Normal Heart Condition

A normal heart condition is a healthy state of the heart in which it functions efficiently, having a regular rhythm and sufficient blood flow to meet the body's needs (Tiwari et al. 2021). The electrical activity of the heart, as recorded by an ECG, presents typical P, QRS, and T waves without abnormalities (Sahoo et al. 2020).

f) Sinus Bradycardia

Sinus bradycardia is just a below-normal heart rate, which is usually defined as less than 60 beats per minute for adults. The condition may be normal in a healthy subject, especially among athletes, or may indicate the presence of some underlying heart condition or even other types of diseases. (Venkataramanaiah & Kamala, 2020).

2.1.3. Web Application Development

2.1.3.1.Software Development Life Cycle (SDLC)

SDLC is an ordered process that gives the stages involved in the development of software right from the conception up to its deployment and its maintenance. Various SDLC model types include waterfall, V-Model, incremental, spiral, and agile by Gupta et al. (2021). All the models follow their unique methodology-for instance, a waterfall follows linearity or sequentially and spiral focuses much on the risk assessments according to Gupta et al. (2021). Agile SDLC stands out as the best due to its iterative nature, which supports continuous feedback, flexibility, and collaboration between cross-functional teams (Gupta et al. 2021). This facilitates quick adaptation toward changes, making the product better in quality, meeting user requirements more precisely.

A. Agile Software Development Life Cycle

Agile SDLC is characterized by iterative development in which the requirements and the solution evolve through collaboration between self-organizing cross-functional teams. It advocates for flexibility, customer feedback, and delivery of functional software as soon as possible. Agile methodology addresses breaking down the project into smaller, manageable units known as iterations or sprints, each producing a potentially shippable product increment.

Key Features of Agile SDLC are:

i. **Iterative Development**: Agile means the web ECG classifier application development can be performed iteratively, which denotes continuous improvement through adaptation of feedback. Each iteration comprises phases of planning, design, coding, testing, and review.
ii. **Flexibility**: The iterative nature provides much-needed room for changes in requirement, which in a research project is most probable as findings and insights can alter anytime.
iii. **Customer Collaboration**: The Agile process encourages close collaboration with the stakeholders, like cardiologists and other health professionals. The approach guarantees that the web ECG classifier application would meet the real needs of its end users.
iv. **Continuous Feedback**: Owing to regular feedback by users and stakeholders, the features and performances are refined to make the application robust and user-friendly.
v. **Rapid Delivery**: Agile aims at delivering functional portions of the application as fast as possible, for which early identification and rectification of issues have to be foreseen-essential in developing a reliable medical diagnosis tool.

2.2. Related Research

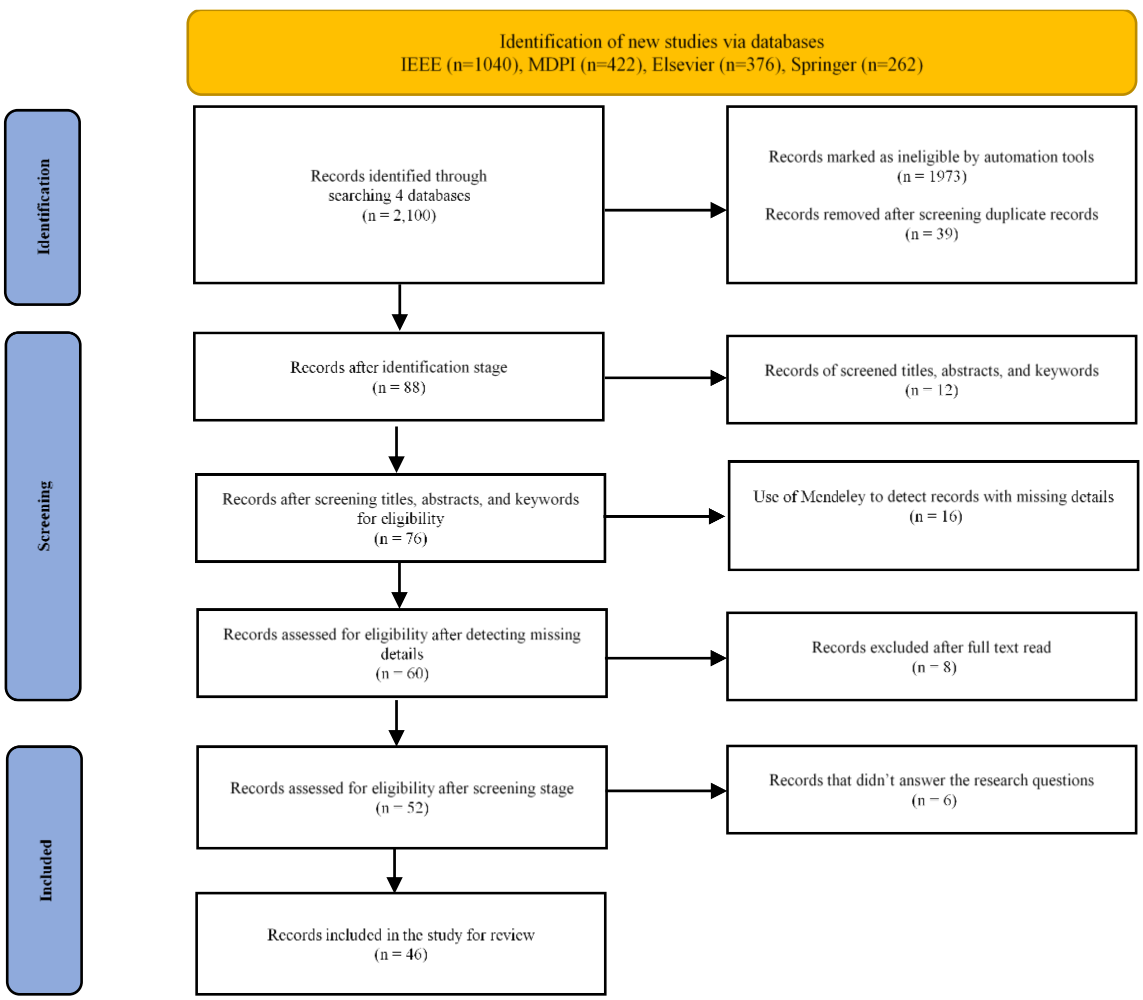
That covers the exiting research with an overview of others conducted research that comprises a critical systematic literature review, a critical bibliometric study, and critical comparative analysis.

2.2.1. Systematic Literature Review (SLR)

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework approach version 2020 by Page et al. 2021, which is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses, has been utilized for carrying out the systematic literature review on "impact of AI, ML, and DL on electrocardiograms in cardiology". The search criteria of the study are the four databases searched, and the number of records found from each database is as follows: IEEE-1040, MDPI-422, Elsevier-376, Springer-262. This resulted as a result of the year boundary set during the search, which was from 2014-2024. The keyword query for searching was formed using the logical expressions: ((Electrocardiogram OR ECG OR EKG) AND (Cardiology OR Cardio OR Heart OR Heart Problems) AND (Artificial intelligence OR Machine Learning OR Deep Learning OR Image processing)). Further, having obtained a significant number of records within the 10-year period, there was the need for selection composed of inclusion and exclusion criteria in such a way that for a record to be considered, it needed to be in one of the four selected databases, published within 2014-2024, in the English language, and related to the aim of SLR; otherwise, it would automatically be excluded. A total of 46 records were finally included for analysis in this research following the selection process as indicated in Figure 2.4.

Figure 2.4:

PRISMA Diagram

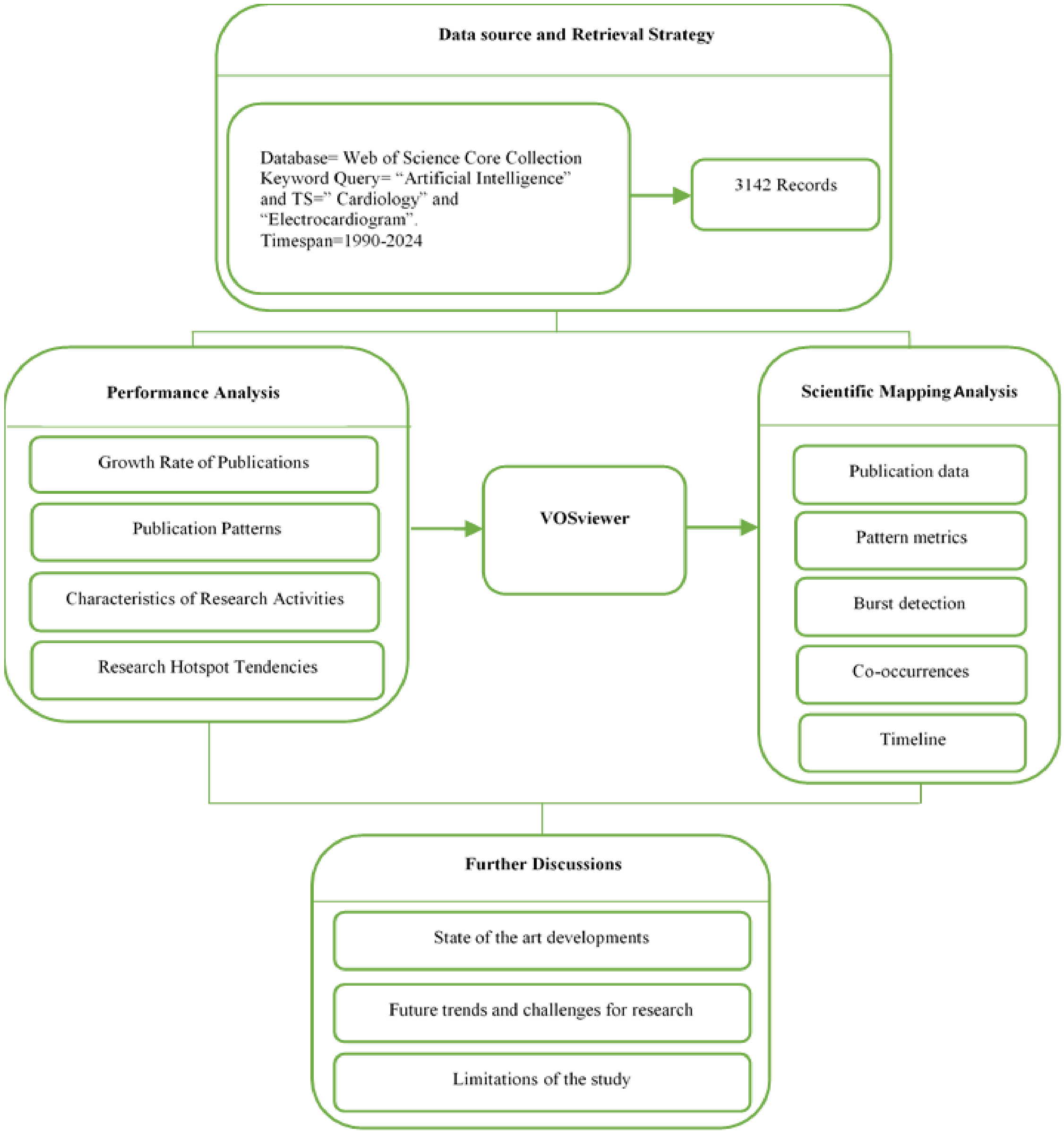


2.2.2. Bibliometric Analysis

In similar vein, a bibliometric analysis approach is implemented in this research to investigate the impact of AI, ML and DL technologies in Cardiology during the last 34 years spanning 1990-2024. This was done through the in-depth analysis of existing literature published in the Clarivate Web of Science (WoS) academic research database. The search strategy for records retrieval was done through a combination of Boolean operators (AND & OR) with the search keywords to form the query: ((“Electrocardiogram" OR "ECG" OR "EKG") AND ("Cardiology" OR "Cardio" OR "Heart" OR "Heart Problems") AND ("Artificial intelligence" OR "Machine Learning" OR "Deep Learning" OR "Image processing")), which resulted in three thousand one hundred and forty-two 3,142 records retrieved as represented in Figure 2.5. The selection process included all the retrieved records which were further analyzed using VOSviewer research software application to determine scientific mapping analysis from performance analysis. The result of the analysis shows the positive impact AI has in the field of cardiology in terms of publication characteristics; authors, their affiliations, countries, as well as top funding agencies in the field and research of cardiology.

Figure 2.5:

Bibliometric Analysis



2.2.3. Comparative Analysis

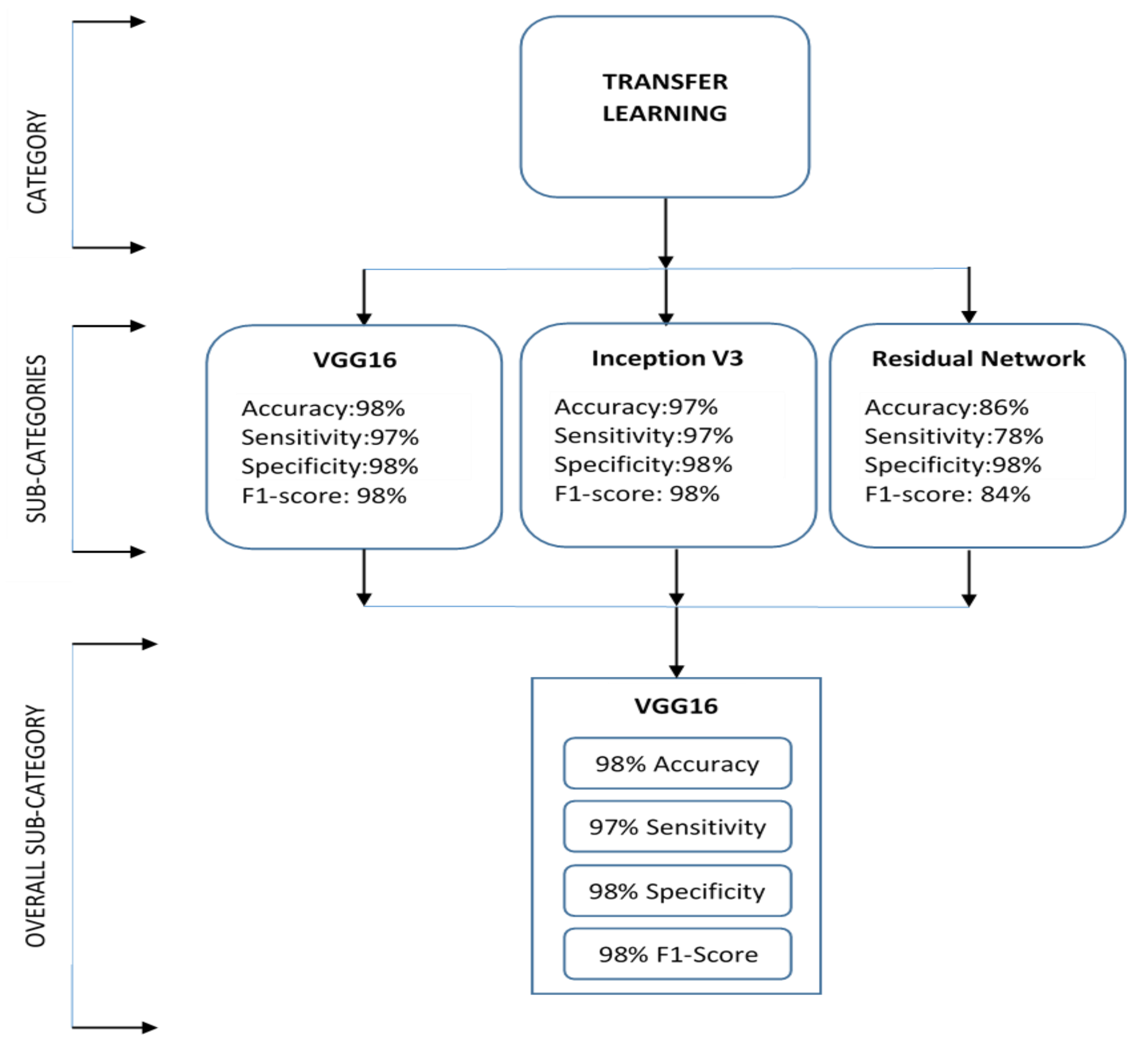
This research was performed using the method of comparative analysis, aimed at assessing the performance of different existing transfer learning models in terms of their individual strengths-accuracy, combination potential with other models presented in Figure 2.6, and how potentially they can perform in real-world applications for the classification of different heart conditions.

The most important result of this study is that, among the pre-trained CNN models, VGG16 had the overall performance, with 97% sensitivity, 98% F1-score, 98% specificity, and 98% accuracy in classifying correctly the heart conditions when compared to other transfer learning models.

The importance of the study serves as a useful guideline for the researchers and cardiologists in advancing patient cardiac diagnosis and clinical decision-making accuracy with artificial intelligence in a short time with minimum human errors. Moreover, due to the presence of valuable comparative insights in the study, as a result, the researchers can have an idea about the combinational approach towards the creation of a hybrid AI model.

Figure 2.6:

Comparative Analysis



2.2.4. The Gap in the Literature

Despite the huge strides that have been made in applying AI to ECG analysis, there still remain a number of gaps within the literature. These are important to address if the accuracy, reliability, and clinical utility of AI-driven cardiac diagnostics are to be further improved.

2.2.4.1. Limited Generalizability

Most of the studies have proven the efficacy of the AI model on specific data sets, normally from either controlled environments or single institutions (Ng et al. 2021). However, the generalization of these models to diverse real-world clinical settings is rather limited (He et al. 2020). Large-scale multicenter studies will be required to validate AI models across different populations, healthcare settings, and varying qualities of ECG recordings (Lin et al. 2024).

2.2.4.2. Data Diversity and Representation

Most of the AI models for ECG analysis were trained on non-representative datasets (Noseworthy et al. 2020).

Demographic diversity, comorbidities, and variation in ECG machines and settings are among the many factors that may affect the performance of such models, according to (Ansari et al. 2023).

Future research should focus on creating more inclusive datasets that encompass a wide range of demographic and clinical variables to ensure AI models perform well across all patient groups (Barda et al. 2020).

2.2.4.3. Lack of Integration with Clinical Workflows

Most of the AI models lack seamless integration within the existing clinical workflow. While much of the research studies dwell on the technical performances of the AI model, little attention is paid to how best these models should be integrated into the routine clinical practices (Yin et al. 2021).

Research is needed to explore the practical aspects of AI implementation, including user interfaces, clinician training, and decision-support systems that complement human expertise (Vasey et al. 2022).

2.2.4.4. Interpretability and Transparency

AI models, particularly deep learning approaches, are often criticized for their "black-box" nature, which limits interpretability and transparency (von Eschenbach, 2021). Clinicians need to understand how these models make decisions if they are to trust them and use them effectively in practice (Asan et al. 2020). The development of methods that will enhance the interpretability of AI models, such as explainable AI techniques, is required for clinician acceptance and ethical use (Shah & Konda, 2021).

2.2.4.5.Longitudinal and Temporal Data

Most studies on AI for ECG analysis use cross-sectional data, focusing on single ECG recordings (Chuang & Yang, 2024). However, heart conditions often evolve over time, and incorporating longitudinal data could enhance predictive accuracy and early detection of conditions (Liu et al. 2022). Future research should explore the use of more temporal data and other neural networks to model the progression of cardiac diseases (Mehmood et al. 2021).

2.2.4.6.Standardization and Regulatory Challenges

There is no uniformity in developing, validating, and reporting the results of AI models in healthcare (Sounderajah et al. 2021). The inconsistency of the studies reduces their reproducibility and comparability. In this regard, developing standardized guidelines and frameworks regarding AI research on ECG analysis will be highly crucial to guarantee the reliability and clinical applicability of AI tools (Nolin Lapalme et al. 2024).

CHAPTER THREE

MATERIALS AND METHODS

This chapter deals with the methodology adopted to arrive at the findings presented in this study. It includes the theoretical framework research design, data analysis, and findings report of how the hybrid AI model was developed, optimized, and deployed successfully thereby providing a valuable tool for ECG image diagnosis and enhancing cardiac care.

3.1.Overview of the Research

This consists of how the gathered data are organized and processed.

Step1: Collection of Primary datasets

Step 2: Collection of secondary datasets

Step 3: Selection of models from comparative analysis

Step 4: Splitting datasets into training, validation and testing

Step 5: Selection of parameters for model training (for example: 80%, 20%)

Step 6: Validation of model performance on dataset (performance metrics)

Step 7: Testing the model using unseen primary dataset

Step 8: Confirming the testing result with cardiologist analysis

Step 9: Saving the trained model

Step 10: Integrating the trained model into web application development

Step 11: Creation of an ECG Classifier Web Application powered with PWA

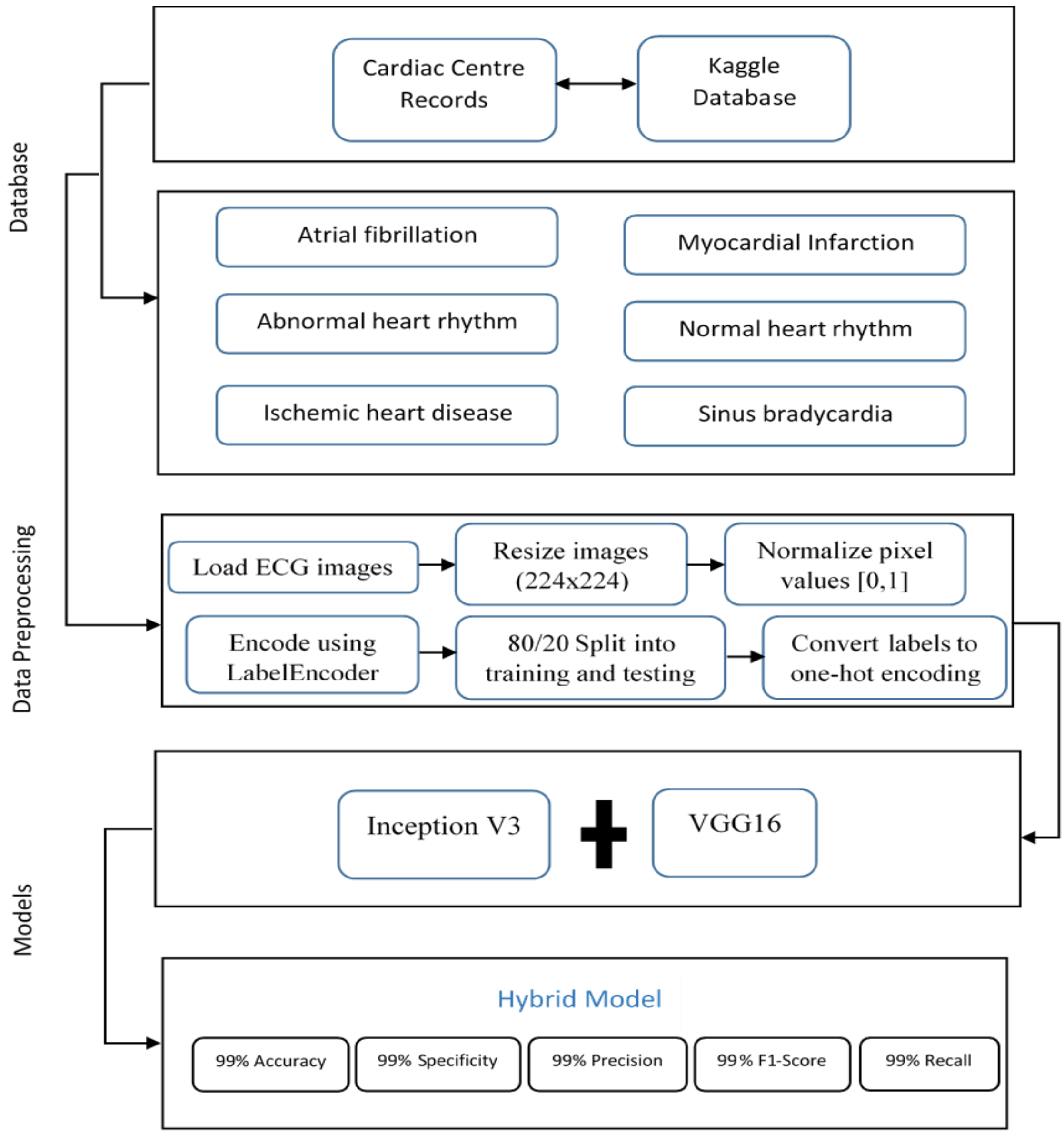
Step 12: Creation of user manual for clinical practitioners

3.2.Proposed Model of the Research

The conceptual framework for this study outlines the integration of advanced AI models to improve the diagnosis and interpretation of ECG images. This framework guides the development, implementation, and evaluation of a hybrid AI model that combines Inception V3 and VGG16 architectures, leveraging their strengths to achieve superior performance in classifying heart conditions for clinical implementation as shown in Figure 3.1.

Figure 3.1:

Proposed Hybrid AI Model Research Design

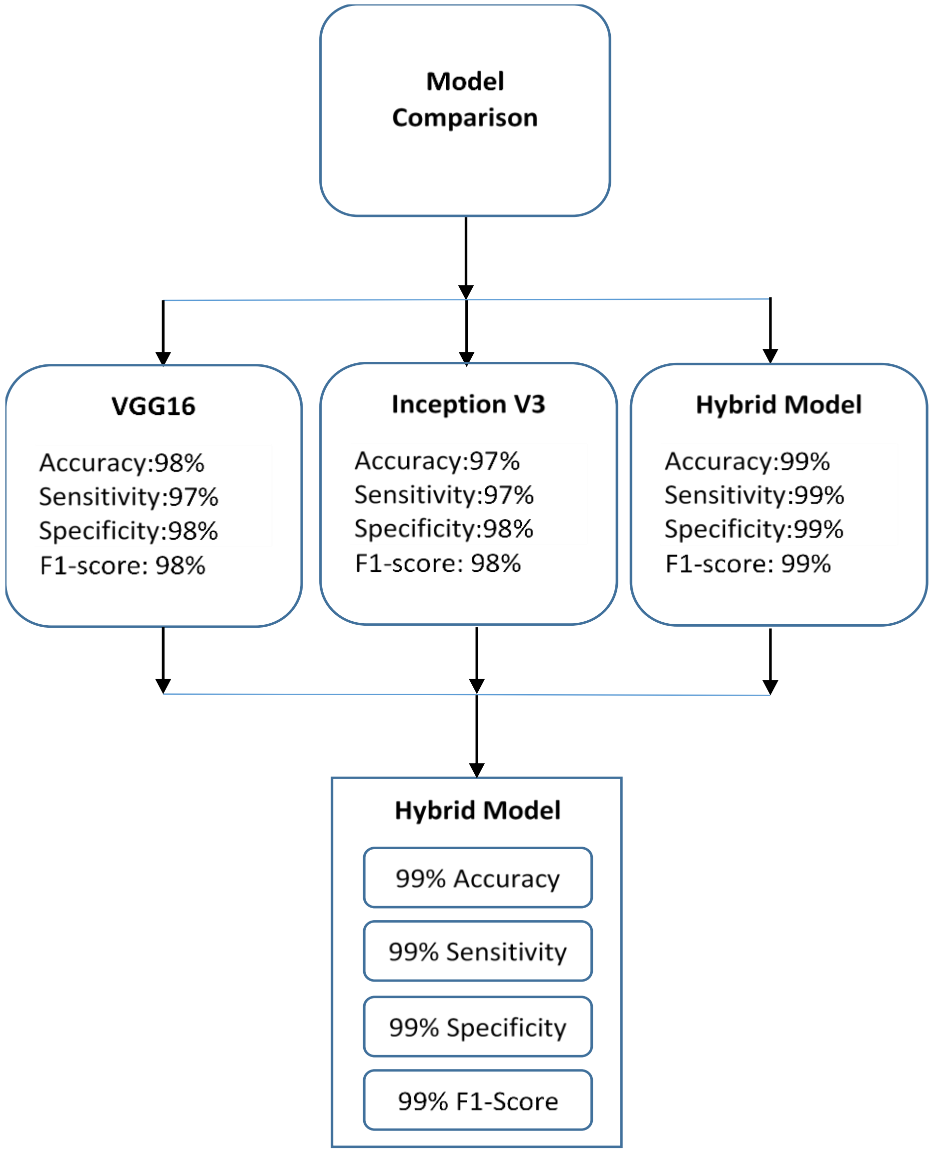


3.2.1. Hybrid AI Model Architecture Overview

The hybrid AI model developed in this study leverages the strengths of two well-established convolutional neural network (CNN) architectures, Inception V3 and VGG16, to enhance the accuracy and robustness of ECG image classification. By combining these models, the hybrid approach aims to capitalize on their complementary features, thereby improving performance metrics across various heart conditions. The hybrid AI model is made up of VGG16 model and Inception V3 model. VGG16 model attention enhancement further enhances the cardiologist domain knowledge by highlighting areas of pathological interest for further detailed analysis (feature importance) and facilitates the integration into existing hospital-end systems for use with the domain knowledge embedded modules (Tian & Fu, 2020). Comparatively, Inception V3 focuses on reducing computational costs and improving efficiency through modularization, factorized convolutions, and auxiliary classifiers and it is more complex with varying convolutional filter sizes and inception modules (Cong & Zhou, 2023). However, while VGG16 is simpler and easier to understand by focusing on depth through many small convolutional layers, it has a straightforward and uniform structure compared to the more intricate Inception V3 (Taye, 2023). Moreover, these architectures represent different philosophical deep neural networks design, with VGG16 emphasizing simplicity and depth (Shah et al. 2023; Younis et al. 2022), and Inception V3 focuses on efficiency and multi-scale feature extraction (Niu et al. 2021). The hybrid AI model approach is a potential enhancement repository of developed visualization strategies for identifying the exact anomalies in ECG images, which provides the apparent diagnostic capabilities of individual diagnosis predictions and the preferred knowledge-based path from the study to the clinical implementation and practice. Furthermore, Figure 3.2 show the hybrid model performance against its individual constituent models (VGG16 and Inception V3).

Figure 3.2:

Proposed Hybrid AI Model Versus Standalone Models



A. Inception V3

Inception V3 is a deep convolutional neural network architecture that was introduced as an improvement as it builds on the principles introduced by the original and previous Inception model version (also known as GoogLeNet) model (Bhavani et al. 2022). It is designed to optimize computational cost efficiency and classification accuracy through a series of factorized convolutions and carefully crafted inception modules (Cong & Zhou, 2023). Inception V3's ability to capture intricate features at multiple scales makes it highly effective for complex image classification tasks, including medical imaging applications.

The Inception architecture has undergone several iterations, each improving upon its predecessor:

a) Inception v1 (GoogLeNet): Introduced in 2014, Inception v1 utilized a novel module called the inception module, which allowed the network to learn multi-scale features by applying convolutional filters of different sizes (Xu et al. 2022).

b) Inception v2: This version introduced Batch Normalization and optimized inception modules, allowing for reduced computational complexity without losing accuracy; thus, the network became faster and more efficient (Bose & Kumar, 2020).

c) Inception v3: It integrated factorized convolutions and much heavier regularization than earlier ones. It made the model much more accurate and also more efficient; hence, ranking as one of the best models for image recognition (Jena et al. 2022).

i. Inception V3 Architecture

Following is the major component and features of the architecture of Inception V3:

a) **Inception Modules**: The inception modules try to capture the multi-scale information by applying different types of convolution, such as 1×1, 3×3, and 5×5, and pooling operations in parallel as shown in Figure 3.3. The outputs from each module is concatenated along the depth dimension (Thangaraj et al. 2024).

b) **Factorized Convolutions**: Inception V3 uses factorized convolutions instead of larger convolutions to reduce the computational cost, such as breaking a 3x3 convolution into two 1x3 and 3x1 convolutions (Sholapur & Indiramma, 2022).

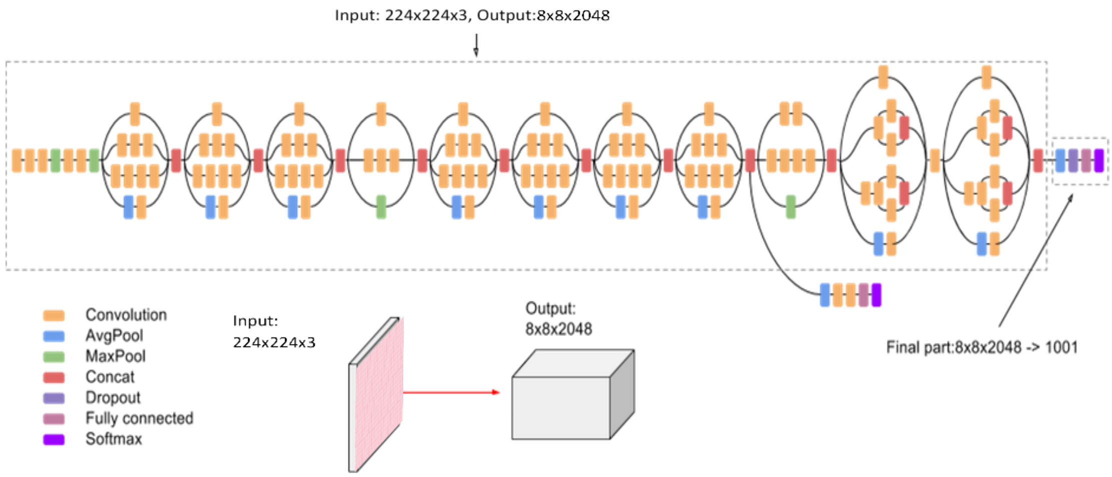
c) **Auxiliary Classifiers**: Auxiliary classifiers are added to the intermediate layers to help propagate useful gradients back through the network and improve training (Kumar et al. 2022).

d) **Grid Size Reduction**: The reduction techniques are applied to reduce the grid size without losing the spatial dimensions. It includes the use of strided convolutions and pooling operations. Sravani et al. (2023).

e) **Batch Normalization**: Batch normalization is used to stabilize the training and also speed up the process. Meena et al. (2023).

Figure 3.3:

Inception V3 Diagram (adopted from (Chulu et al. 2019))



B. VGG16

VGG16 is another impactful CNN model architecture that was mainly brought out for its simplicity for depth. Developed by the Visual Geometry Group of the University of Oxford, VGGNet introduced its first form back in 2014 with two authors going by the name of K. Simonyan and A. Zisserman in a paper called "Very Deep Convolutional Networks for Large-Scale Image Recognition," showing its emergence. It ranked very high amongst those that placed the top lot for the challenge (Han et al. 2019; Zou et al. 2023). The model was one of the highlights of the ImageNet Large Scale Visual Recognition Challenge, ILSVRC 2014, where it attained a top-5 accuracy of 92.7% (Humayun et al. 2022). VGG16 has been influential in many deep learning models that have emerged since then. It contains 16 weight layers, consisting of 13 convolutional layers followed by 3 fully connected layers as shown by Rao & Mahantesh, 2021. VGG16 architecture is characterized and emphasized by its simplicity and depth with small (3x3) convolutional filters that are consistent throughout the network, allowing it to capture and learn intricate fine-grained and hierarchical features across different layers in images (Younsi et al. 2024). Since its inception, this architecture has been adopted into a wide array of image recognition tasks because of its strong performance and straightforward architecture design as represented in Figure 3.4.

i. VGG16 Architecture

Following is a rundown of the main components and features of the VGG16 architecture:

a) **Convolutional Layers**: VGG16 solely relies on 3x3 convolutional layers stacked on top of one another. The use of small filters ensures capturing the fine-grained spatial details (Albardi et al. 2021).

b) **Depth**: VGG16 is made up of 16 weight layers: 13 convolutional layers, 5 pooling layers, and 3 fully connected layers (Mascarenhas & Agarwal, 2021).

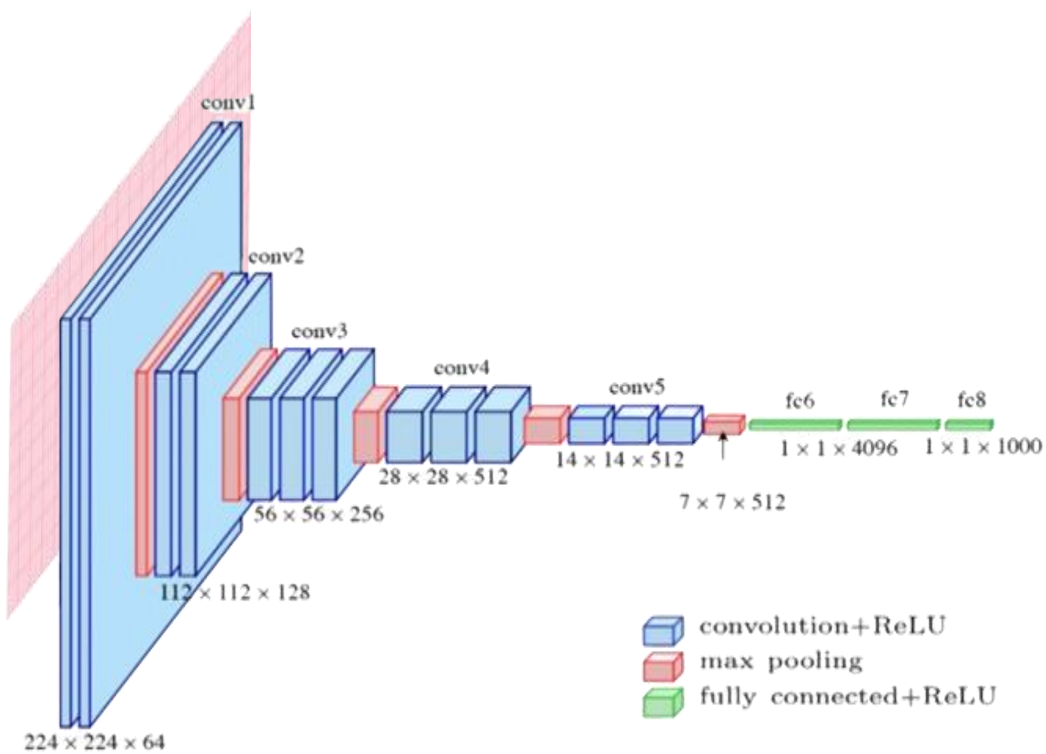
c) **Pooling Layers**: Max-pooling is applied after some of the convolutional layers to reduce the spatial dimensions (2x2 pooling with a stride of 2) (Sowmya et al. 2023).

d) **Fully Connected Layers**: The network ends with three fully connected layers, where the last layer outputs the classification scores.

e) **ReLU Activation**: Rectified Linear Units (ReLU) are used as the activation function for all convolutional and fully connected layers.

Figure 3.4:

VGG16 Diagram (adopted from (Barriada & Masip, 2022))



3.2.1.1.Hybrid AI Model Integration

The hybrid AI model integrates the Inception V3 and the VGG16 AI model architectures and leverages their respective unique strengths. The integration has been done parallel to both networks, where the ECG images are fed independently into each network. The two networks extract features that are then concatenated, ensembled, and passed through additional layers to provide the final classification. This helps the proposed hybrid AI model to represent a larger feature space, which can help in improving its performance in the proper classification of ECG images across six different classes for heart conditions. The integration process of these models includes:

a) **Feature extraction**: Inception V3 and VGG16 both input ECG images and generate high-level features from the images.

b) **Feature concatenation**: Further, the output features from both the models are then concatenated to create one full featured vector.

c) **Classification Layers**: The concatenated features are then fed into fully connected layers, followed by a softmax layer for the final classification, which provides a clear and normalized probability distribution across all classes in multiclass classification.

This hybrid architecture is proposed to improve the generalizability and accuracy of the model by leveraging the complementary strengths of Inception V3 and VGG16 to enhance performance along different metrics, including accuracy, sensitivity, specificity, precision, and F1-score.

i. Performance and Benefits

The hybrid AI model performs much better compared to stand-alone models with high efficiency in the classification of ECG images. The multi-scale feature extraction of Inception V3 working in conjunction with a deepened net of VGG16 for deep feature learning brings excellent results in the current proposed hybrid model. The hybrid AI model is, therefore, superior in diagnosing heart conditions by integrating such architectures hence appropriate for clinical applications.

3.2.2. Image Processing vs. Time Series or Signal Processing for ECG Data

While ECG data can be processed as time series or signals, using image processing offers several distinct advantages, especially with the hybrid AI model VGG16 + Inception V3. The hybrid AI model is better suited for ECG image processing compared to other models and processing types due to its superior feature extraction, multi-scale learning capabilities, high performance metrics, computational efficiency, and the advantages of image-based analysis.

a) **Rich Feature Representation**: Image processing allows the model to utilize the visual representation of ECG data, capturing not only temporal patterns but also spatial relationships and morphological details that are essential for accurate diagnosis (Wong et al. 2020).

b) **Model Robustness**: Image-based models, such as the hybrid VGG16 and Inception V3, are robust to variations in ECG signals that might arise due to noise or artifacts. This robustness ensures consistent performance across different data sources and patient conditions (Mohd Sagheer & George, 2020).

c) **Visualization and Interpretability**: Image processing allows better visualization and interpretability of ECG data by clinicians themselves, as stated by Sutanto (2024). The model's visual output will directly correspond to the actual ECG tracings and hence can be interpreted for better understanding and building trust in AI diagnostic capability.

d) **Transfer Learning and Pre-Trained Models**: Image processing by Salehi et al. (2023) allows for transfer learning on pre-trained models, such as large image datasets like ImageNet. This reduces training time and resources greatly, which increases model accuracy and generalization at the same time, according to Yu et al. (2022).

3.3.Datasets

By getting ethical approval from the ethics committee to be able to use available datasets from consulting with cardiologists at NEU cardiac centre and accessing a reputable online database, two thousand eight hundred and fifty-four (2,854) ECG image datasets were obtained in total, with six hundred and six (606) records of randomized heart conditions gotten from Near East University cardiac centre and two thousand two hundred and forty-eight (2248) records of abnormal heart condition, atrial fibrillation, ischemic heart disease, myocardial infarction, normal heart condition, and sinus bradycardia gotten from Kaggle online database repository (https://www.kaggle.com/datasets/rewanhishamsultan/ecg-images-modified, and https://www.kaggle.com/datasets/joonrisse/ecg-original-segmented-images) as shown in Table 3.1. Both sources served as the primary and secondary data respectively, making it possible to create a hybridized dataset with every obtained dataset anonymized and belonging to a particular heart condition class as shown in Figure 3.5.

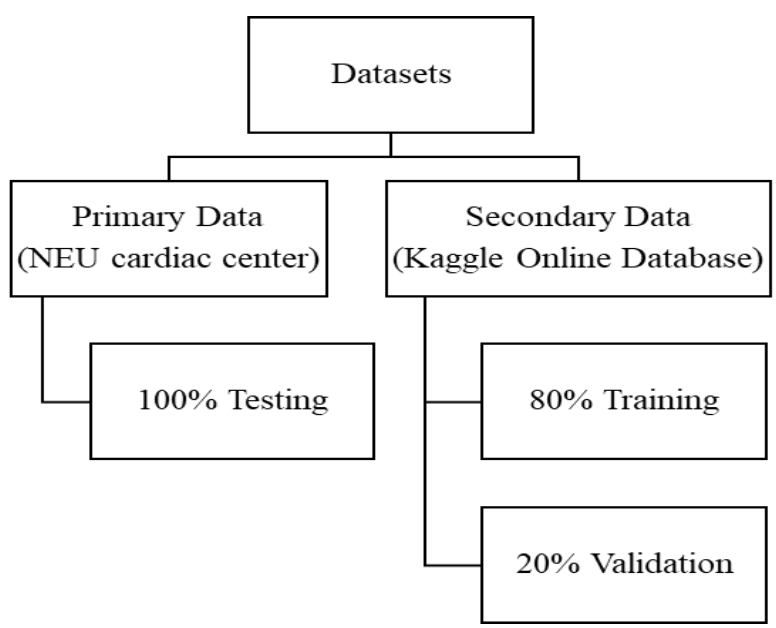
Table 3.1:

Dataset Sources

Sources	Records
Primary Datasets (Near East University Hospital)	606
Secondary Datasets (Kaggle database)	2248
Total	**2854**

Figure 3.5:

Dataset Overview



3.3.1. Preprocessing

In terms of preprocessing, standard preprocessing steps were applied. They included resizing images, normalizing pixel values, and cropping 10% of the ECG image data at the backend in the Web App for clinical implementation. The secondary hybrid data were labelled and categorized based on the 6 cardiac classes as shown in Table 3.2. This was concurrently done with data cleaning by ensuring that every included ECG image record is clearly visible and of high quality for use during training.

Table 3.2:

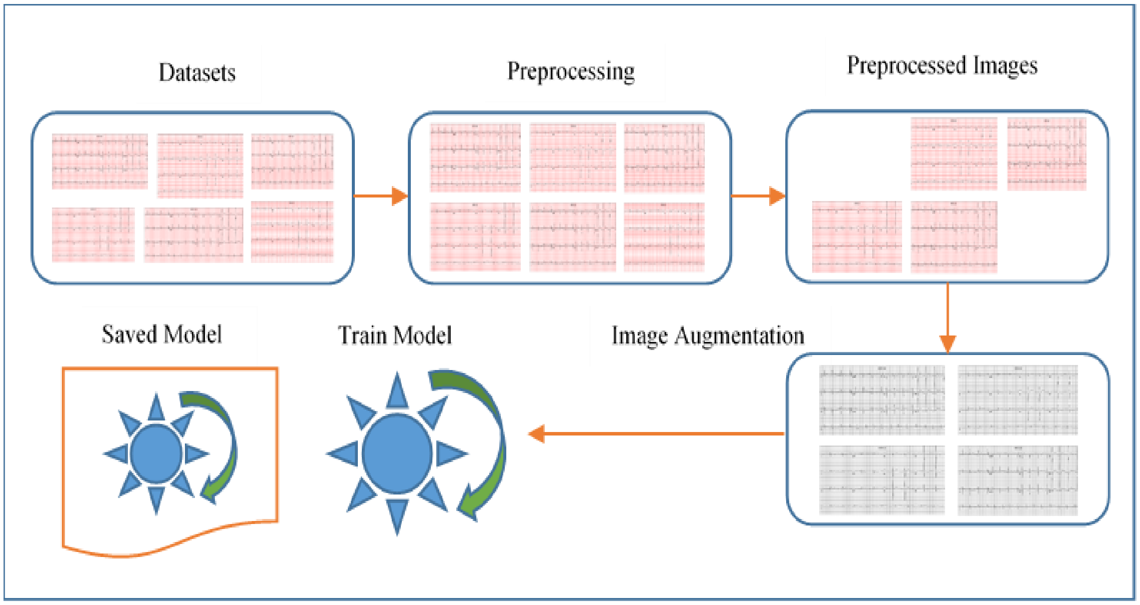
Secondary Dataset Cardiac Classes

Secondary Data Cardiac Classes	Records
Abnormal	345
Atrial fibrillation	121
Ischemic	673
Myocardial infarction	351
Normal	396
Sinus bradycardia	362
Total	**2248**

By the end of the cleaning process, no data was excluded from the batch as all data were of high quality. Furthermore, augmentation techniques were applied on both primary and secondary data as displayed in Figure 3.6. This included, rotation of wrong image datasets layout, scaling of the datasets, dataset flipping and in some instances, and noise removal on some data, all of which ensure the datasets is a good fit for the hybrid AI model training, as good quality data produces good result.

Figure 3.6:

Model Process Cycle



3.4. Model Development

This section comprises of the architectural build-up of the hybrid model. It includes:

A. Inception V3 Architecture: Utilized for its efficient and effective multi-scale feature extraction capabilities (Joshi & Nayak, 2022).

i. **Inception V3 Model Overview**: Inception V3 is a sophisticated convolutional neural network designed for efficiency and performance, incorporating inception modules that process input at multiple scales simultaneously. It combines 1x1, 3x3, and 5x5 convolutions, leveraging different kernel sizes to capture diverse features efficiently. Its auxiliary classifiers and batch normalization layers enhance optimization and reduce overfitting. The model excels at extracting diverse and comprehensive features, contributing to its effectiveness in this hybrid architecture.

ii. **Inception V3 Layers**: Inception V3 relies on an inception module that processes an image using different-sized filters all in one layer. This architecture has:

- **Input layer:** (224, 224, 3) (RGB image)
- **Convolutional layers and MaxPooling:**
  - Convolution (3x3 kernels)
  - Convolution (7x7 kernels)

- Inception modules with 1x1, 3x3, 5x5 convolutions, and 3x3 MaxPooling in parallel

- **Batch normalization:** Maintains stability and speeds up convergence
- **Reduction modules:** Dimension reduction to prevent overfitting and manage computational complexity
- **Global average pooling layer (instead of flattening in VGG16)**
- **Output Layer (used in pre-trained form):** Fully connected layer for ImageNet classes (1000 neurons)

Only the convolutional layers and global average pooling were used (include_top=False), enabling feature extraction without classification.

B. **VGG16 Architecture**: Used for its depth and simplicity in learning fine-grained features as mentioned by Li & Monga, 2020.

i. **VGG16 Model Overview**: VGG16 is a deep convolutional neural network characteristically simple and structured, containing 16 weight layers composed of convolutional and fully connected layers. It makes use of very small 3 × 3 filters and uses an identical architecture in extracting low-level and high-level patterns of spatial features from images. VGG16 performs very well on applications that involve fine-grained image recognition because of the layer-by-layer stacking of its layers; thus, it is suitable for feature extraction in this research.

ii. **VGG16 Layers**: VGG16 architecture is a straight-forward convolution neural network. It only follows simple stacking of convolutional layers, max-pooling layers, and fully connected layers.

- **Input layer:** (224, 224, 3) (RGB image)
- **Convolutional layers:**
  - Block 1: 2 convolutional layers, 64 filters each, kernel 3x3, followed by MaxPooling 2x2
  - Block 2: 2 convolutional layers, 128 filters each, kernel 3x3, followed by MaxPooling 2x2
  - Block 3: 3 convolutional layers, 256 filters each, kernel 3x3, followed by MaxPooling 2x2
  - Block 4: 3 convolutional layers (512 filters each, 3x3 kernel), followed by

MaxPooling (2x2)

- Block 5: 3 convolutional layers (512 filters each, 3x3 kernel), followed by MaxPooling (2x2)

- **Flattening layer**
  - Fully connected layers: Three Dense layers with 4096, 4096, and 1000 nodes
  - Dropout layers: Improve generalization
- **Output Layer (used in pre-trained form):** Final fully connected layer (1000 neurons for classification in imagenet)

The fully connected layers were excluded (include_top=False), keeping only the convolutional layers to generate feature maps.

C. **Details of Feature Extraction**: The flattened output after the feature extraction layers of VGG16 contributes 7x7x512 = 25,088 features, while the flattened output after the feature extraction layers of InceptionV3 contributes 5x5x2048 = 51,200 features.

D. **Hybrid AI Model Integration**: The hybrid model concatenates these outputs, resulting in 25,088 + 51,200 = 76,288 features, which are subsequently passed to custom dense layers for classification. Combined features from both models are concatenated and fed into additional layers for final classification.

E. **Hybrid AI Model Overview**: The hybrid model integrates two pre-trained deep learning architectures, VGG16 and InceptionV3, to classify ECG images into six heart condition categories. These architectures serve as feature extractors where their convolutions are frozen, leveraging their diverse representations of visual patterns. The extracted features are flattened, concatenated, and passed through a custom-built dense network for classification followed by the final softmax output. The hybrid approach enhances the model's ability to identify complex and subtle features in the ECG images, ultimately leading to robust and accurate predictions.

i. **Hybrid Model Architecture Layers**: The hybrid model combines extracted features from VGG16 and Inception V3.

- **Input Layer:** (224, 224, 3) (RGB image)
- **Feature extraction:**
  - VGG16: Features from the convolutional blocks were flattened.

  - Inception V3: Features from the convolutional blocks/global average pooling were flattened.
  - The custom hybrid model concatenates the flattened features obtained from the pre-trained VGG16 and Inception V3 networks.
  - Both feature sets are inputs to the subsequent custom layers.
- **Concatenation Layer:** Combines flattened outputs from both models.
- **Fully Connected Layers (Custom Layers):**
  - Dense Layer 1: A fully connected layer with 256 neurons and ReLU activation. This layer learns the combined features from VGG16 and Inception V3.
  - Output Layer: A dense layer with 6 neurons, corresponding to the number of output classes, using softmax activation for classification.

These are the added layers (custom parts) applied after combining the pre-trained features extracted from VGG16 and Inception V3.

The hybrid approach leverages the high-level features extracted from both VGG16 and Inception V3 for a more robust prediction model.

3.4.1. Model Training

This section comprises of data splitting, training the models, algorithm and pseudocode of the hybrid model, and hyperparameter fine-tuning and optimization.

3.4.1.1. Data Splitting

In this experiment, the image dataset was divided into three subsets, namely, the training set, validation set, and testing set. From the secondary data, it was allocated that 80% went to the training set and 20% to the validation set, while 100% of the primary data went into the testing set. It does this because the division is adapted from Mohammad et al. 2022, ensuring that the models were learning well from the training data while being validated and tested on unseen data. The secondary datasets will be used for training the model and supporting the validation of model selection and hyperparameter tuning, while the primary datasets will be used for testing and evaluating model performance on unseen data.

3.4.1.2. Training the Models

Models used in this paper, such as Inception V3 and VGG16, were trained with the secondary data as training set, while the hyperparameters tuning was performed on the validation set of secondary data, which are represented in Figure 3.7. These models have gone through an optimization process by minimizing the loss function, classifying ECG images into six distinct classes for various heart conditions.

3.4.1.3. Algorithm/Pseudocode of the Hybrid Model

This section describes the step-by-step process for the implementation of the hybrid model in classifying ECG images into six different conditions of the heart. They include:

Input: Folder containing ECG images divided into six labelled classes
Output: Classified ECG images into six heart conditions.

A. Data Preprocessing

Load ECG images from the specified folder.

Resize images to 224×224224 \times 224224×224 resolution.

Normalize pixel values to range [0,1][0, 1][0,1].

Encode class labels using LabelEncoder.

Split the dataset into training and testing sets (80/20 split).

Convert labels to one-hot encoding format.

B. Model Construction

- Load pre-trained VGG16 and InceptionV3 models with ImageNet weights:
    - Exclude their top layers (set include_top=False).
- Freeze the pre-trained layers to retain learned features.
- Pass the input image data through both models separately:
    - Input size: (224,224,3) (224, 224, 3) (224,224,3).
- Flatten the outputs from both models into feature vectors.
- Concatenate the feature vectors.
- Add custom dense layers for classification:
    - Dense Layer 1: Fully connected layer with 256 neurons and ReLU activation.
    - Output Layer: Fully connected layer with 6 neurons (for six classes) and softmax activation.
- Compile the model using the Adam optimizer with categorical cross-entropy loss and accuracy as a metric.

C. Model Training

• Fit the hybrid model on the training data:

- Epochs: 10
- Batch Size: 32
- Learning rate: 0.001
- Validation Data: Testing set.

D. Model Evaluation

• Evaluate model performance on the testing set using the following metrics:

- Accuracy.
- Sensitivity and specificity (calculated using confusion matrix).
- Classification report for precision, recall, and F1-score.

E. Prediction on Unseen Data

• Load the trained hybrid model from file (hybrid_model.keras).

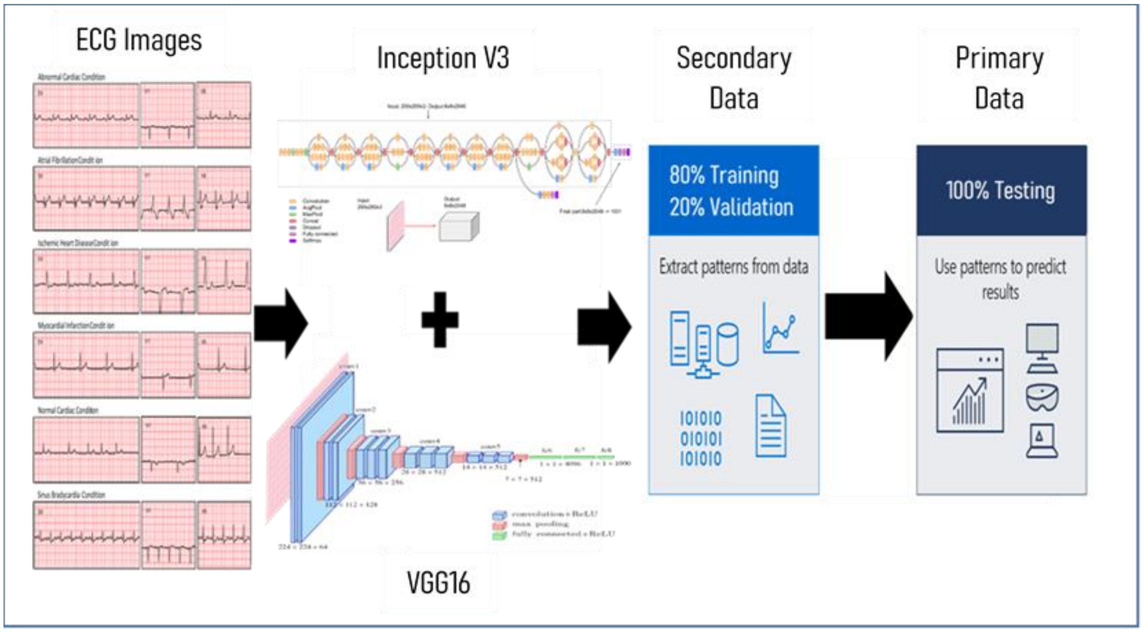
• For unseen data:

- Preprocess each image (resize, normalize, batch dimension).
- Predict class probabilities for the image using the model.
- Identify the class with the highest probability as the predicted label.
- If the probability is below 50%, classify as "Unknown."

End of Algorithm.

Figure 3.7:

Model Training



3.4.1.4. Hyperparameter Fine-Tuning and Optimization

Hyperparameters with 0.001 learning rate, 32 batch size, 10 number of epochs, and Adam optimizer type were tuned using the validation set. This process aimed to improve and optimize the model's performance and prevent overfitting. Techniques like early stopping and dropout were also employed to enhance model generalization.

a) Architectural Experiments

The hybrid AI model architecture was experimented on for the identification of the optimal configuration for ECG image classification. This included modifying the number of layers, the types of layers (convolutional, pooling, etc.), and their respective parameters.

b) Hyperparameter and Optimization Algorithms

Furthermore, different sets of hyperparameters were tested systematically to find the best combination. Adam Optimization algorithm was implemented as it provided the best performance for the hybrid AI model.

c) Transfer Learning and Ensemble Learning

Transfer learning was utilized by leveraging pre-trained weights from the Inception V3 and VGG16 models and this was coherently bonded together using a majority voting ensemble learning technique which involved combining the predictions of both InceptionV3 and VGG16 models to create a more reliable final prediction thereby improving the overall accuracy and robustness of the hybrid AI model.

3.5.Model Evaluation

3.5.1. Performance Metrics

The performance of the hybrid AI model was assessed using accuracy, precision, recall, and F1-score. These metrics gave an overall analysis of the model's ability in correctly classifying ECG images. A confusion matrix of the different heart conditions was drawn to analyze the performance of the Hybrid AI model VGG16 + Inception V3. It included the true positives, false positives, true negatives, and false negatives that helped in ascertaining the areas which the model performed well and those that needed improvement.

3.5.2. Superiority of the Selected Hybrid AI Model (VGG16 and Inception V3)

The VGG16 and Inception V3 combined hybrid AI model was chosen due to its best performance in ECG image processing for several reasons:

a) **Feature Extraction**: VGG16, with a deep architecture and small 3x3 convolutional filters, is very effective at extracting fine-grained features from images. This capability to extract minute image features is important in identifying subtle patterns in ECG images indicative of specific heart conditions.

b) **Multi-Scale Feature Learning**: Inception V3 is designed with inception modules that will enable the model to capture multi-scale features at the same level. This kind of multi-scale approach enhances the model's capability in recognizing complex patterns in ECG images over different resolutions.

c) **Performance Metrics**: The hybrid AI model achieved high accuracy of 99% in metrics related to the assessment of sensitivity, specificity, precision, and F1-score. These metrics mean that standalone models such as ResNet, DenseNet, MobileNet, AlexNet, and U-Net, though having strength and promise in general image classification, lack the combined strengths offered by VGG16 and Inception V3 while handling the ECG images.

d) **Computational Efficiency**: The hybrid AI model uses the efficient architecture of Inception V3 in combination with a simpler one from VGG16, balancing the computational demand with accuracy well enough to make practical applications possible in clinical environments where test accuracy and speed are crucial.

3.6.Implementation and Deployment

3.6.1. Software Development Life Cycle (SDLC)

It summarizes the development life cycle of a web ECG classifier application presented in Fig. 3.7, based on the guide about the main principles of SDLC and in the field of ECG image classification using the Inception V3-VGG16 hybrid model. This structured process helped to be systematic and go smoothly from initial conception to deployment and maintenance stages. The Agile Software Development Life Cycle would be the fittest of them all in the case of developing the web application of the ECG classifier for image classification of ECG, as described in the research. Iterative, flexible, and collaborative-just perfect for the vibrant dynamic evolving needs of the research project and the delivery of a robust and user-centric diagnostic tool.

3.6.1.1. Agile SDLC Implementation in Web Application Development

This focuses on software development life cycle using the Agile methodology approach based on its flexibility to web application development that emphasizes collaboration, adaptability, and rapid delivery as shown in Figure 3.8.

i. **Planning**: Initial project planning defines the main functionalities for which the web ECG classifier application must be used, such as image preprocessing, model integration, classification, and result visualization.

ii. **Requirements Analysis**: Requirements are gathered from cardiologists and all related stakeholders with respect to realistic demands.

iii. **Design**: Design the architecture of the web ECG classifier application with a user interface and an integrated hybrid AI model. In this stage, mockups and prototype development can also be included.

iv. **Development Iterations**: Divide application development into small iterations where each iteration may be devoted to embedding some specific functionality or feature within the application. For example,

Iteration 1: Basic UI design and establishment of the server using Flask.

Iteration 2: Integration of the hybrid AI model; implementation of the image classification feature. Iteration 3: To develop the feature of results visualization and reporting.

v. **Testing**: Heavy testing at each iteration to find bugs and fix them. Testing will include unit tests, which ensure that each component works properly, and integration tests, which ensure that the application works seamlessly.

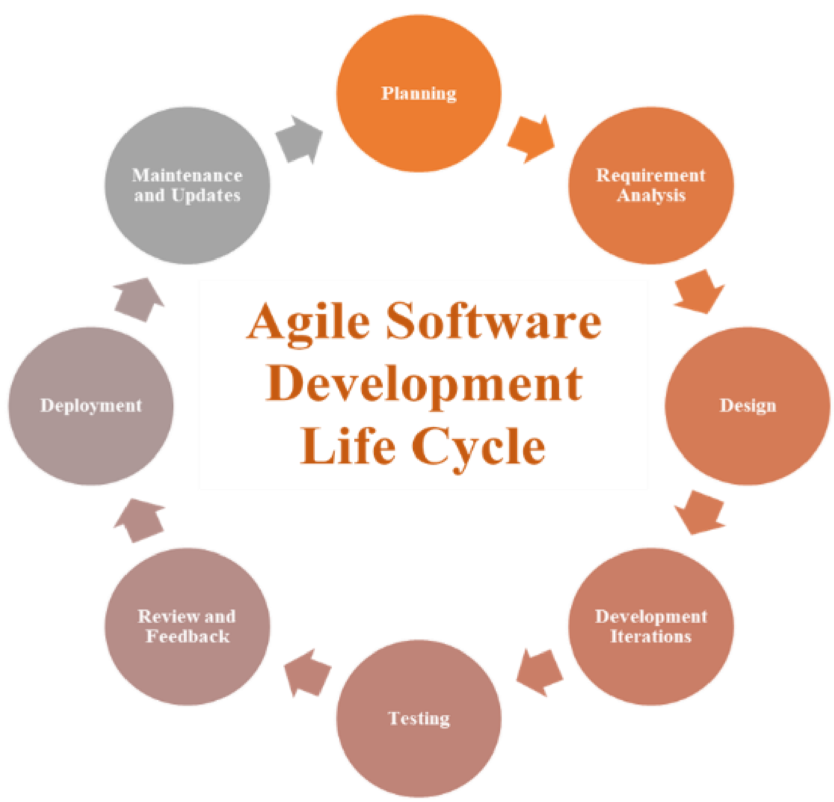
vi. **Review and Feedback**: After each iteration, present the developed features to the stakeholders and take feedback. Further refinement and improvements in the application are done using this feedback in subsequent iterations.

vii. **Deployment**: The web ECG classifier application is deployed in a staging environment for final testing. Once validated, it is deployed in a live clinical setting.

viii. **Maintenance and Updates**: Agile allows for ongoing maintenance and updates as per users' feedback and requirements change. Frequent updates maintain the applicability and usefulness of the application.

Figure 3.8:

Agile Software Development Life Cycle



3.6.2. Clinical Deployment

Web ECG classifier application deployment has been done via following tools and environments:

a) *Visual Studio Code Integrated Development Environment (IDE)*: This strong and versatile IDE was used for writing and debugging the code of the application.

b) *Jupyter Notebook*: This was the interactive environment used for coding, training, and refining the hybrid AI model.

c) *CMD*: The command line interface was used for running scripts and managing the deployment process.

3.6.2.1. Coding Frameworks

This consists of frontend and backend steps and approach process for the development of the web application.

a) Front-End Development

The web ECG classifier application is built to be appealing and user-friendly for clinicians and users to easily upload ECG images and retrieve diagnostic results. It was created with a combination of HTML for structuring, CSS for presentation, JavaScript for the interactive elements, the Bootstrap framework for responsiveness, and Python for integrating the machine learning model. Technologies used:

i. *HTML*: Organized the content and structure of web pages.

ii. *Cascading Style Sheets (CSS)*: Designed the web pages to ensure a professional look and consistency throughout.

iii. *JavaScript*: Designed the web pages to be interactive and dynamic.

iv. *Bootstrap Framework*: Boosted responsiveness and aesthetics in the web ECG classifier application, ensuring it functions well on multiple devices.

v. *Backend (Python)*: Integrate saved model into the frontend, process the uploaded ECG images, show results for its classification.

b) Back-End Development

The Flask server developed the back-end of the application, which plays a very important role in managing the logics and data processing of the application. It provides an interface for handling requests, integrating the machine learning model, and communicating between the front-end and back-end. The following tasks are handled by the Flask server:

i. Receive and handle image upload requests from the front-end.

ii. Preprocess the uploaded ECG images to prepare them for classification.

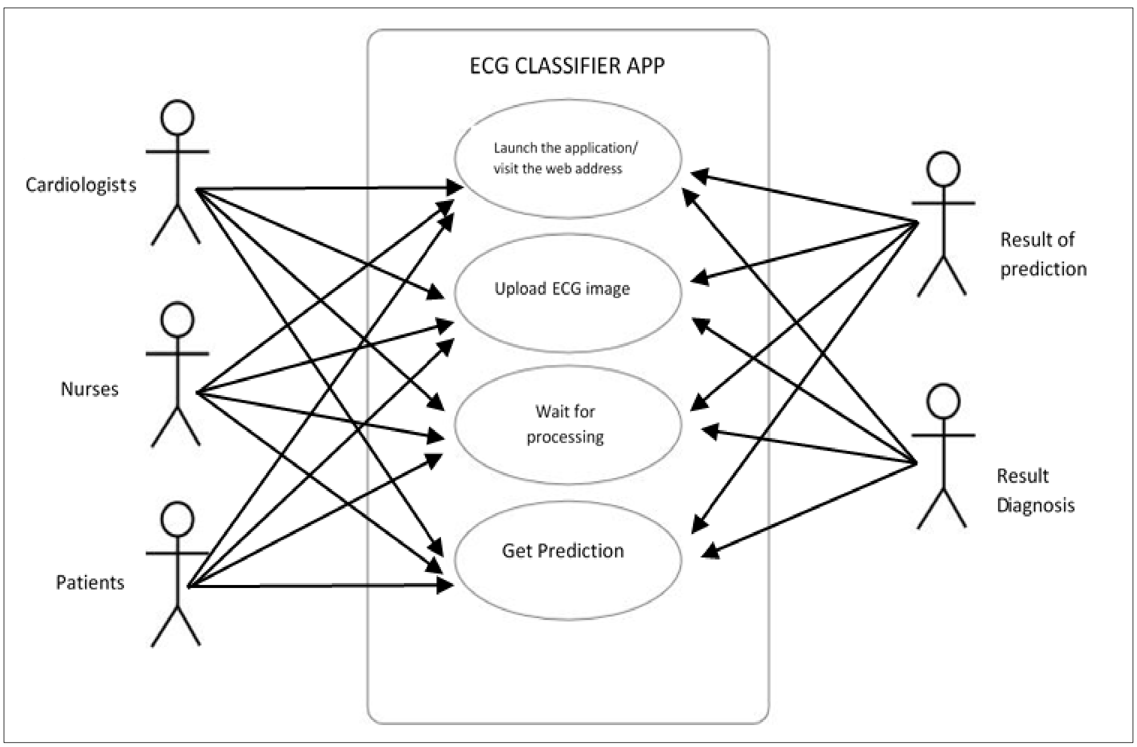
iii. Executing the hybrid Inception V3-VGG16 models to classify ECG images.

iv. Returning the classification results to the front-end for display to the user.

By integrating these technologies and adhering to the SDLC framework, the web ECG classifier application was designed to be robust, efficient, and user-friendly, providing an effective tool for ECG image classification in clinical practice as shown in the use case diagram in Figure 3.9.

Figure 3.9:

Use case diagram



3.6.3. Saving the Model

After the model training completion, the final hybrid AI model was saved using the Keras library: hybrid_model.save('hybrid_model.keras'). This facilitated easy deployment and future use.

3.6.4. ECG Classifier Application Development

The developmental requirements of the web application had to integrated to the cardiac center using the following:

3.6.4.1. Flask Server Deployment

The model was deployed on a Flask server, making it accessible as a web ECG classifier application. This server handled requests from users, processed the input ECG images, and returned the classification results. Thus enabling healthcare professionals to input ECG images and obtain predictions as displayed in Figure 3.10.

3.6.4.2. Integration with Cardiac Center

The Cardiologists employed this web ECG classifier application at the cardiac center. 10% of image data was cropped to keep the anonymity of the patients. With this deployment, the cardiologist was able to make use of model predictions with assured anonymity of the patients.

3.6.4.3. Handling Uncertain Predictions

In the cases where model prediction was zero probability, the system was designed in a way to flag for further review by a cardiologist, and none of those issues could get passed on.

3.6.5. Computer Configuration

The computational requirements of the hybrid model had to be a judicious mix of performance and efficiency. These were as follows:

3.6.5.1. Hardware Specifications

The operating system (OS) on which training and testing were performed was Windows 10, on an Intel i7 processor with 8GB RAM and 512GB Storage. For real-time usage, clinically, a GPU-based system was used to bring the inference times down.

3.6.5.2. Optimization Techniques

Some techniques that were employed to further optimize the performance of the model without excessive computational overhead are batch normalization, learning rate scheduling, and dropout. These methods ensure scalability without significant hardware upgrades.

3.6.5.3. Inference Time

The average inference time per image is about 30 milliseconds, hence can be used in real-time diagnostic settings.

3.6.5.4. Implementation Requirements

The hybrid model was implemented using scientific computing methodology Jupyter Notebook based on Anaconda's package management tool version 2.6, which distributes Python programming language and other popular libraries such as TensorFlow, Keras, and scikit-learn.

3.6.6. Implementation

3.6.6.1. User Interface

A friendly interface has been developed that would permit easy uploading of ECG images by the healthcare professional for getting the predictions. The interface was designed in such a way that it is easy to use, and the results were presented in an understandable format.

3.6.6.2. Visualization

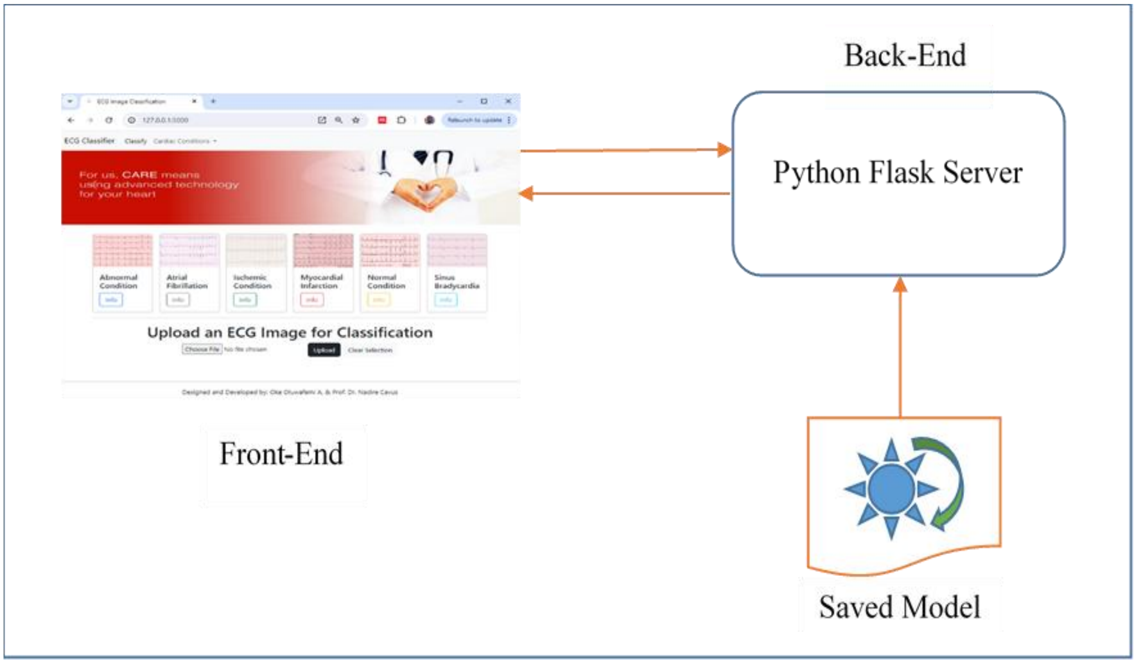
The web ECG classifier application included visualization tools to display the classification results clearly. A Progressive Web App (PWA) version was also developed for mobile devices, enhancing accessibility for healthcare professionals on the go.

3.6.6.3. Final Deployment

This model, after performing considerably well, was then deployed in a real clinical environment, and an easy-to-use interface was present for real-time diagnosis and interpretation. The deployment of the web ECG classifier application in a real clinical environment required the application to be handy enough.

Figure 3.10:

Flask Server Development



CHAPTER FOUR

RESULTS

The result of implementing the hybrid AI model Upon completing the methodological processes in chapter 3 presented in this chapter. It consists of tabular representations and visual representations to enhance the performance interpretation.

4.1.The Hybrid AI Model Performance

The hybrid AI model classification report displayed in Table 4.1 shows the overall metrics of the 6 heart conditions in terms of accuracy, macro average (avg) and weighted average (avg). The Accuracy shows the ratio of correctly predicted instances to the total instances. Here, the model's accuracy is 0.99, indicating it correctly classified 99% of the instances. The Macro avg implies the unweighted mean of precision, recall, and F1-score across all classes. This treats all cardiac classes equally, regardless of the number of actual occurrences of the class in the dataset (support). Hence, having a result of 99% Precision, 99% Recall, and 99% F1-score.

On the other hand, the weighted avg means the weighted mean of precision, recall, and F1-score across all classes, where the weights are the number of instances for each cardiac class. Thus, this gives more importance to classes with more instances. It also had an output of 99% Precision, 99% Recall, and 99% F1-score, 99% Sensitivity, 99% Specificity. Finally, the classification report of this study indicates that the hybrid AI model has learned to classify each cardiac class as it performs exceptionally well across all classes, leading to an overall high performance with very high precision, recall, and F1-scores. The macro and weighted averages being the same suggests a well-balanced performance across all classes, regardless of their frequency in the dataset.

Table 4.1:

Hybrid AI Model Classification Report

	precision	recall	f1-score	support
Abnormal	1.00	0.97	0.99	74
Atrial Fibrillation	0.95	1.00	0.97	36
Ischemic heart disease	1.00	1.00	1.00	127
Myocardial Infarction	1.00	1.00	1.00	69
Normal	0.97	1.00	0.99	72
Sinus bradycardia	1.00	0.97	0.99	72
accuracy			0.99	450
macro avg	0.99	0.99	0.99	450
weighted avg	0.99	0.99	0.99	450

4.1.1. Training and Validation Metrics

This contains the plots of the training and validation accuracy and loss over the 10 epochs. The first plot shows the accuracy, and the second plot shows the loss as displayed in Figure 4.2 and Figure 4.3 respectively.

4.1.2. Epochs

With a batch size of 32, 10 epochs and 57 steps per epoch, overall, both training and validation accuracies have increased significantly from the first epoch to the last epoch as shown in Figure 4.1. The hybrid AI model shows a consistent improvement, suggesting effective learning and convergence. Hence, the consistency between high training and validation accuracies indicates that overfitting is minimal, meaning the model is likely to perform well on new data.

Figure 4.1:

Epoch Snapshot

```
Epoch 1/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1564s 26s/step - accuracy: 0.7505 - loss: 8.7488 - val_accuracy: 0.9133 - val_loss: 0.7711
Epoch 2/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1342s 23s/step - accuracy: 0.9195 - loss: 0.7672 - val_accuracy: 0.9200 - val_loss: 0.9262
Epoch 3/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1152s 20s/step - accuracy: 0.9738 - loss: 0.2000 - val_accuracy: 0.9378 - val_loss: 0.2355
Epoch 4/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1120s 20s/step - accuracy: 0.9817 - loss: 0.1361 - val_accuracy: 0.9867 - val_loss: 0.1014
Epoch 5/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1094s 19s/step - accuracy: 0.9886 - loss: 0.0406 - val_accuracy: 0.9844 - val_loss: 0.1192
Epoch 6/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1075s 19s/step - accuracy: 0.9828 - loss: 0.1706 - val_accuracy: 0.9711 - val_loss: 0.3696
Epoch 7/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1116s 20s/step - accuracy: 0.9719 - loss: 0.2674 - val_accuracy: 0.8311 - val_loss: 2.3867
Epoch 8/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1076s 19s/step - accuracy: 0.9496 - loss: 0.6290 - val_accuracy: 0.9156 - val_loss: 0.5445
Epoch 9/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1096s 19s/step - accuracy: 0.9654 - loss: 0.4856 - val_accuracy: 0.9911 - val_loss: 0.0610
Epoch 10/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 1085s 19s/step - accuracy: 0.9908 - loss: 0.2336 - val_accuracy: 0.9911 - val_loss: 0.1481
15/15 ━━━━━━━━━━━━━━━━━━━━ 261s 15s/step
Test Accuracy: 0.9911111111111112
```

4.1.3. Training and Validation Accuracy

Figure 4.2 shows how the training accuracy starts at around 0.75 and increases steadily to nearly 0.99. Validation accuracy starts at around 0.91, with a small increase over the epochs, reaching nearly 0.99 by the end. Validation accuracy provides a good indication of the model's performance on unseen data. The overall accuracy, particularly the final validation accuracy, is 99.11%. This high accuracy indicates that the model performs well on the validation set and suggests it will likely perform well on new, unseen ECG images as well.

Figure 4.2:

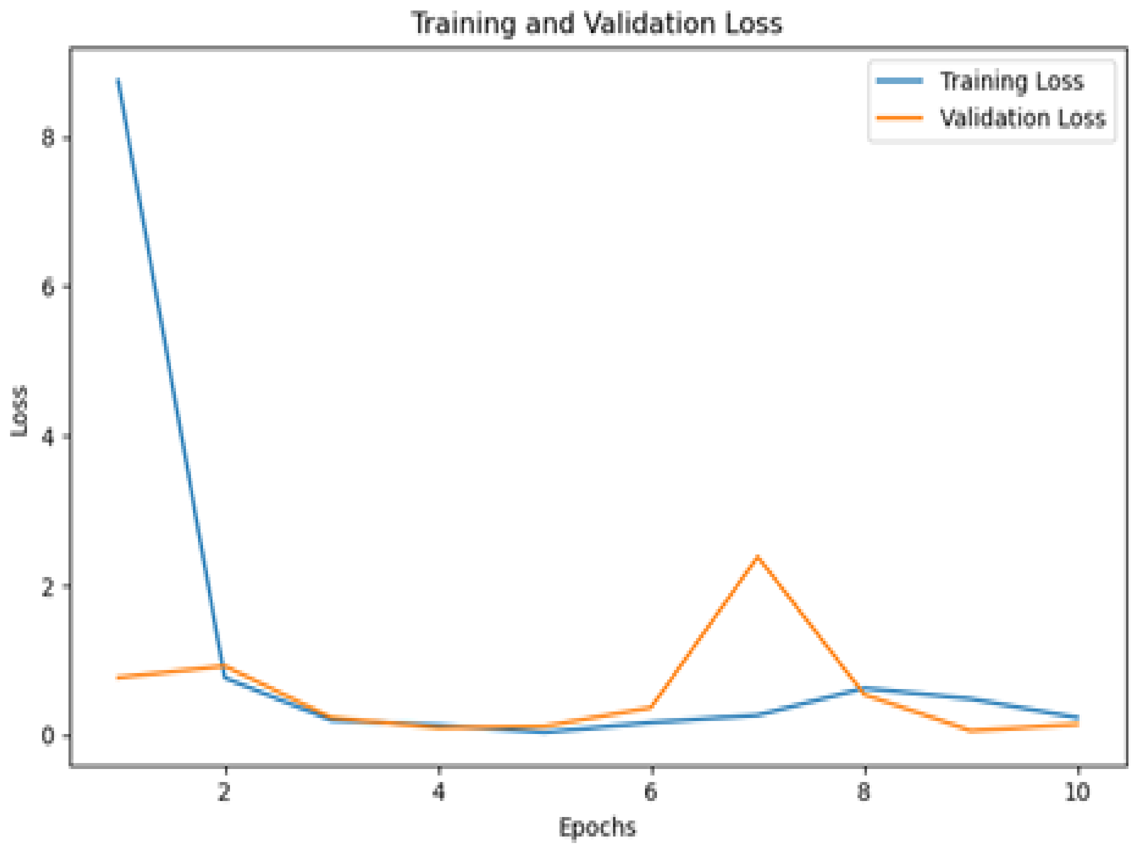
Training and Validation Accuracy

4.1.4. Training and Validation Loss

Figure 4.3 shows how the hybrid AI model training loss starts high at around 8.75, drops sharply in the second epoch, and continues to decrease with some fluctuations. Validation loss starts relatively low at around 0.77, fluctuates over the epochs, but ends up low at around 0.15.

Figure 4.3:

Training and Validation Loss



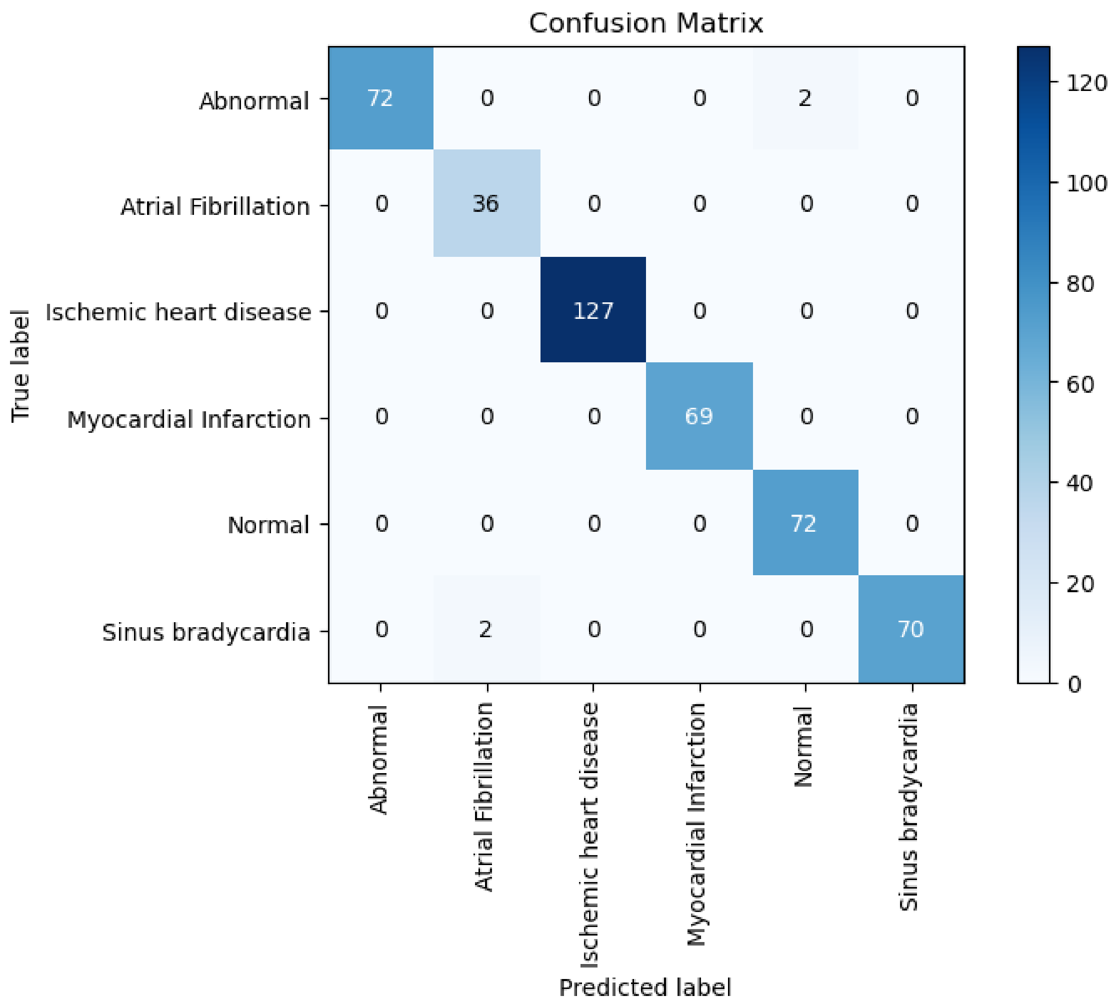
4.1.5. Confusion Matrix

A confusion matrix is a summary of prediction results on a classification problem. The matrix shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each class. With each rows representing the true cardiac classes and each column representing the predicted classes as displayed in Figure 4.4.

The analysis of the confusion matrix shows that for Abnormal cardiac class, 72 instances correctly predicted as Abnormal with 2 instances of Abnormal misclassified as Normal and there were no other misclassifications. For Atrial Fibrillation cardiac class, 36 instances correctly predicted as Atrial Fibrillation with no misclassifications. For Ischemic heart disease cardiac class, 127 instances correctly predicted as Ischemic heart disease with no misclassifications. For the Myocardial Infarction cardiac class, 69 instances correctly predicted as Myocardial Infarction with no misclassifications. For the Normal cardiac class, 72 instances correctly predicted as Normal and no misclassifications. For the Sinus bradycardia cardiac class, 70 instances correctly predicted as Sinus bradycardia with 2 instances of Sinus bradycardia misclassified as Atrial Fibrillation and there were no other misclassifications.

Figure 4.4:

Confusion Matrix

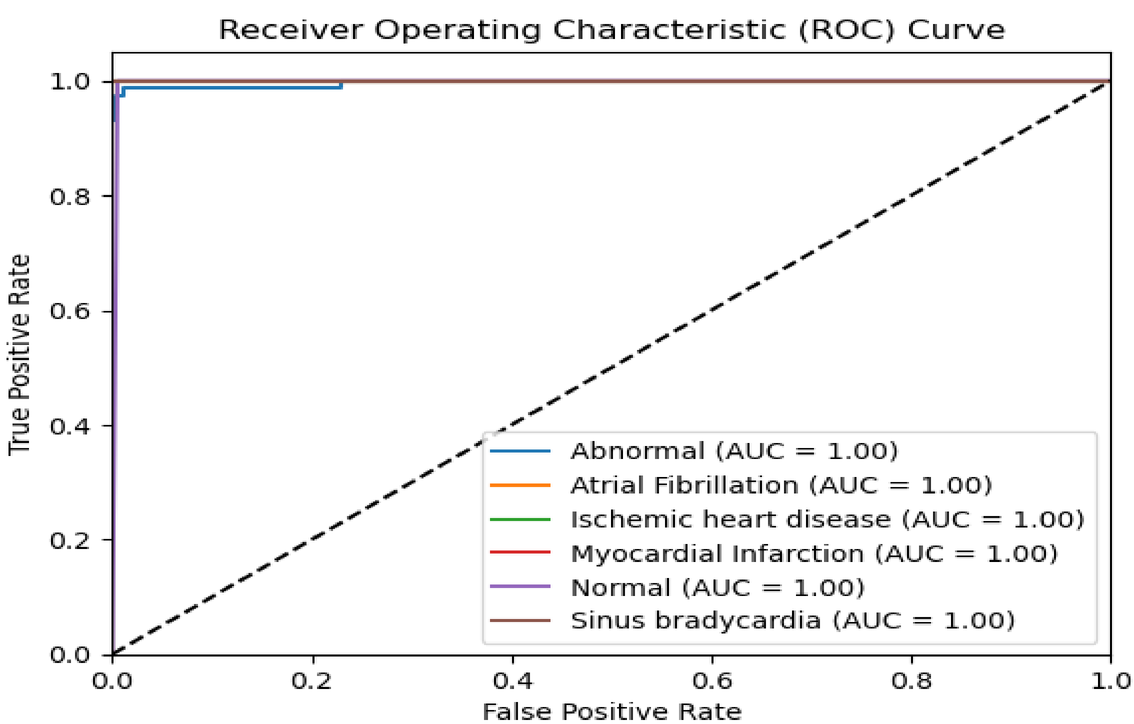


4.1.6. AUC-ROC Curve

The AUC-ROC curve from Figure 4.5 shows the classification performance of the hybrid AI model across the six heart conditions classes. Thus, the AUC scores shows that All cardiac classes have an AUC score of 1.00 which is an indication of perfect classification performance. This means the hybrid AI model perfectly distinguishes between the positive and negative classes for each heart condition. There are no false positives or false negatives for most of the cardiac classes. In addition, the ROC curve for each class reaches the top left corner of the plot and this point represents 100% sensitivity (True Positive Rate) and 0% false positive rate (False Positive Rate), which is the ideal performance for a classifier. Meanwhile, the dashed diagonal line represents the performance of a random classifier (which is not the hybrid AI model but rather a theoretical concept to illustrate the baseline performance of random guessing). The ROC curves for all classes being far above this line signifies the excellent performance of the hybrid AI model, and this level of performance is ideal and indicates that the hybrid AI model is highly reliable for classifying these heart conditions.

Figure 4.5:

AUC-ROC Curve

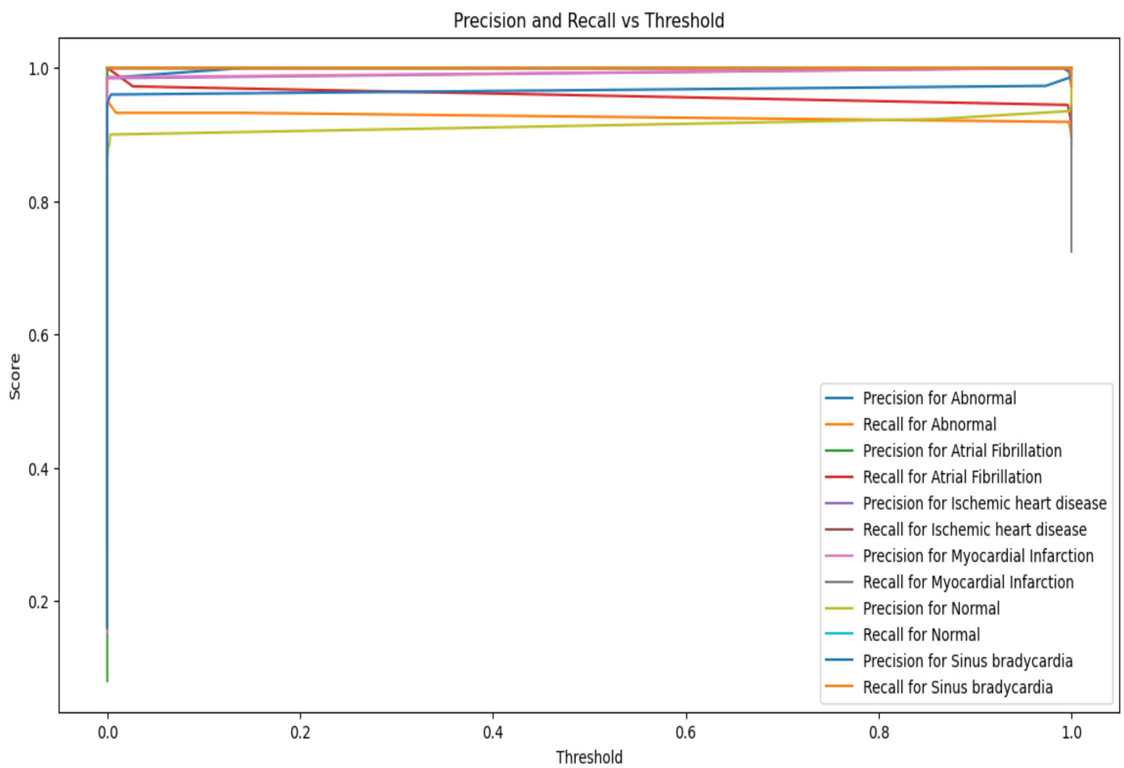


4.1.7. Precision and Recall Vs Threshold Graph

The model exhibits high performance and a near-perfect precision and recall for all classes across a wide range of thresholds. This suggests a robust classifier that is highly effective in distinguishing between different heart conditions. In terms of the model reliability, the high precision and recall values across thresholds indicate the model's reliability in making accurate predictions for all heart conditions and accurate in classifying ECG images into the respective heart conditions as shown in Figure 4.6.

Figure 4.6:

Precision and Recall Vs Threshold Graph



4.1.8. Train-Test Split

In this study, the dataset was divided into two subsets: training and testing. The training set comprised 80% of the data and was used to train the hybrid model, while the testing set constituted the remaining 20% and was used to evaluate the model’s performance. This splitting approach ensures that the model is trained on one subset of data while its accuracy and generalizability are tested on unseen examples from the other subset. The absence of cross-validation in this study means the model's evaluation is limited to a single split, emphasizing the importance of balanced and representative data distributions in both subsets to avoid biases in performance assessment.

4.2. Testing the Hybrid AI Model with Primary Data

This entails clinically testing the trained and validated model from the secondary data with unseen primary data obtained from the cardiac center as shown in Table 4.2. The model clinical performance testing classification shows that the NEU cardiac center result distributes mainly across ischemic heart disease, sinus bradycardia and atrial fibrillation. However, there are instances in the result which is depicted as unknown classification as a result of having a probability of 0.00% as visualized in the scatter plot shown in Figure 4.7 and prediction statistics in Figure 4.8. Thus the hybrid AI model recognizes the ECG image as a heart condition, however, no classification can be made. This could be a label error with the secondary dataset as a result of the heart condition not being part of the 6 previously trained heart conditions.

Figure 4.7:

NEU Cardiac Center Scatterplot Classification

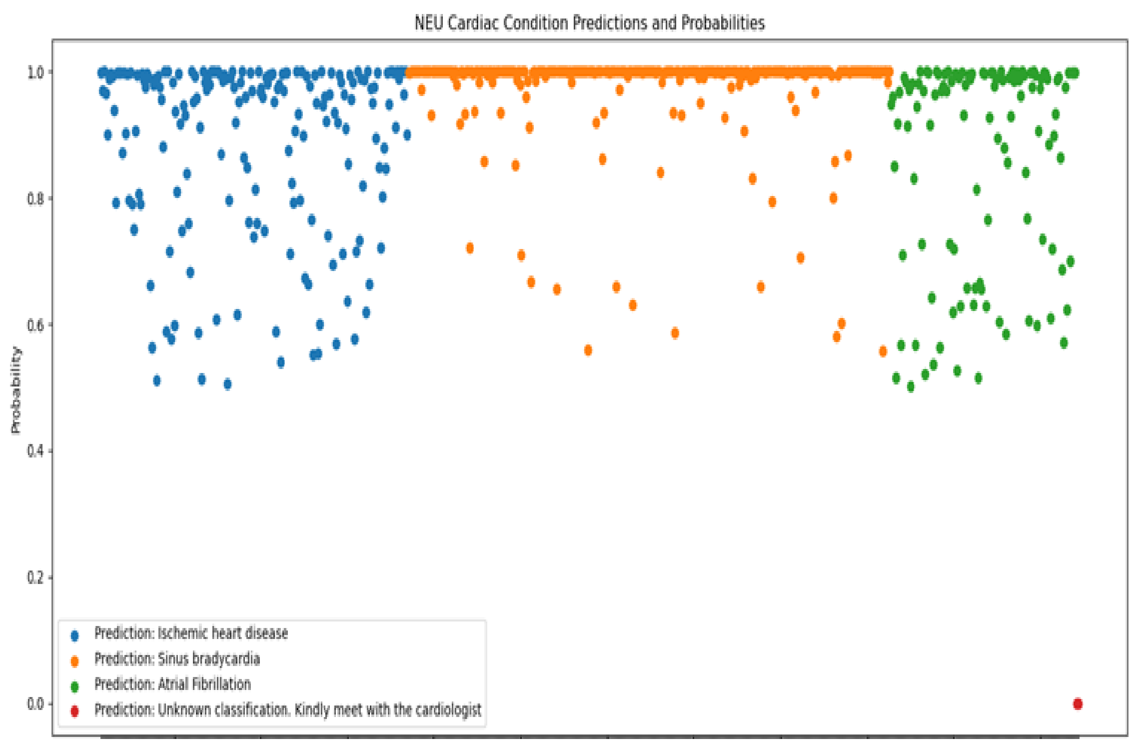


Figure 4.8:

NEU Cardiac Center Prediction Statistics

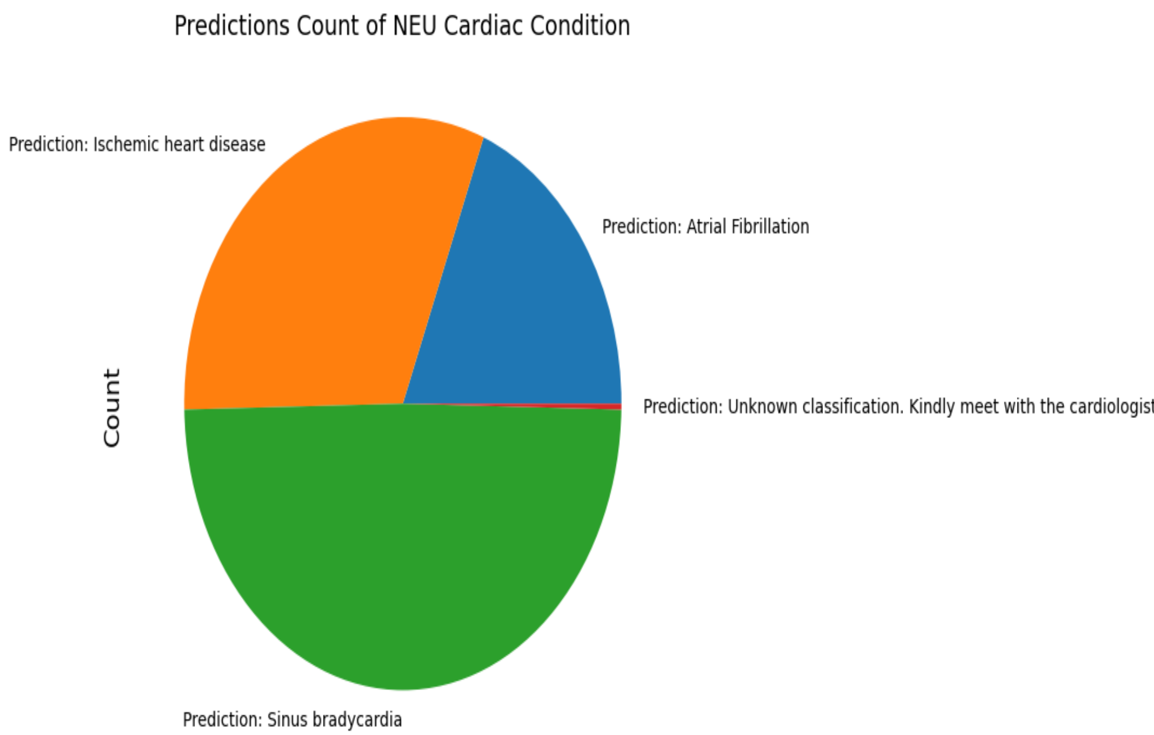


Table 4.2:

NEU Cardiac Center Prediction Statistical Data

NEU Cardiac Prediction Statistical Data	Count
Prediction: Atrial Fibrillation	115
Prediction: Ischemic heart disease	190
Prediction: Sinus bradycardia	299
Prediction: Unknown classification. Kindly meet with the cardiologist	2

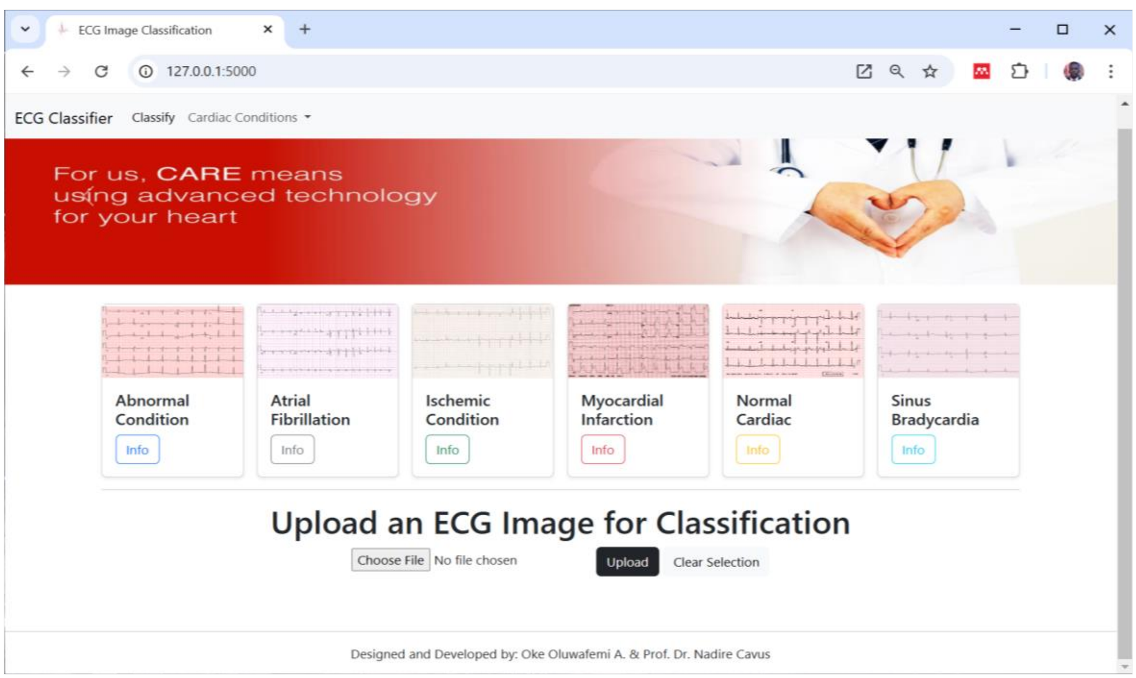
4.3. Clinical System Implementation

This entails testing the trained and validated model from the secondary data with unseen primary data obtained from the cardiac center. The model testing classification shows that 49.33% of the entire dataset comprised of Sinus bradycardia heart condition; 31.35% comprising of Ischemic heart disease, 18.97% comprising of Atrial Fibrillation, and 0.33% being unknown and inconclusive classification. Furthermore, with respect to the built system in place, the results of the hybrid AI model clinical performance are displayed below via Web App Visualization, Mobile App visualization powered by PWA for iOS and android.

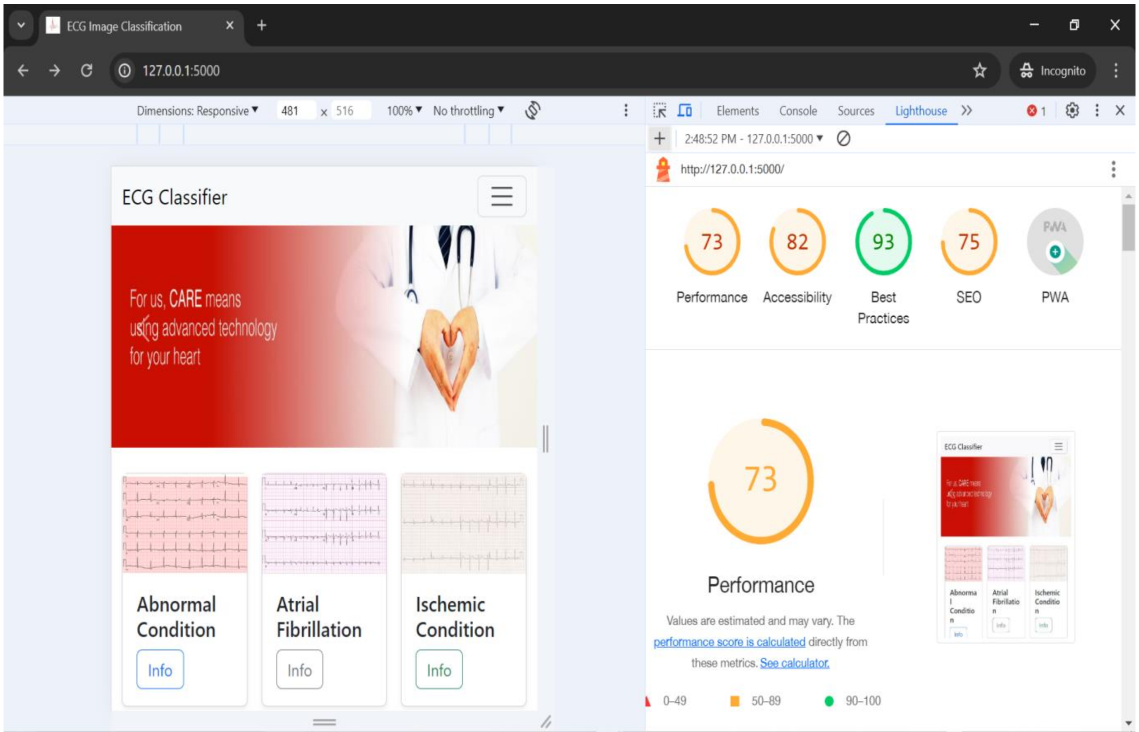
Figure 4.9a shows the developed Web App view of the system interface which consist of the six heart conditions and information on each of them. Followed by a section in which an ECG can be uploaded to be analysed. Figure 4.9b shows the lighthouse metric of the system to provide information on the overall performance of the system in terms of accessibility, search engine optimization (SEO). Figure 4.9c shows the instance of an ECG image uploaded to the system for analysis. Figure 4.9d shows the aftermath of the analysis which took place at the backend of the system from the server side. Hence displaying the result of the classification analysis as Ischemic heart condition alongside the probability of it being the heart condition.

Figure 4.9:

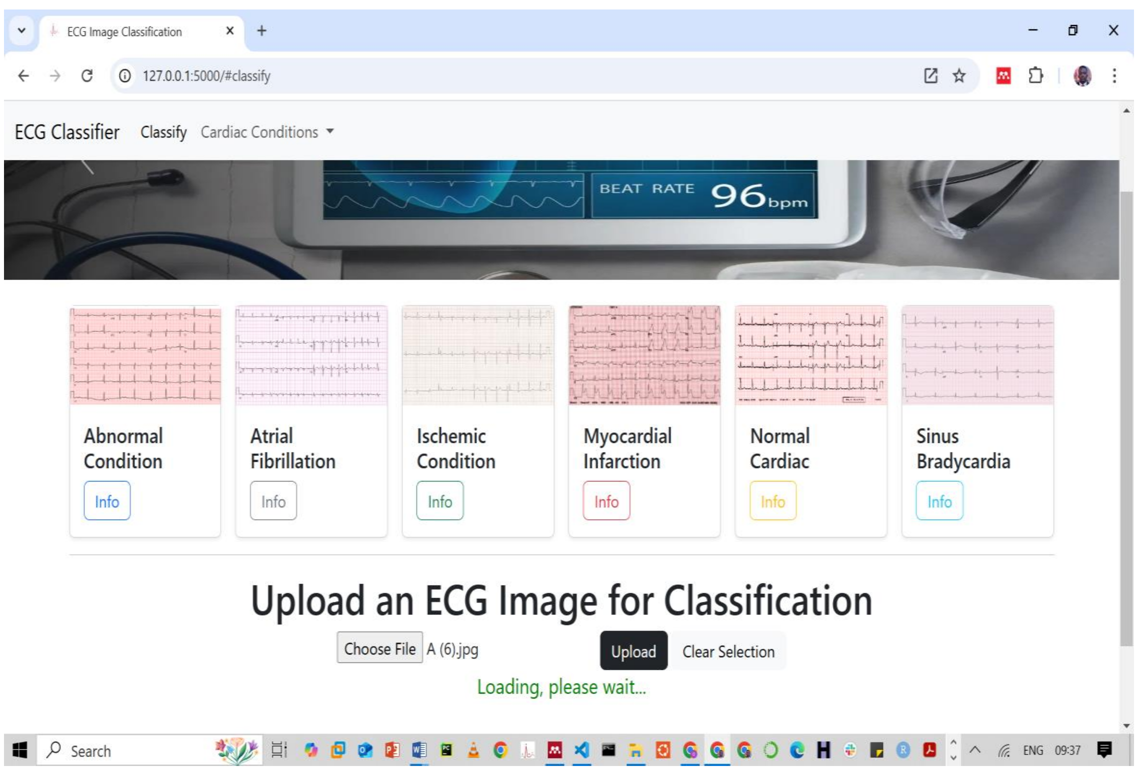
Snapshot of the Developed Web App



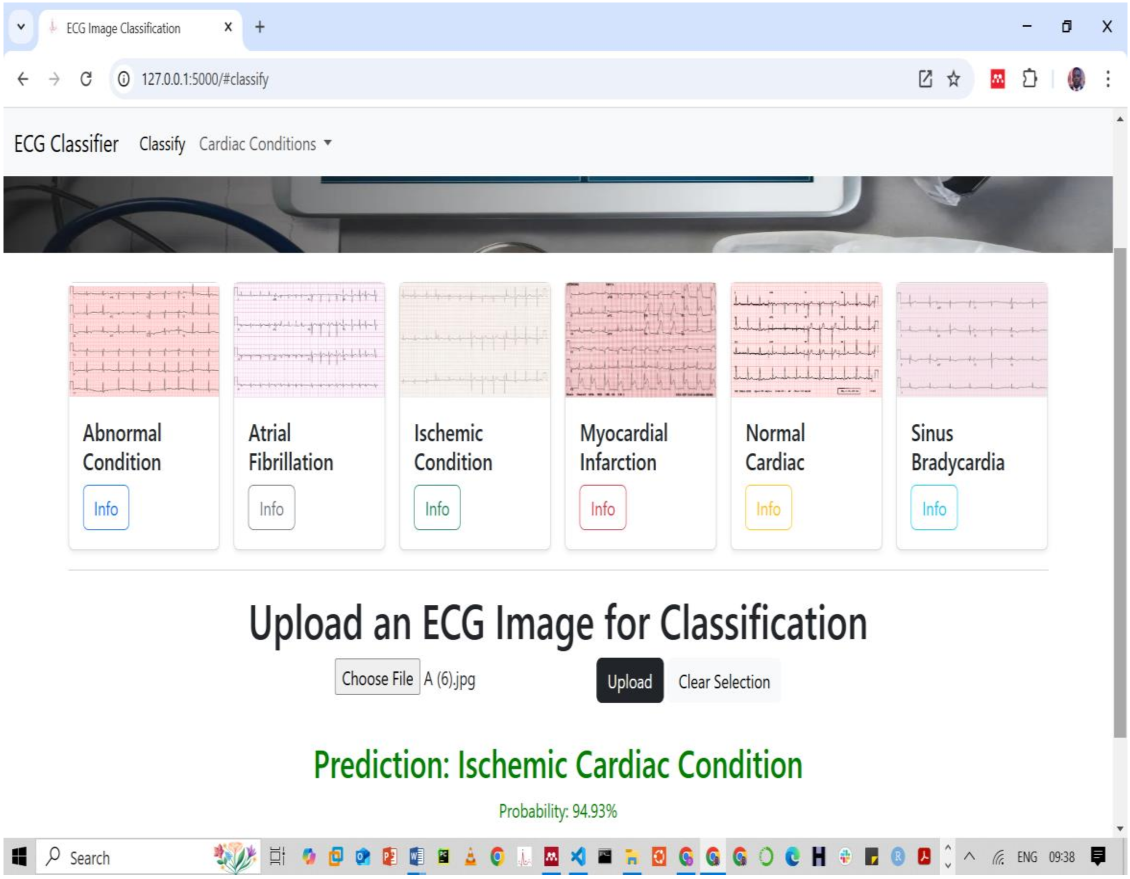
(a) Web App Interface



(b) Lighthouse Metrics



(c) Classification Processing

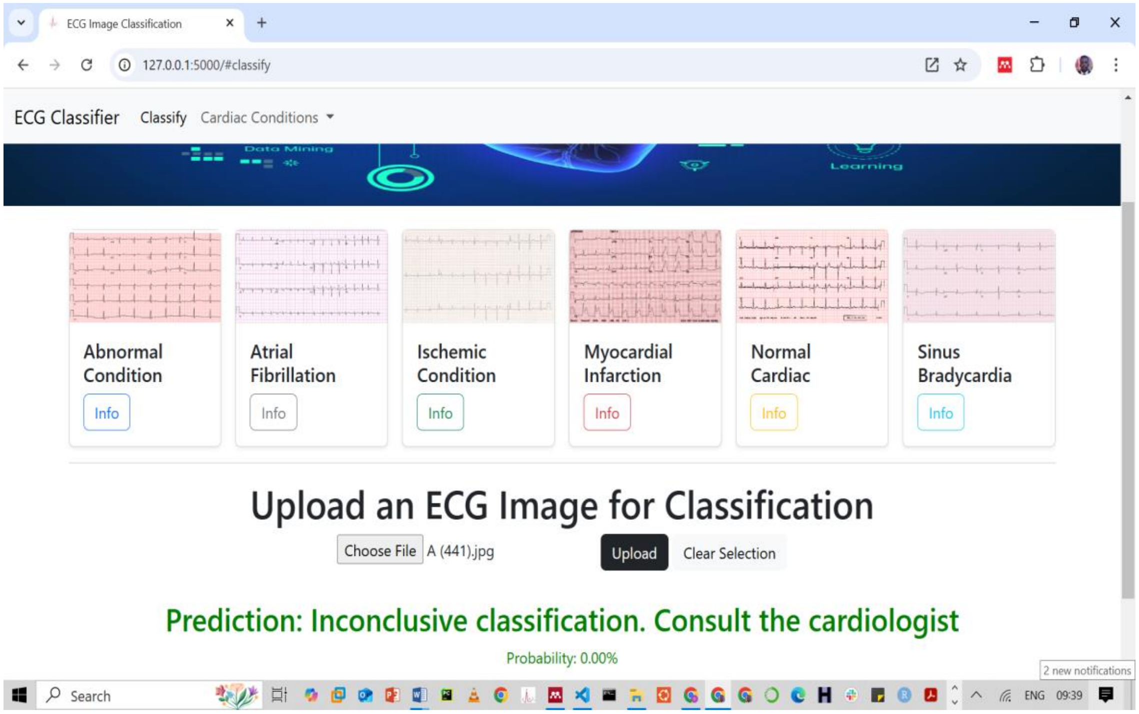


(d) Prediction and Probability

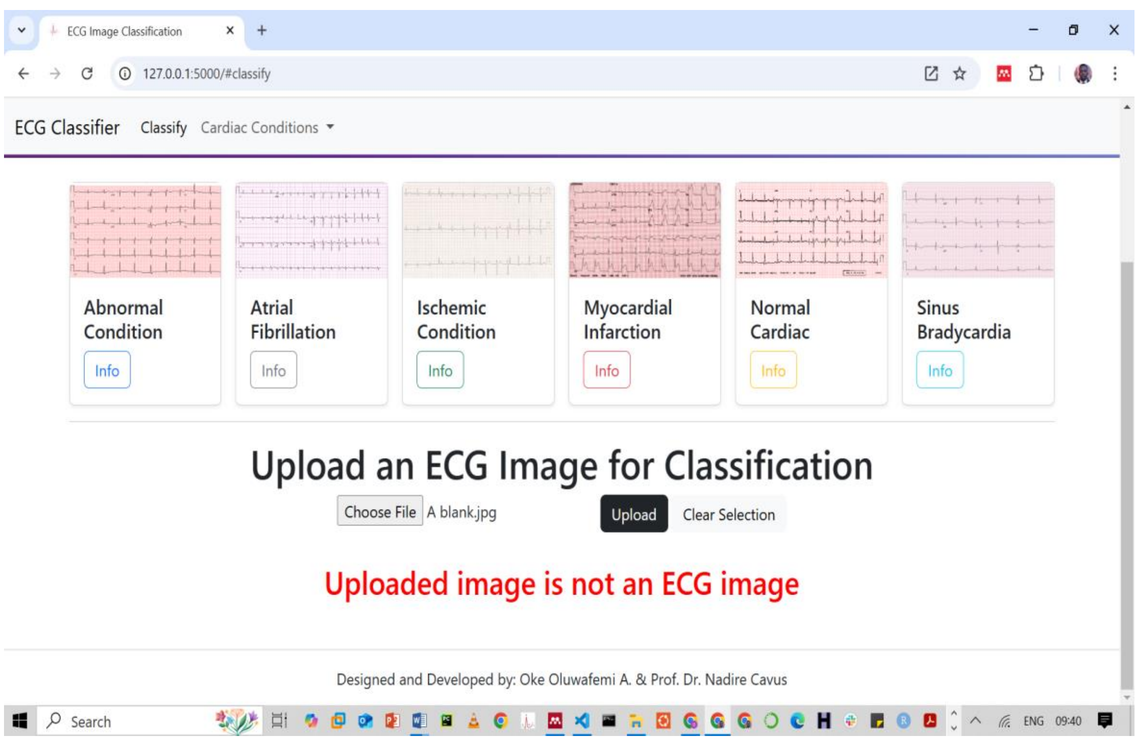
In the case of an uploaded ECG image not corresponding to the existing six heart conditions, the system has inbuilt algorithms to determine that and produce output which states that the prediction is inconclusive and this is followed by a recommendation to consult the cardiologist as shown in Figure 4.10a. furthermore, in the case of uploading a blank ECG image, an algorithm has been put in place such that as soon as the model is unable to determine the QRS complex from the sheet, it return an error saying “uploaded image is not an ECG image” as shown in Figure 4.10b. This error message also pertains to instances like uploading an unrelated file or picture like a picture of a dog a cup or even a video file format file as shown in Figure 4.10c and Figure 4.10d which reads “Error occurred while making prediction”.

Figure 4.10:

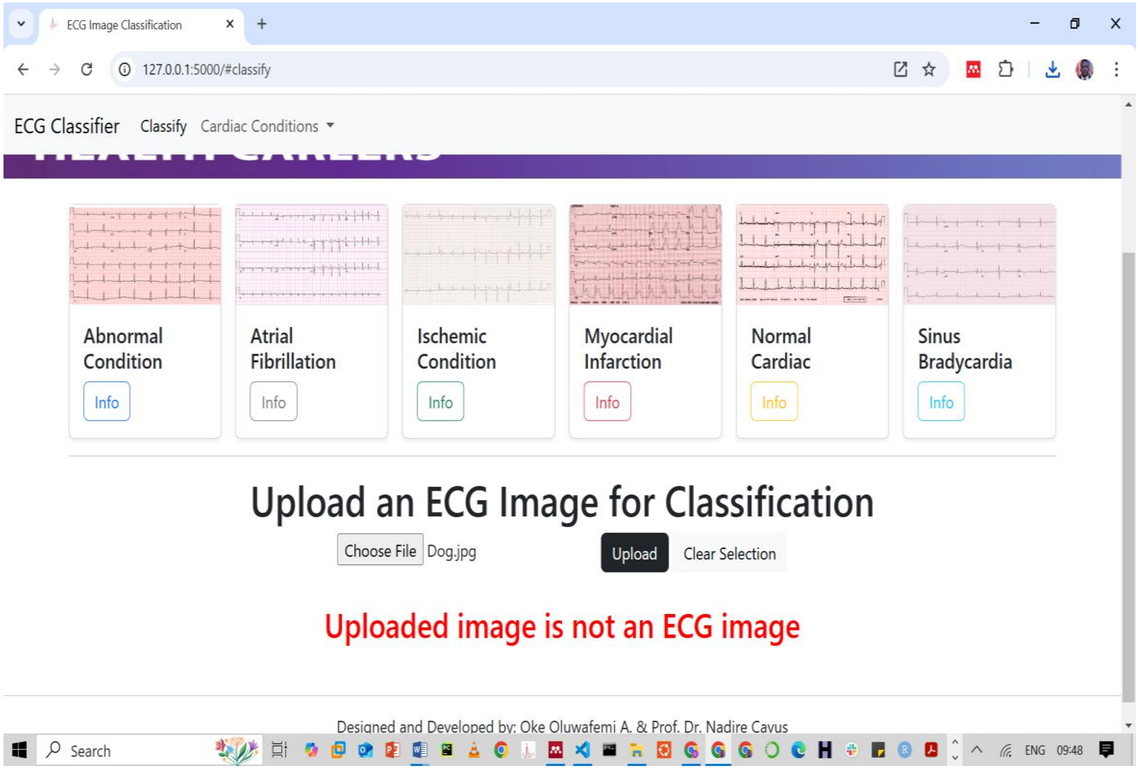
Web App Classification and Analysis Snapshot



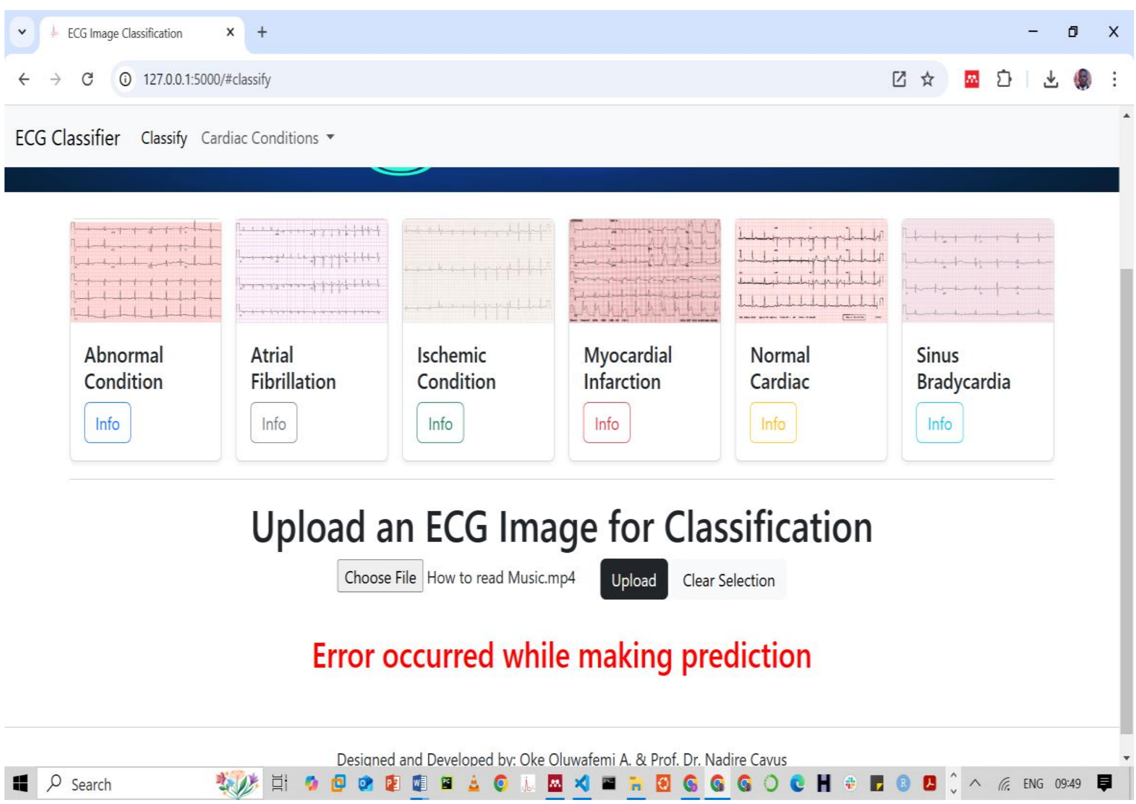
(a) Inconclusive Classification



(b) Blank ECG Image Upload Error Message



(c) Non-ECG Image Upload Error Message

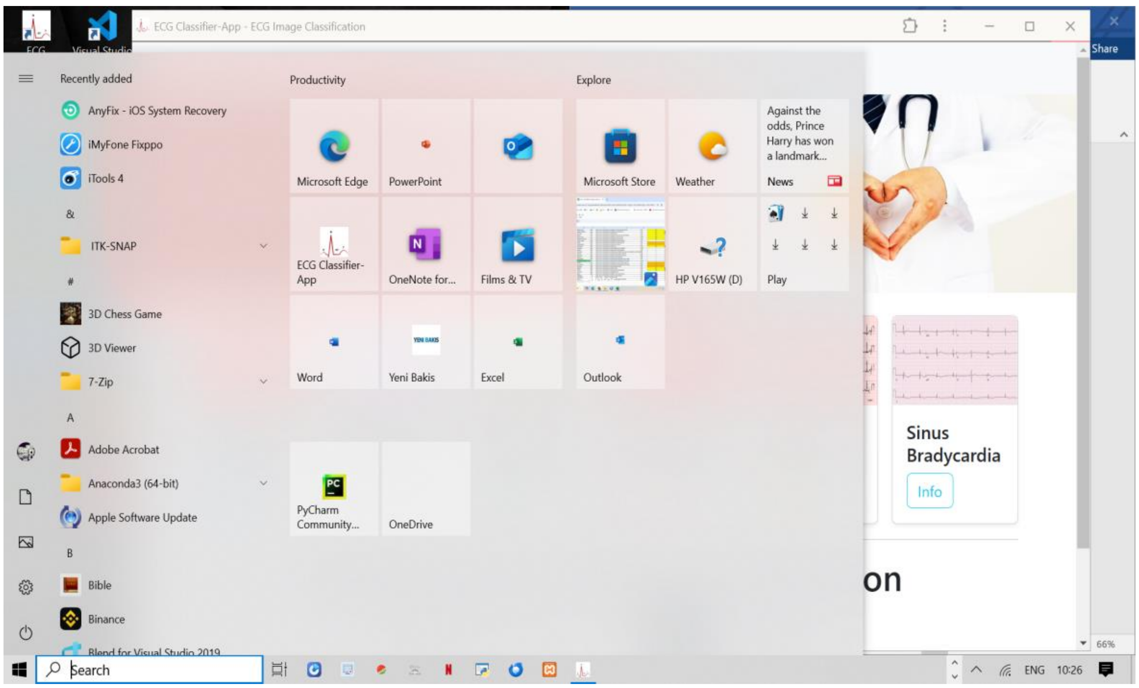


(d) Non-Picture Format Upload Error Message

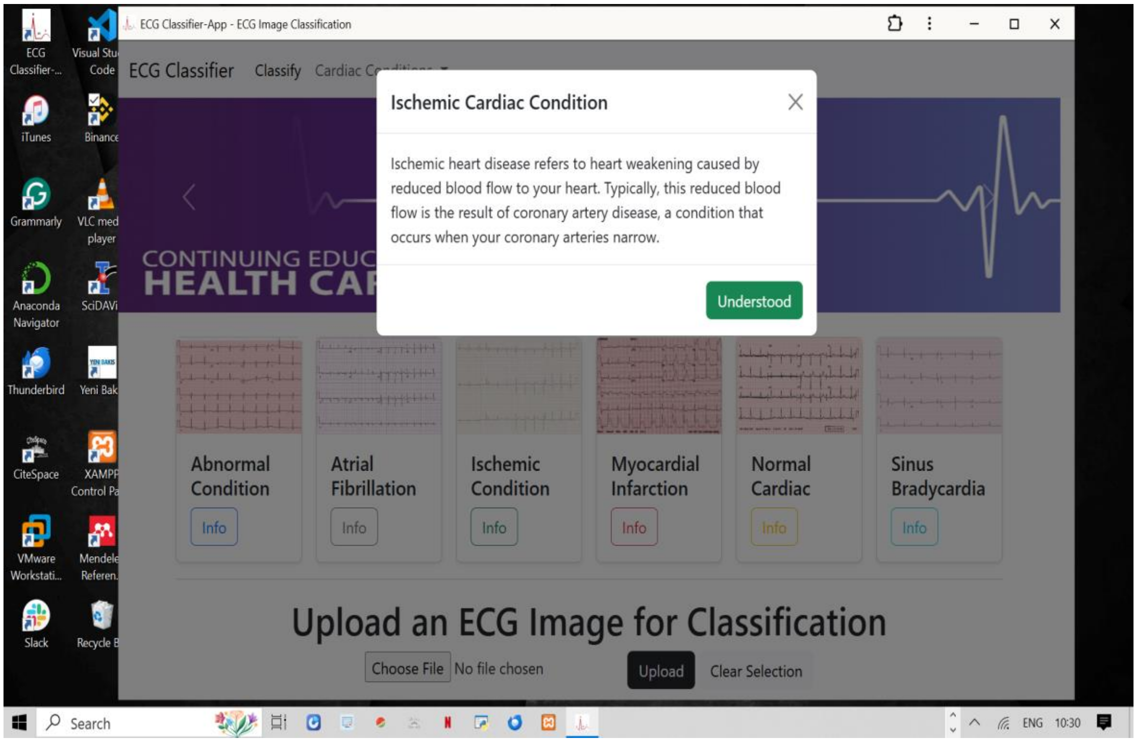
In addition, due to the fact that the system was built as a solution with for cardiac centers, the system has been integrated with installable features for east accessibility such that it runs as a native desktop application and due to the fact that it is installable, it can also be pinned to taskbar just as any desktop application as shown in Figure 4.11a. in addition, the launched application in Figure 4.11b opens directly without having to go through a web browser.

Figure 4.11:

Desktop Application View Snapshot



(a) ECG Desktop App Pinned and in Taskbar



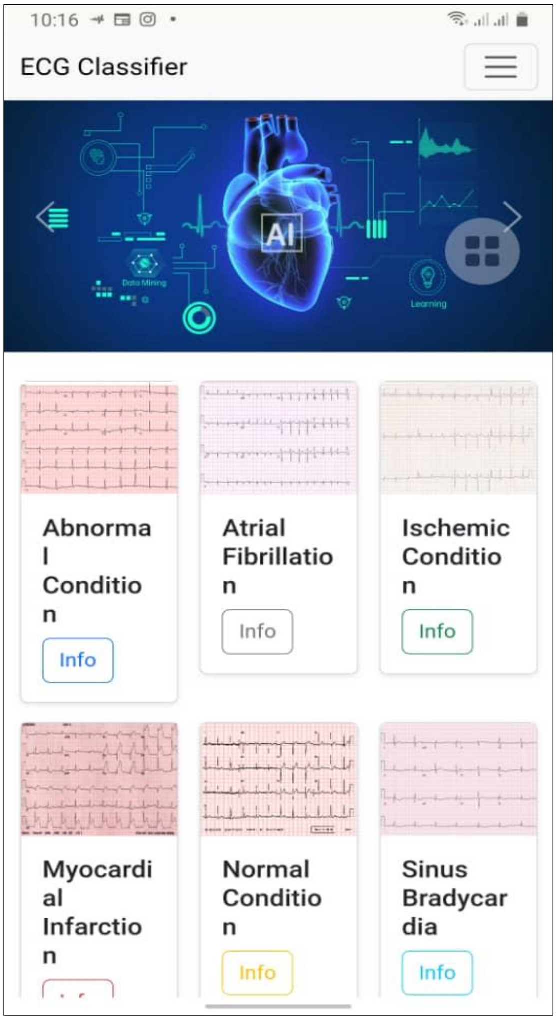
(b) ECG Launched Application

The classification system was built with also a mobile first mindset such that it integrates mobile architectural features alongside Web Server Gateway Interface (WSGI) infrastructure, thus, turning a regular phone into a portable powerful classification device that is capable of analyzing ECG images and performing diagnosis on patients ubiquitously.

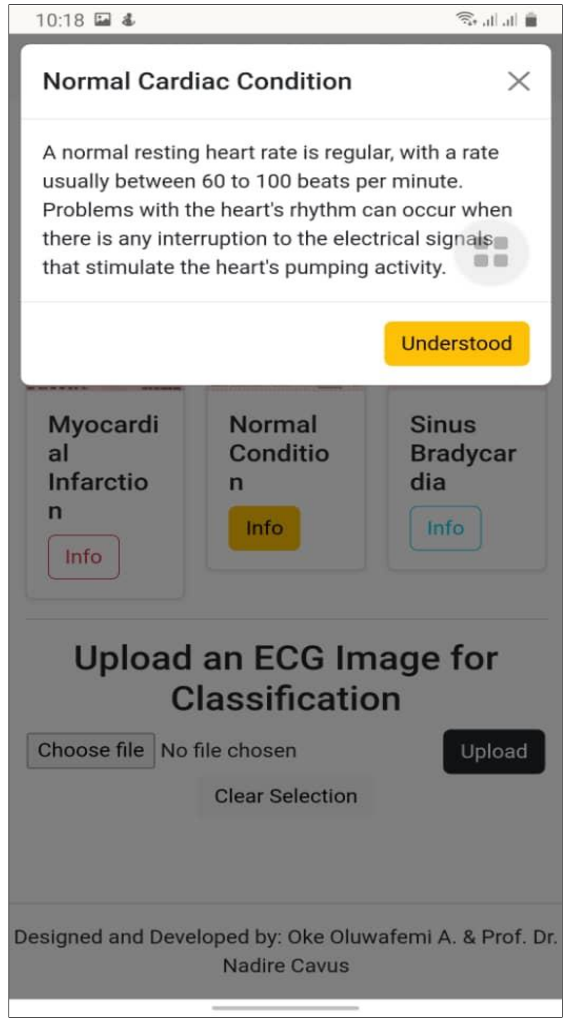
Furthermore, for the implementation of the system in an android powered device, using a Samsung device as displayed in Figure 4.12a and Figure 4.12b shows how the system operates and responds just as it did with the Web App and Desktop App. Which shows that any android powered device can run the application.

Figure 4.12:

Android Mobile View Screenshot



(a) Android Interface A

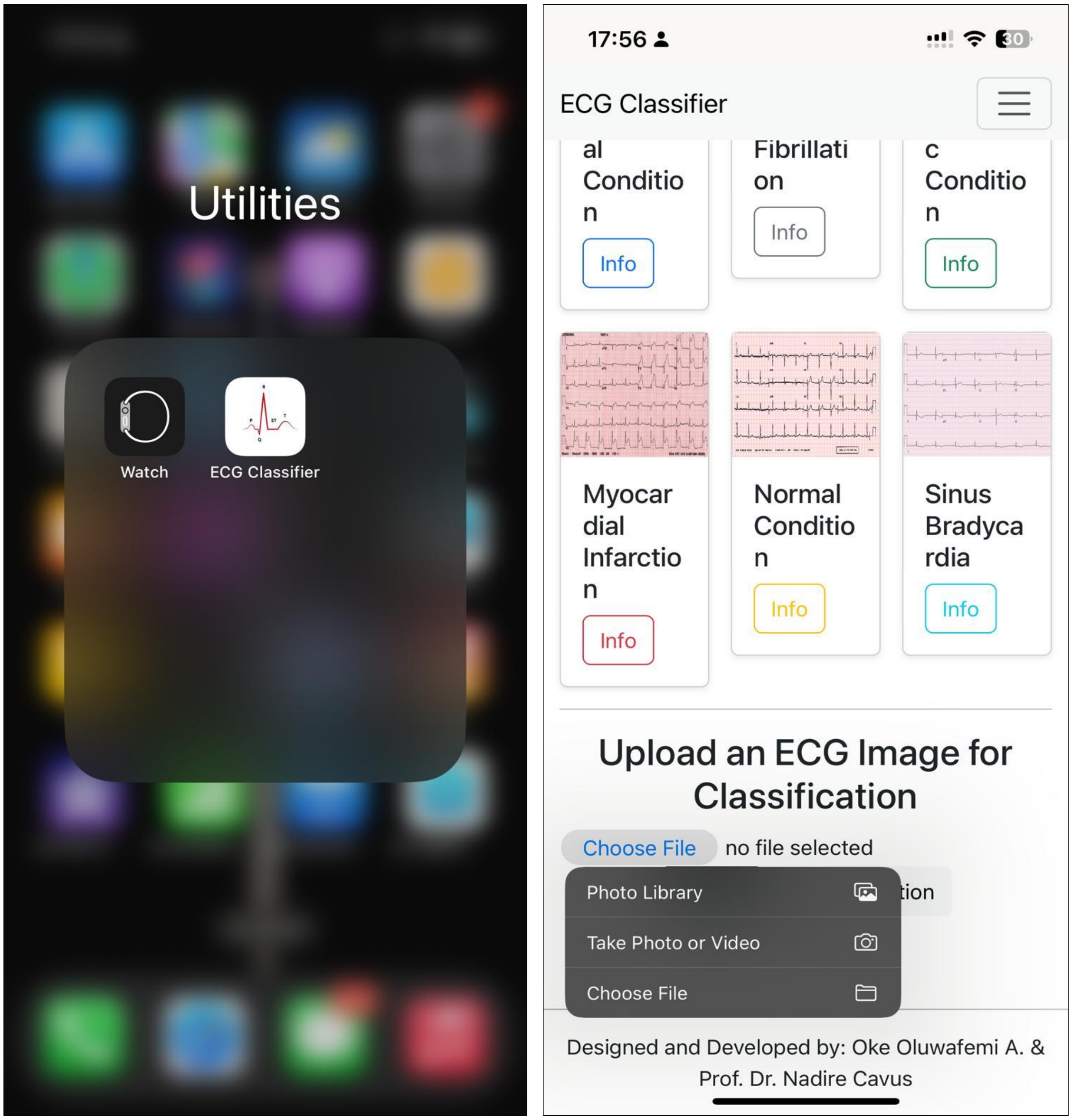


(b) Android Interface B

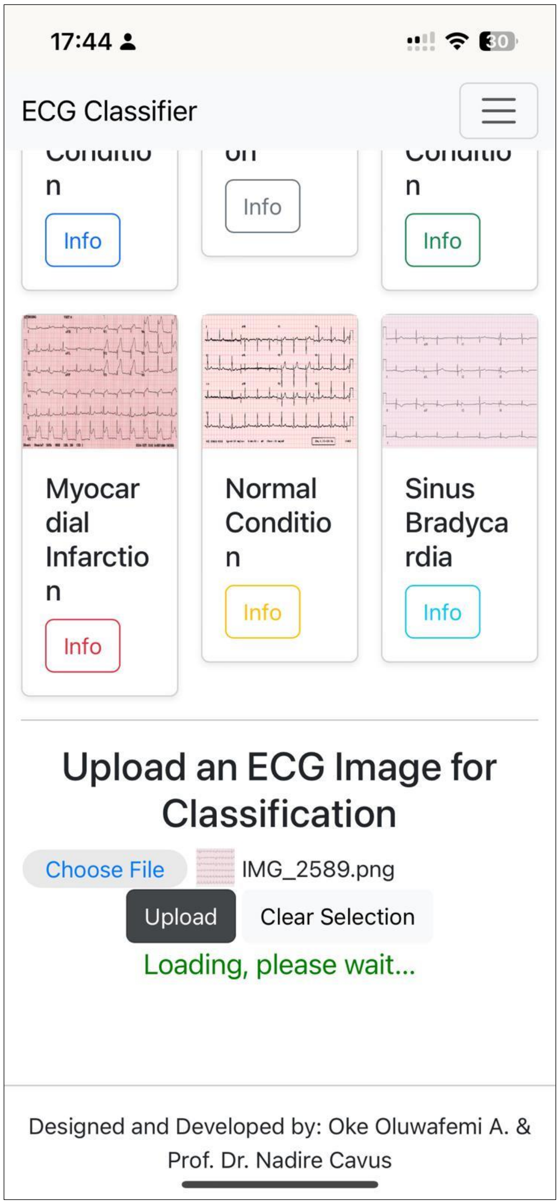
Similarly, running the application on an iPhone 13Pro which is an iOS powered device, the result also shows how the systems perfectly executes every classification just as it did in other operating systems and devices as shown in Figure 4.13a. It also offers a user with options to either take a picture of an ECG image, or upload an Existing ECG image from handheld devices as displayed in Figure 4.13b, after which it loads the image and performs a classification as shown in Figure 4.13c, then output the prediction and probability as shown in Figure 4.13d.

Figure 4.13:

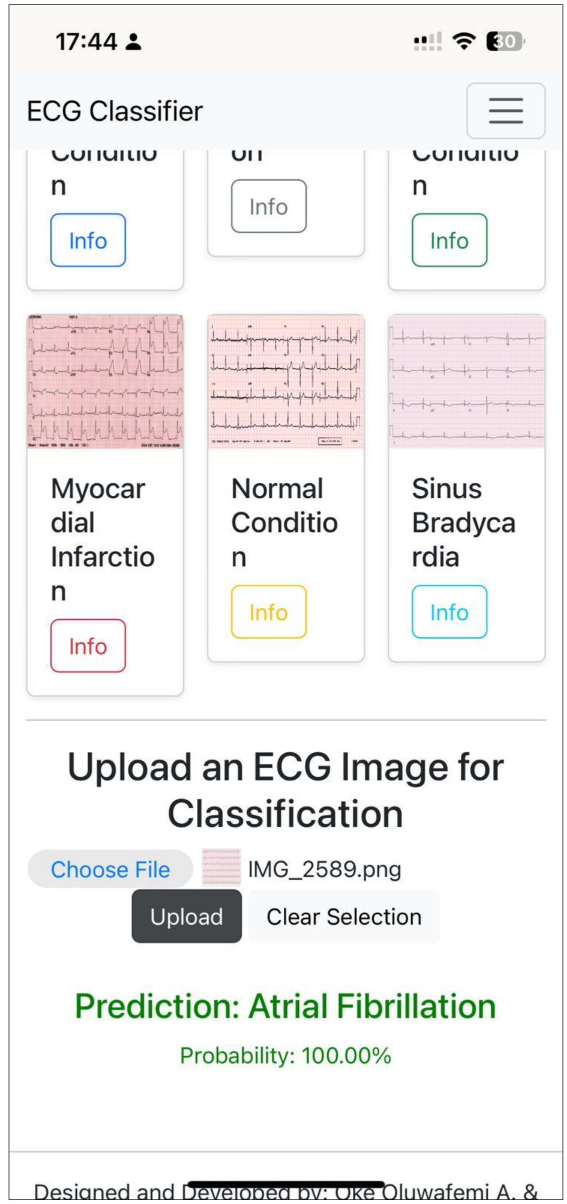
iOS Mobile View Screenshot



(a) iOS Interface A **(b)** iOS Interface B: Upload Options



(c) Loading



(d) Classification Result

CHAPTER FIVE
DISCUSSION

This chapter entails a discussion of the found results presented in chapter four with the related literature.

5.1. Clinical Implications

The findings of this study have considerable implications for clinical practice. Most importantly, high accuracy and reliability of the hybrid AI model may bring great improvements in heart disease diagnosis since one can identify heart conditions more speedily and precisely (Reshan et al. 2023). This can lead to timely and appropriate management of patients, potentially reducing the incidence of severe cardiac events (Almansouri et al. 2024). Additionally, the model's ability to classify six distinct heart conditions makes it a versatile tool in the clinical setting, covering a broad spectrum of cardiac issues.

Beyond ubiquity, since this is an appropriate hybrid model AI for use in a Web ECG Classifier Application, making a deployment as a web application with a server based on Flask can ensure accessibility of the very application ubiquitously, basically from any other geographical part of the world. Global access especially fosters equality among regions suffering from poor, limited access to specialist cardiac diagnosis-related services (Gao et al. 2022). Therefore, all that the healthcare professional needed to do was to upload the ECG images to the web ECG classifier application and get the diagnostic results then and there, thereby democratizing access to advanced cardiac care.

Not least, maintenance or updates: considering the technical sophistication of the Web ECG Classifier Application, the same is pretty easy to maintain and keep its performance at high levels. Every six months, the system needs checks that everything is functioning right and can handle any problem that may arise. This hybrid AI model has the advantage that, once more data is structured and categorized with respect to other types of heart conditions, it can easily classify other types of heart problems by retraining the model. It enhances the utility and scope of this hybrid AI model.

5.2. Challenges and Limitations

While current AI and hybrid models give great promise, they also have inherent challenges. These are inclusively: high computational requirements, probable difficulties in integration with existing healthcare systems, and algorithmic bias, which raises a question in making the model generalizable across different populations and clinical settings (Albahri et al. 2023).

Consequently, data scarcity and variability in ECG interpretation present significant challenges as the availability of high-quality, labelled ECG data is often limited, and there can be considerable variability in how ECGs are interpreted by different clinicians which can impact the training and performance of AI models (Gu et al. 2024).

Another important issue is algorithm bias, since biases in the training data can lead to disparities in diagnostic performance across different demographic groups. Thus, regulatory considerations are very important because the deployment of AI models in clinical practice needs to be done according to healthcare regulations and standards to ensure patient safety and data privacy (Morley et al. 2022).

Besides, high computational needs for the hybrid AI models might even further restrict the deployment of these models in resource-constrained settings. Additionally, though the performance of the model has been great in the used datasets, the generalizability to other populations and clinical environments needs further validation.

5.3. Future Directions and Opportunities

Future research should be directed to multimodal data fusion, such as fusing ECG data with other medical data like imaging and lab results, for improved diagnostic and predictive capabilities. Integration of AI models with electronic health records will, therefore, allow continuous learning and adaptation by refining algorithms in the light of real-world data.

Equally important will be the development of APIs for seamless integration with existing electrocardiographs, enhancing practicality and usability in clinical settings. Further expansion to various types of ECG recordings other than the standard 12-lead ECG will increase the applicability of the model.

In addition, further improvements can be made by training models on gender, age, and regional variations in future research. This can help address issues of algorithm bias and make the model perform more equitably on diverse patient populations.

5.4. Comparisons

This includes comparison with Standalone Models hybrid AI model, relevant research based on Kaggle data using InceptionV3 and VGG16 and comparison with existing approaches.

5.4.1. Comparison with Standalone Models

The hybrid AI model, which combined Inception V3 and VGG16, has performed very well, touching 99% for many metrics such as accuracy, sensitivity, specificity, F1-score, and precision. Compared to individual models, this hybrid approach has significantly outperformed each of the individual models, inception V3 with 4 misclassifications and VGG16 with 3 misclassifications from the comparative study in section 2.2.3 and Figure 9 by correctly classifying the heart conditions and giving an overall good performance. Additionally, in order to contextualize the results from the hybrid AI model, a comparison between the hybrid AI model and other models that use machine learning, deep learning, and transfer learning must be made.

Classical machine learning techniques for ECG data classification include, but are not limited to, Support Vector Machines, Random Forests, and k-Nearest Neighbors. These models typically require extensive feature engineering and are often less effective in capturing the complex patterns present in ECG data compared to deep learning models (Wasimuddin et al. 2020). For instance, SVM models have shown good performance in binary classification tasks but tend to struggle with multi-class classification problems due to their inherent limitations in handling high-dimensional data (Hsu, 2020).

Relatively, inception V3 outcompeted VGG16 and the different traditional machine learning models. Also, inception v3 is considered an efficient architecture based on factorized convolutions while in VGG16 its main value is regarded as simplicity combined with its depth. Nonetheless, each has its strengths and weaknesses. Inception V3 excels at capturing varied spatial hierarchies (Fang et al. 2022), whereas VGG16's deeper architecture allows it to learn more abstract features (Jiang et al. 2021). By combining these models, the hybrid approach leverages the strengths of both architectures, leading to improved performance metrics such as accuracy, precision, recall, and F1-score.

Likewise, transfer learning is also adopted for medical imaging, which essentially pre-trains a model on a large dataset and then finetunes it on new datasets. ResNet50, DenseNet, and MobileNet have been fine-tuned by different researchers in the ECG classification task (Malik & Anees, 2024). Since such models are pre-trained on large datasets, their performance becomes very high even when the training sets of medical applications are small. Transfer learning models have occasionally demonstrated overfitting and lack of generalization to specific domains for ECG classification. Gupta et al. (2020) illustrated how this hybrid AI model used a form of transfer learning, which overcame such issues by bringing together the beneficial aspects of two of the most robust architectures and thereby enhanced further its generalizability and robustness.

5.4.2. Relevant Research Based on Kaggle Data Using InceptionV3 and VGG16

Several studies have been able to demonstrate the fact that the integration of Kaggle datasets with advanced deep learning models, such as Inception and VGG16, has been highly instrumental in the advancement of ECG image classification. These collectively show the synergistic use of Kaggle datasets and the application of Inception V3 and VGG16 models in ECG image classification.

One of the recent studies on effective ECG image classification using lightweight CNNs incorporated with an attention module discusses converting ECG signals into images for classification using different deep learning techniques such as AlexNet, Inception V3, and VGG16 (Sadad et al. 2023). This study established the efficiency of the models discussed in assisting physicians in diagnosing cardiac disorders.

Another related study on Automated ECG Image Classification using InceptionV3 presented the fine tuning of the pre-trained Inception V3 model on PTB-XL containing 21,799 12-lead ECG recordings, by Gitau et al. (2024). The efficiency of the model in classifying the ECG images is huge.

Another ensemble approach was proposed using a transfer learning-based model architecture like VGG16 and InceptionResNetV2, which is modified for ECG signal classification. They claimed to have a great improvement in the accuracy by 99.98% compared to the prior algorithms, with 5-fold cross-validation on the Physionet dataset (Ovi et al. 2022).

In the direction of one such study on a robust framework that combines image processing with deep learning for ECG classification, a hybrid deep convolutional neural network architecture which combines InceptionV3 and ResNet50 has been used to classify paper-based ECG images into five classes, including myocardial infarction, history of myocardial infarction, normal heartbeat, abnormal heartbeat, and COVID-19. The proposed model achieved a testing accuracy of 98.34%, demonstrating the effectiveness of combining multiple deep learning models for ECG classification (Fatema et al. 2022). Furthermore, a related studies comparison using Kaggle dataset, Inception module and VGG16 model is displayed in Table 5.1.

Table 5.1:

Related Studies Using Kaggle, Inception V3 and VGG16

Reference	**Model**	**Heart Problem**	**Hybrid Dataset**	**Train Ratio**	**Literature**	**Results**
(Fatema et al. 2022)	VGG16, Inception V3	Myocardial Infarction, Normal Heartbeat, Abnormal Heartbeat, COVID-19	Kaggle + Paper-Based ECG Dataset	70:20:10	A robust framework combining InceptionV3 and ResNet50 for ECG classification	98.34% Accuracy
(Sadad et al. 2023)	Inception V3, VGG16	Myocardial Infarction, Atrial Fibrillation, Sinus Bradycardia, Normal Rhythm, Abnormal Heart Rhythm	Kaggle ECG Dataset	80:20	Efficient classification of ECG images using lightweight attention CNN (MDPI: Sensors)	98.39% Accuracy
(Gitau et al. 2024)	Inception V3	Various Cardiac Conditions	PTB-XL ECG Dataset	80:20	Automated ECG image classification (CinC Archive)	40% F1-scoree
(Ovi et al. 2022)	VGG16, Inception ResNetV2	Cardiac Abnormalities	Physionet + Modified ECG Dataset	80:20 5 fold cross-validation	Transfer-learning based ensemble architecture	99.98% accuracy

5.4.3. Comparison with Existing Approaches

The hybrid models have gained much popularity in the field of ECG analysis because it can take the best of several architectures, making the classification performance increase. However, when compared with the existing approaches in the literature, the proposed study with a hybrid AI model performs much better. Manual feature extraction and simpler machine learning algorithms are generally used to classify the ECG, and mostly with much lower accuracy. Among other effective deep learning approaches of the day are those that do not typically combine models to leverage complementary strengths as effectively as the hybrid AI model in this research. This therefore presents a very important landmark in the fusion of Inception V3 and VGG16 for AI-based diagnostics of the heart. Various other hybrid models have been proposed in the literature, combining different architectures with various techniques. For example, Islam et al. (2022) proposed a hybrid model for arrhythmia detection that was based on the combination of BiGRU-BiLSTM and Multilayered Dilated CNN, which achieved 96.25 % in terms of accuracy. Similarly, Hasbullah et al. 2023 used a hybrid model combining CNNs and RNNs for the analysis of sequential ECG data, thereby enhancing the capability of the model to capture temporal dependencies in the data with an overall accuracy of 89%. However, compared to these existing hybrid models, the combination of Inception V3 and VGG16 offers distinct advantages. It does this by exploiting the hybrid AI model's strength in effectively modeling spatial hierarchies and fine-grained features using the Inception V3 component, with the depth needed for abstraction given by its VGG16 component to learn higher-order and fine patterns in ECG data. This synergistic combination indeed leads to not just a high-accuracy model but also one exhibiting better sensitivity and specificity for several heart conditions. The hybrid AI model's performance, with 99% in accuracy and other metrics, outperforms many existing hybrid approaches, hence highlighting its potential for clinical application. A comparison of hybrid models from comparative analysis-related research is shown in Table 5.2.

Table 5.2:

Hybrid AI Model Comparison with Existing Studies from Related Research

Reference	Model	Heart Problem	Hybrid Dataset	Literature	Results
(Alfaras et al. 2019)	Echo State Networks	Arrhythmias	MIT-BIH AR + AHA.	A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection	Accuracy 86.1%
(Al-Issa & Alqudah, 2022)	CNN + LSTM	Heart Sound Abnormalities	Open heart sound dataset + PhysioNet/Computing in Cardiology 2016 challenge dataset	A lightweight hybrid deep learning system for cardiac valvular disease classification	F1-score 85.59%
(Al Bataineh & Manacek, 2022)	MLP +PSO	Normal and abnormal heart disease	Cleveland Heart Disease dataset	MLP-PSO Hybrid Algorithm for Heart Disease Prediction	Accuracy 84.61%.
(Pham et al. 2023)	CNN Conv1D + Evo_norm	Arrhythmia and Myocardial Infarction	MIT-BIH + PTB	Electrocardiogram Heartbeat Classification for Arrhythmias and Myocardial Infarction	F1-score 86.71%
(Haq et al. 2018)	Logistic regression + K-NN + ANN + SVM + NB + DT + random forest	Normal and abnormal	Cleveland heart disease dataset 2016	A Hybrid Intelligent System Framework for the Prediction of Heart Disease Using Machine Learning Algorithms	Accuracy 89%

(Nagavelli et al. 2022)	SVM + DO	Ischemic heart disease	PhysioNet database	Machine Learning Technology-Based Heart Disease Detection Models	Accuracy 89.4%
(Hassab allah et al. 2023)	Meta-Heuristic Optimization (MOH) + ML classifiers	Arrhythmia	MIT-BIH + EDB + INCART	ECG Heartbeat Classification Using Machine Learning and Metaheuristic Optimization for Smart Healthcare Systems	Sensitivity 99.81%
(Khan et al. 2021)	Single Shoot Detection (SSD) MobileNet v2-based Deep Neural Network architecture	Myocardial infarction, abnormal heartbeat, previous history of MI, normal class	Health care institutes	Cardiac Disorder Classification by Electrocardiogram Sensing Using Deep Neural Network	Accuracy 98%
Hybrid model	Hybrid AI Model (Inception V3 + VGG16)	Abnormal heart rhythm, atrial fibrillation, ischemic heart disease, myocardial infarction, normal heart rhythm, and sinus bradycardia	Cardiac centre + Kaggle online database	ECG Diagnosis, Analysis, And Interpretation in Cardiology Using Deep Learning Models for Classification and Prediction	99% Specificity, 99% precision, 99% F1-score 99% accuracy, 99% Recall/ Sensitivity

CHAPTER SIX
CONCLUSION AND RECOMMENDATIONS

This chapter presents the important conclusions extracted from the research alongside recommendations for future research.

6.1.Conclusion

This study has demonstrated that the hybrid AI model, combining the strengths of Inception V3 and VGG16, achieves exceptional performance in classifying ECG images into six distinct heart conditions. In contrast, the hybrid AI model returned results with 99% accuracy on all key metrics concerning sensitivity, specificity, F1-score, and precision-considerably outperforming standalone models and many state-of-the-art approaches. This very high diagnostic accuracy is of serious consequence to clinical implications. In providing reliable and precise diagnoses, the model can assist cardiologists in informed decision-making, with a view to reducing diagnostic errors and ensuring timely intervention for heart disease patients.

All of this gets implemented into an even greater impact by deploying this model as a web ECG classifier application on a Flask server. Further, making the web ECG classifier application globally accessible means high-quality cardiac diagnostic equipment shall be at the fingertips of different health practitioners across the world, especially in settings with limited access to specialized cardiology services. This opens up better prospects for improving patient outcomes due to early detection and management of heart diseases, thereby resulting in reduced morbidity and mortality.

6.2.Recommendations

Though promising, the results of this study point to a number of avenues for further research and development that can extend the usefulness and impact of the hybrid AI model.

6.2.1. Recommendations for Researchers

6.2.1.1. *Refinement of Model Architecture*: The hybrid AI model architecture should be further refined in future research. Further deep learning techniques, such as attention mechanisms or transformer models, could be explored for possible further improvements in the performance of the model.

6.2.1.2. *Prospective Clinical Trials*: In addition, large-scale prospective clinical trials will be performed to validate the performance of the hybrid AI model in various clinical settings, which is an important factor for the generalization and reliability of the model in various patient populations and healthcare settings.

6.2.1.3. *Integration with Multimodal Data*: Investigations into integrating the hybrid AI model with other types of medical data, such as genetic information, patient history, and other diagnostic tests, are encouraged. Such a multimodal approach might yield a more holistic understanding of heart conditions and increase predictive accuracy.

6.2.1.4. *Making Algorithms Free from Bias*: A very important fact is that such a hybrid AI model needs to be trained with diverse datasets representative of different demography. A researcher should progress toward creating data that reflects inclusive diversity.

6.2.1.5. *Other forms of ECG*: This hybrid AI model will be used to extend its clinical feasibility by investigating further whether it could be applied to some other forms of ECG studies other than those already defined 12-lead, single-lead or 3-lead ECGs.

6.2.1.6. *Regulatory and Ethical Considerations*: It becomes of great importance that regulatory and ethical considerations be taken into account for the successful translation of AI models into clinical practice. Conformity with healthcare regulations and standards will need to be adhered to, and ethical concerns regarding data privacy and algorithmic bias also need consideration in order to gain trust and acceptance among healthcare providers and patients.

6.2.1.7. *Interpreting Results*: If an application interface is used, then the result section or page should give an explanation of the condition predicted, with recommendations for further action if any. This may be made possible by incorporating Grad-Cam technique.

6.2.2. Recommendations for Cardiologists

6.2.2.1. *Adoption of AI Tools*: Cardiologists should be advised to adapt and use AI-based diagnostic tools, such as the hybrid AI model, in clinical diagnosis and practice to enhance their performance and efficiency. Such tools can thus act like decision-support systems in complicated cases.

6.2.2.2. *Continuous Training and Education in AI/Machine Learning*: A cardiologist should be updated about all recent advances related to AI and machine learning. Continuous training and professional development programs will help them in putting these technologies into effective use in their practice.

6.2.2.3. *Patient Data Privacy*: Cardiologists should ensure the privacy and security of patient data when using AI tools. Best practices in data anonymization and adherence to regulatory standards are important in maintaining patient trust and confidentiality.

6.2.2.4. *Collaborative Approach*: Multidisciplinary collaboration with AI researchers and data scientists could help cardiologists understand the capabilities and limitations of AI models, thus being able to integrate them more effectively into clinical workflows.

6.2.3. Recommendations for Patients

6.2.3.1. *Informed Participation*: A patient should be informed about the application of an AI tool in his or her diagnosis and treatment. Understanding the benefits and limitations of these technologies will help the patients make better decisions regarding their healthcare.

6.2.3.2. *Data for Research*: Patients can contribute by giving consent to share anonymized medical data for research into AI in medicine, with the view to helping enhance robustness and accuracy in AI models.

6.2.3.3. *AI Diagnosis -Trust*: Many patients will require an understanding of the fact that this diagnostic tooling is meant to assist their healthcare professional rather than replace the doctor. Extra layers of accuracies can be provided, ensuring more precise diagnoses.

6.2.3.4. *Engagement and Feedback*: The active contact and feedback provided by the patients after experiencing AI-based diagnosis can surely be one way hospitals and researchers alike perfect their tools in serving the needs of such patients effectively.

6.2.4. Recommendations for Hospitals

6.2.4.1. *Infrastructure Investment*: The basic infrastructure investment for installing high-performance computing systems, data storage solutions, and secure networks to support AI-driven diagnostic tools.

6.2.4.2. *Training Programs for Staff*: It would be upon the hospitals to institute training programs, which would train both their medical and administrative staff on how to use AI tools. This will definitely enhance the rate at which such tools are adopted and also confidence in integrating AI technologies into the staff's workflow.

6.2.4.3. *Standardized Implementation Mechanisms*: Harmonized protocols and workflows are being developed to embed the AI model into clinical use for consistency, reliability, and safety in patients' interests.

6.2.4.4. *Regular Audits and Updates*: Regular review and updating of AI tools are necessary in order for the performances to conform to the medical standards currently at stake and that problems, such as algorithmic bias or data inaccuracy, are detected as early as possible.

6.2.4.5. *AI Ethics Committees*: It is worth mentioning the establishment of specialized ethics committees focused on AI implementation in clinical applications, which will improve most issues related to the consent of patients, personal information privacy, and ethical dilemmas.

6.2.5. Recommendations for Policymakers

6.2.5.1. *Regulatory Frameworks*: Policymakers have mandates to enact complete and appropriate regulatory frameworks that assure safety, responsibility, and equity in the establishment of AI applications in health services.

6.2.5.2. *Funding and Grants*: More funds and grants for AI-based medical research increase the pace and quality of AI models in use today within the medical field.

6.2.5.3. *Interoperability Standards*: Policymakers need to encourage efforts toward standards of interoperability so that the use of AI tools is shared with ease, just like incumbent systems and platforms of EHRs.

6.2.5.4. *Public Awareness Campaigns*: There is a dire need to educate the general public about the role, benefits, and limitations of AI in healthcare through appropriate campaigns to ensure greater trust and acceptance among patients and health professionals regarding these technologies.

6.2.5.5. *Data Privacy Legislation*: Strict data privacy legislation with respect to AI in health would go a long way in safeguarding patient information, thus inspiring responsible innovation.

6.2.5.6. *Incentives for Adoption*: Tax breaks or subsidies of some kind in financial terms will go a long way in incentivizing hospitals and healthcare providers to integrate AI-based solutions into their services.

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APPENDICES

APPENDIX A: Ethical Committee Approval

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

31.03.2023

Dear Oke Oluwafemi Ayotunde

Your application titled **"ECG Diagnosis, Analysis, and Interpretation in Cardiology Using Machine Learning Models for Classification and Prediction"** with the application number NEU/AS/2023/176 has been evaluated by the Scientific Research Ethics Committee and granted approval. You can start your research on the condition that you will abide by the information provided in your application form.

Prof. Dr. Aşkın KİRAZ

The Coordinator of the Scientific Research Ethics Committee

APPENDIX B: Turnitin Similarity Report

FULL THESIS-AFTER JURY

by OKE OLUWAFEMI AYOTUNDE -FULL THESIS

Submission date: 05-Feb-2025 03:46PM (UTC+0200)
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NEAR EAST UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF COMPUTER INFORMATION SYSTEMS

ECG DIAGNOSIS, ANALYSIS, AND INTERPRETATION IN CARDIOLOGY USING DEEP LEARNING MODELS FOR CLASSIFICATION AND PREDICTION

PhD THESIS

Oluwafemi Ayotunde OKE

SUPERVISOR
Prof. Dr. Nadire CAVUS

Nicosia

JUNE 2024

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57	"Optimization and Data Science in Industrial Engineering", Springer Science and Business Media LLC, 2025 Publication	<1%
58	Alex Khang, Vugar Abdullayev, Babasaheb Jadhav, Shashi Kant Gupta, Gilbert Morris. "AI-Centric Modeling and Analytics - Concepts, Technologies, and Applications", CRC Press, 2023 Publication	<1%
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63	Khadidja Benchaira, Salim Bitam. "Enhancing ECG signal classification through pre-trained stacked-CNN embeddings: a transfer learning approach", Biomedical Physics & Engineering Express, 2024 Publication	<1%
64	S Krishnakumar., M Yasodha., J Veronica Priyadharshini., J Bethanney Janney., Sindu Divakaran, V Lumen Christy.. "Detection of Arrhythmia and Congestive Heart Failure Through Classification of ECG Signals Using Deep Learning Neural Network", 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), 2021 Publication	<1%
65	S. Prasad Jones Christydass, Nurhayati Nurhayati, S. Kannadhasan. "Hybrid and Advanced Technologies", CRC Press, 2025 Publication	<1%
66	Pethuru Raj, N. Gayathri, G. Jaspher Willsie Kathrine. "Artificial Intelligence for Precision	<1%

Agriculture", CRC Press, 2024
Publication

Exclude quotes	On	Exclude matches	< 5 words
Exclude bibliography	On		

APPENDIX C: Dataset Permissions

ATTACHMENT 2: ***Permission Letter from Near East University Hospital staff to use the dataset***

November 28, 2022

Oke Oluwafemi Ayotunde

Near East University, Cyprus

Oke.oluwafemi_a@yahoo.com

PERMISSION TO USE ECG DATASET FOR PHD THESIS

Dear Doctor Hamza,

My name is Oke Oluwafemi Ayotunde. I am a PhD student at Computer Information Systems, Near East University. I am conducting a research on ECG analysis, interpretation and prediction of heart related problems using Artificial Intelligence models. I need ECG results of patient data located in Near East University under the supervision of Dr. Hamza, Head Cardiologist.

The data will be trained and integrated with Artificial Intelligence models and algorithms for accuracy and prediction of results related to my thesis topic titled "ECG DIAGNOSIS, ANALYSIS, AND INTERPRETATION IN CARDIOLOGY USING MACHINE LEARNING MODELS FOR CLASSIFICATION AND PREDICTION". The permissions include, rights to use the data and rights of publication of research related to the thesis study. The data will not be used in other researched unrelated to the thesis.

The needed data description includes heart problems and reading results of patients gotten from any ECG monitoring device for more than 1500 patients. **The confidentiality of the patients in terms of name, age, sex, and any personal information is not needed and would not be used in the research.**

I would like to greatly appreciate your consent to my request.

Three copies of this request has been provided for your records. If you agree with the above terms, please sign the release form below.

Sincerely,

Oke Oluwafemi Ayotunde

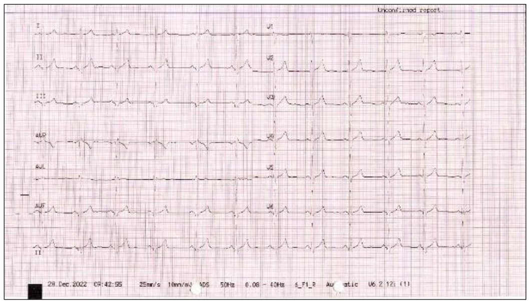
Permission granted for the use of the data as described above:

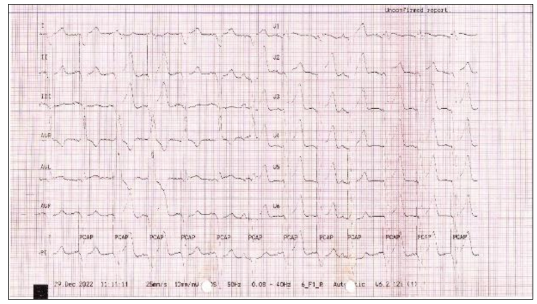
Agreed to: Oke Oluwafemi Ayotunde to Use the ECG result dataset for thesis research as described above.

Dr. Name: Job Title: Signature:

APPENDIX D: Sample Images

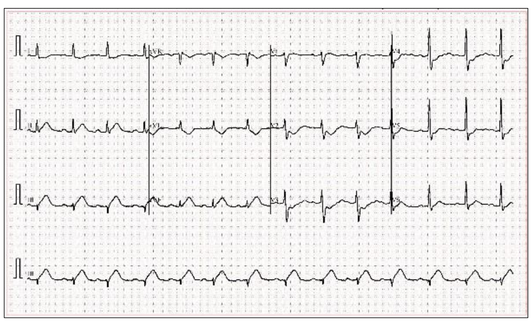
CARDIAC CENTER



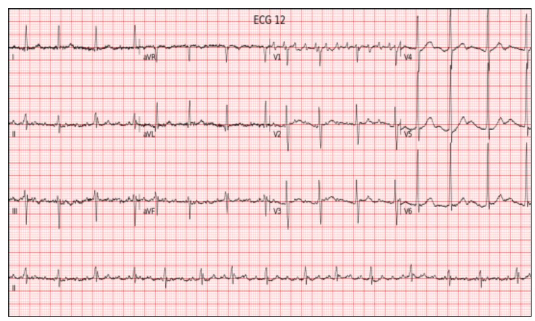


KAGGLE

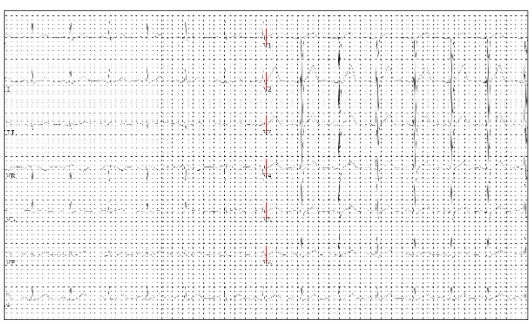
MI



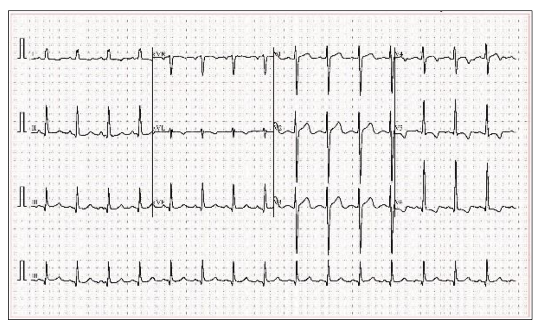
AF



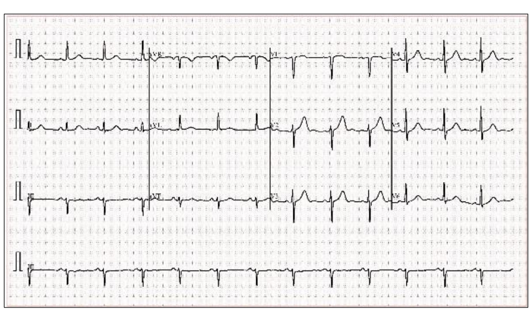
IS



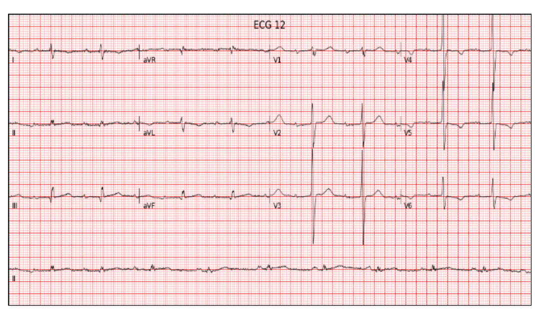
AB



NOR



SB



APPENDIX E: Sample Code for the Model

```python
import os
import cv2
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, classification_report
from keras.applications import InceptionV3, VGG16
from keras.models import Model
from keras.layers import Flatten, Dense, Input, concatenate
from keras.utils import to_categorical

# Function to load and preprocess images
def load_images(folder_path, img_size=(224, 224)):
    X = []
    y = []
    labels = os.listdir(folder_path)
    for label in labels:
        label_path = os.path.join(folder_path, label)
        for img_file in os.listdir(label_path):
            img_path = os.path.join(label_path, img_file)
            img = cv2.imread(img_path)  # Read image
            img = cv2.resize(img, img_size)  # Resize image
            X.append(img)
            y.append(label)
    return np.array(X), np.array(y)

# Path to the folder containing ECG images
folder_path = "main_dataset"

# Load and preprocess images
X, y = load_images(folder_path)
X = X.astype('float32') / 255.0  # Normalize pixel values to range [0, 1]
y = LabelEncoder().fit_transform(y)  # Encode labels

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Convert labels to one-hot encoding
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

# Load pre-trained InceptionV3 and VGG16 models
inception_base = InceptionV3(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
vgg_base = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
```

```python
import os
import cv2
import numpy as np
from keras.models import load_model

# Load the hybrid model
model = load_model('hybrid_model.keras')

# Path to the folder containing ECG images
folder_path = "Cropped"

# Function to preprocess images
def preprocess_image(image_path, target_size=(224, 224)):
    img = cv2.imread(image_path)
    img = cv2.resize(img, target_size)
    img = img.astype('float32') / 255.0  # Normalize pixel values
    img = np.expand_dims(img, axis=0)  # Add batch dimension
    return img

# Function to make predictions for all images in a folder
def predict_folder_images(model, folder_path):
    class_names = ["Abnormal", "Atrial Fibrillation", "Ischemic heart disease", "Myocardial Infarction", "Normal", "Sinus bradycardia"]
    results = []

    for filename in os.listdir(folder_path):
        if filename.endswith(('.png', '.jpg', '.jpeg')):
            file_path = os.path.join(folder_path, filename)
            preprocessed_image = preprocess_image(file_path)

            # Make prediction
            predictions = model.predict(preprocessed_image)
            predicted_class = np.argmax(predictions, axis=1)
            predicted_probability = np.max(predictions) * 100

            # Check if the predicted probability is below a threshold
            if predicted_probability < 50:  # Threshold for unknown classification
                predicted_label = "Unknown classification. Kindly meet with the cardiologist"
                predicted_probability = 0.0
            else:
                predicted_label = class_names[predicted_class[0]]

            # Append result
            results.append({
                'filename': filename,
```

APPENDIX F: User Manual of the Developed ECG Classifier Application

User Manual for ECG Classification Web ECG Classifier Application

I. Introduction

This user manual provides detailed instructions for using the ECG Classification web ECG classifier application, developed as part of the research on "ECG Diagnosis, Analysis, and Interpretation in Cardiology Using Deep Learning Models for Classification and Prediction" The application is designed to classify ECG images into six heart conditions using a hybrid AI model.

II. System Requirements

- **Operating System**: Windows, macOS, or Linux
- **Web Browser**: Latest versions of Chrome, Firefox, Safari, or Edge
- **Internet Connection**: Stable internet connection for accessing the web ECG classifier application.

III. Installation Instructions

a) **Clone the Repository**

Clone the project repository from GitHub:

git clone https://github.com/BrosFemo/ECG-Classification-WebApp.git

b) **Navigate to the Project Directory**

Open a terminal or command prompt and navigate to the project directory:

cd ECG-Classification-WebApp

c) **Install Dependencies**

Install the required Python libraries using pip:

pip install -r requirements.txt

d) **Run the Flask Server**

Start the Flask development server:

flask run

e) **Access the Web ECG Classifier Application**

Open a web browser and go to http://localhost:5000 to access the application.

f) **Alternate Web ECG Classifier Application Access (for non-developers)**

Open a web browser and go to http://10.62.4.216:5000/ to access the application

IV. User Interface Overview

- **Home Page**: Provides an overview of the application and instructions for uploading ECG images.
- **Upload Section**: Allows users to upload ECG images for classification on the home page.
- **Results Section**: Displays the classification results, including the predicted heart condition.

V. Using the Application

a) **Uploading an ECG Image**

- Navigate to the Upload Section by clicking on the "Choose File" button to select an ECG image from your computer.
- Once, selected, click the "Upload" button to submit the image for classification.
- Click the "Clear Selection" button to cancel a selection.

b) **Viewing Classification Results**

- After uploading, the application will process the image and display the classification results in the Results Section.
- The results include the predicted heart condition (one of the six predefined conditions), along with a probability score indicating the model's confidence in the prediction.

VI. Routine Maintenance

- **Data Privacy**: The system has been fitted with anonymity algorithm to ensure that all uploaded ECG images are anonymized to protect patient privacy.
- **Software Updates**: The developers of the system regularly update the software dependencies and the hybrid AI model to ensure optimal performance and accuracy.
- **Model Retraining**: In ensuring that the hybrid AI model is on par, a periodic

retrain of the hybrid AI model with new data would be carried out to improve its generalizability and accuracy.

VII. Troubleshooting

- **Server Issues**: If the Flask server does not start, ensure all dependencies are correctly installed and there are no port conflicts.
- **Upload Problems**: If the ECG image fails to upload, check the file format and size. The application supports standard image formats (JPEG, PNG) and files up to 10MB.
- **Classification Errors**: If the classification results are inconsistent or incorrect, verify the quality and clarity of the ECG images or contact the cardiologist.

Contact Information

For further assistance, please contact the research team:

- **Email**: oke.oluwafemi_a@yahoo.com, 20206831@std.neu.edu.tr,
- **Phone**: +90-ECGClassification
- **Address**: Near East University, Department of Computer Information Systems, Nicosia 99138, Cyprus
- **Address2**: Computer Information Systems Research and Technology Centre, Turkey

Conclusion

This user manual aims to guide users through the installation, usage, and maintenance of the ECG Classification web ECG classifier application. By following the instructions provided, users can effectively utilize the application for accurate and reliable ECG image classification, contributing to improved cardiac care and diagnosis.

APPENDIX G: Curriculum Vitae

PERSONAL INFORMATION

Surname, Name : Oke, Oluwafemi Ayotunde
Nationality : Nigerian
Date and Place of Birth : 5 May, Lagos
Marital Status : Single
Phone : +90 539 108 20 67
e-mail : oke.oluwafemi_a@yahoo.com

EDUCATION

Degree	Institution	Year of Graduation
Ph.D.	NEU, Computer Information Systems	2024
M.Sc.	Babcock University, Department of Software Engineering	2020
B.Sc.	Babcock University, Department of Computer Engineering (Technology)	2016

WORK EXPERIENCE

Year	Place	Enrollment
Sep,2023- present	Near East University	Part-Time Lecturer
Feb,2022- present	Near East University	Research Assistant
Feb,2022- Feb,2024	National Association of Nigerian Students	Assistant Director of IT and Communications
Aug,2021-Dec,2021	GIFA INC	IT Engineer
Sep,2021-Dec,2021	Yeni Bakis	IT Developer
May,2021-Sep,2021	Daxlinks Global	Design Engineer
Sep,2020- Dec,2020	Computer Professionals of Nigeria	Graduate Research Assistant
Sep,2019 –Jan,2020	E-library, Dstreet, Jitsi Meet, Get Foods	Software Tester
Feb,2018-Jan,2019	Taidob College	Head of Audiovisuals
Mar,2018-present	Winners Chapel International	Technical Member
Mar,2017-Feb,2018	Corporate Affairs Commission	Head of ICT
Jan,2017-Feb,2017	National Youth Service Corps	Data Analyst
May,2015-Aug,2015	Cadbury Nigeria Plc	Internship

FOREIGN LANGUAGES

- Fluent in English, Yoruba
- Beginner in Turkish, French, Hausa

CERTIFICATIONS

- Kaggle (2024) - *Machine Learning*
- Kaggle (2024) - *Programming*
- Kaggle (2024) - *Python*
- IBM (2023) - *AIWorkflow: AI in Production*
- IBM (2023) - *AIWorkflow: Machine Learning, Visual Recognition and NLP*
- IBM (2021) - *Oil & Gas Industry Operations and Markets*
- Duke University (2021) - *Cybersecurity Roles, Processes& Operating System Security*
- Yale University (2021) - *The Science of Well-Being Introduction to Cybersecurity Tools & Cyber Attacks*
- Android Certified Application Developer (2016)
- CompTIA Network + (2016)
- CompTIA A+ (2015)
- *Master of Computer Science, M.Sc.* (2019) – Babcock University, Graduate School of Computer Science, Department of Software Engineering.
- *Bachelor of Science, B.Sc.* (2016) - Babcock University, Faculty of Computer Engineering, Department of Computer Engineering, Ilishan-Remo, Ogun State.

COURSES

- Huawei Certified Network Associate (HCIA) - *Artificial Intelligence*
- Huawei Certified Network Associate (HCIA) - *Big Data*
- Huawei Certified Network Associate (HCIA) - *Security*
- Course Huawei Certified Network Associate (HCIA) - *Cloud Service TTT*
- *Master of Computer Science, M.Sc.* (2019) – Babcock University, Graduate School of Computer Science, Department of Software Engineering.
- *Bachelor of Science, B.Sc.* (2016) - Babcock University, Faculty of Computer Engineering, Department of Computer Engineering, Ilishan-Remo, Ogun State.

RESEARCH AWARD NOMINATIONS

- International Research Awards on Cybersecurity and Cryptography; ID 1896

PUBLICATIONS IN INTERNATIONAL REFEREED JOURNALS (IN COVERAGE OF SSCI/SCI-EXPANDED, AHCI AND ESCI):

- Oluwafemi Ayotunde Oke & Nadire Cavus (ARALIK 2024 GONDERDIK). Environmental Determinants of Cardiovascular Health in Northern Cyprus. *Archives of Cardiovascular Diseases.* (İnceleme aşamasında-WOS)

- Oluwafemi Ayotunde Oke & Nadire Cavus (GONDERDI_26-11-2024). A Comparative Study On the Classification of Cardiac Conditions Using Artificial Intelligence Models On Electrocardiogram Image Data. *Engineering Applications of Artificial Intelligence.* (İnceleme aşamasında-WOS)

- Oluwafemi Ayotunde Oke & Nadire Cavus (GONDERDI_6-01-2025). Advancing Cardiac Care: Clinical Integration of Hybrid Model for Automated Heart Disease Diagnosis. *Journal of Cardiovascular Translational Research.* (İnceleme aşamasında-WOS)

- Oluwafemi Ayotunde Oke & Nadire Cavus (KASIM 2024 GONDERDIK). An Investigative Bibliometric Analysis On the Impact of AI, ML and DL Technologies in Cardiology. *Archives of Cardiovascular Diseases.* (İnceleme aşamasında-WOS)

- Oluwafemi Ayotunde Oke & Nadire Cavus (GONDERDI_12-12-2024). Bibliometric Analysis of Cardiology and Cardiovascular Medicine in Western Europe. *Health Affairs.* (İnceleme aşamasında-WOS)
- Oluwafemi Ayotunde Oke & Nadire Cavus (MART 2024 GONDERDIK). Use of machine learning models for ECG analysis, diagnosis and interpretation in cardiology: A systematic review. *Revista Portuguesa de Cardiologia.*
- Oluwafemi Oke, Cavus, N. (GONDERDI_6-01-2025). Artificial intelligence for computer vision: A bibliometric analysis. *International Journal of Data Science and Analytics.* (İnceleme aşamasında-WOS)
- Oluwafemi Ayotunde, O., & Cavus, N. (ACCEPTED-2023). Digital Money and Financial Inclusion: Bridging the Gap. In Proceedings of the 4th International Conference on Data Science and Applications (ICDSA 2023), July 14-15, 2023, Malaviya National Institute of Technology Jaipur, India.
- Oke, O. A., & Cavus, N. (2025). (GONDERDI_26-11-2024). Electrocardiogram image classification for six classes of heart diseases. *Iran Journal of Computer Science 2025, 1–21*.
- Oke, O. A., & Cavus, N. (2025). A systematic review on the impact of artificial intelligence on electrocardiograms in cardiology. *International Journal of Medical Informatics*, *195*, 105753. https://doi.org/10.1016/J.IJMEDINF.2024.105
- Oluwafemi Ayotunde, O., & Cavus, N. (2024). The role of AI in financial services: A bibliometric analysis. *Journal of Computer Information Systems,* 1-13. https://doi.org/10.1080/08874417.2024.2304545
- Oluwafemi Ayotunde, O., Jamil, D. I., & Cavus, N. (2023). The impact of artificial intelligence in foreign language learning using learning management systems: A systematic literature review. *Information Technologies and Learning Tools, 95*(3), 215-228, https://doi.org/10.33407/itlt.v95i3.5233

PUBLICATIONS IN INTERNATIONAL REFEREED JOURNALS (IN COVERAGE OF British Education Index, ERIC, Science Direct, Scopus, IEEE):

- Ayotunde, O. O., & Cavus, N. (2023). Ethical considerations in AI and machine learning: A roadmap for researcher/end-user. *Paper Presented at the* Vl-International Antalya Scientific Research and Innovative Studies Congress. 02-04 December 2023, Antalya, Turkey.
- Ayotunde, O. O., Nuriye, N., & Cavus, N. (2023). *The future of water management: IoT-based solutions for ıntelligent distribution design (2023). Paper Presented at the 3rd International Conference on Water Problems in Mediterranean Countries (WPMC-2023).* 15-17 Aralık 2023. Lefkoşa, Cyprus.
- Ayotunde, O. O., Sancar, N., & Cavus, N. (2023). Building tomorrow: Green and sustainable ımperatives in smart city development. *Paper Presented at the 6th International Conference on Natural Resources and Sustainable Environmental Management (NRSEM-2023).* 15-17 Aralık 2023. Lefkoşa, Cyprus.
- Ayotunde, O. O., & Cavus, N. (2024). Climate Change, Sustainability, and Healthcare in Northern Cyprus: Predictive Insights for Tourists and Professionals. *Paper Presented at the 7th Global Healthcare Travel Forum GHTF-2024.* 17-21 Nisan 2024. Lefkoşa, Cyprus.

- Ayotunde, O. O., & Cavus, N. (2024). The Role of Health Tourism in the GDP and Development of Northern Cyprus: Exploring International Health Insurance and Beyond. *Paper Presented at the 7th Global Healthcare Travel Forum GHTF-2024.* 17-21 Nisan 2024. Lefkoşa, Cyprus.

BOOK CHAPTER

- Cavus, N., Oke, O.A., Yahaya, J.Mu. (2023). Brain-Computer Interfaces: High-Tech Race to Merge Minds and Machines. In: Daimi, K., Alsadoon, A., Coelho, L. (eds) Cutting Edge Applications of Computational Intelligence Tools and Techniques. Studies in Computational Intelligence, vol 1118. Springer, Cham. https://doi.org/10.1007/978-3-031-44127-1_1

WEBINARS

- Ayotunde, O. O., & Cavus, N. (2023). Machine Learning in Health Sciences. *Webinar Presented at the Department of Computer Information Systems-Computer Information Systems Research and Technology Center.* 9 Mart, 2023. Lefkoşa, Cyprus.
- Ayotunde, O. O., & Cavus, N. (2023). Smart Campus. *Webinar Presented at the Department of Computer Information Systems-Computer Information Systems Research and Technology Center.* 25 Ekim, 2023. Lefkoşa, Cyprus.

THESISES

Ph.D.: Oke, O.A. (2024). *ECG Diagnosis, Analysis, And Interpretation in Cardiology Using Deep Learning Models for Classification and Prediction*. Dissertation, Near East University, Graduate School of Applied Sciences, Department of Computer Information Systems, Nicosia, Cyprus.

Master: Oke, O.A. (2019). *Hybrid Intelligent Internet of Things (IOT) Systems for Automated Homes*. Thesis, Babcock University, Graduate School of Computer Science, Department of Software, Ilishan-Remo, Ogun State.

Lisans: Oke, O.A. (2016). *Radio Frequency Identification in Doors*. Graduation Project (B.Sc.), Babcock University, Graduate School of Computer Science, Department of Computer Technology (Engineering), Ilishan-Remo, Ogun State.

ADMINISTRATIVE DUTIES

- Assistant Director of IT and Communications - National Association of Nigerian Students (Feb, 2022 – Feb, 2024)
- Head, Audiovisual - Taidob College (Mar, 2018-Jan, 2019)
- Head, ICT– Corporate Affairs Commission (Feb, 2017-Feb, 2018)
- Project Manager - National Youth Service Corp (Jan, 2017-Feb, 2017)

HOBBIES

- Technology, Travel, Food and Music.

SKILLS

Technical Skills: System Analyst, Artificial Intelligence, Embedded Systems, Software Engineering, UI/UX design, SQLServer, DataVisualization, Machine Learning, Cloud Computing, Web Development, PHP and Python Development, Mobile development: Flutter and Dart, Cybersecurity and Information Security.

Soft Skills: Leadership, Self-awareness, Communication skills, Emotional intelligence.

Hard Skills: Problem-solving, Coding, Experimentation, Computer and technology knowledge, Programming languages, Technical writing, Software development.

COURSES TAUGHT OVER THE LAST TWO ACADEMIC YEARS

Academic Year	Term	Course Name	Hours/Week		Number of Students
			Theoretical	Applied	
2023-2024	Fall	CIS340+CIS240- Internet Programming	3	0	24
	Spring	CIS348+MIS321- E-Business	3	0	30
		CIS488+CIS288+MIS488 - Web Development	3	0	2
2024-2025	Fall	CIS340+CIS240- Internet Programming	3	0	14
		CIS363+CIS263- Software Engineering	2	0	25