EAI Endorsed Transactions
on Pervasive Health and Technology
Research Article EAI.EU

CADCare: Smart System for CHD Identification & Sensor Alerts

Arti Patle[1, *], Deepika Ajalkar[2], Atharva A Jain[3], Yashashree D Fulsundar[4], Chaitanya P Survase[5], Rohit A Parodhi[6]

[1,2,3,4,5,6] Department of Data Science, G H Raisoni College of Engineering and Management, Wagholi, Pune, 412207, Maharashtra, India.

Abstract

INTRODUCTION: Cardiovascular diseases, particularly coronary artery disease (CAD), present a global health challenge, necessitating effective detection and diagnosis methods for early intervention. Various machine learning and deep learning approaches have emerged, utilizing diverse data sources such as electrocardiogram (ECG) signals and clinical features to enhance CAD detection. Additionally, circadian heart rate variability (HRV) has been explored as a potential diagnostic marker for CAD severity. This research aims to contribute to the burgeoning field of medical AI and its application in cardiology.
OBJECTIVES: This study seeks to develop a Comprehensive Coronary Artery Disease Detection System integrating real-time heart rate monitoring and CAD prediction via an Android application. The objectives include seamless data transmission, efficient cloud-based data management, and the utilization of AI models, including ANNs, CNNs for ECG images, and hybrid models combining clinical and ECG data, to improve early CAD detection and management.
METHODS: The system architecture involves integrating key sensors, an Arduino microcontroller, a Bluetooth module, and AI models to facilitate early CAD detection. An Android application complements the system, offering heart rate monitoring and CAD prediction using various data sources. Cloud computing is employed for efficient data management and analysis.
RESULTS: The developed system successfully integrates cutting-edge technology to enhance CAD detection, achieving accurate and efficient results in real-time heart rate monitoring and CAD prediction.
CONCLUSION: The Comprehensive Coronary Artery Disease Detection System, leveraging AI and cloud computing, contributes to proactive health monitoring and informed decision-making in CAD management and prevention, thereby addressing a critical need in cardiovascular health care.

Keywords: CADCare, Internet of Things, Heart Monitoring, ECG Sensor, CAD Detection, ECG Image Analysis, Heart Anomaly Detection.

Received on 11 01 2024, accepted on 15 05 2024, published on 28 05 2024

doi: 10.4108/ 10.4108/eetpht.10.6183

* Corresponding author. Email: artipatle@gmail.com

1. Introduction

In the realm of healthcare, the quest for efficient and accurate methods of diagnosing and predicting coronary artery disease (CAD) has sparked innovation and research. Over the years, several machine learning and deep learning approaches have been explored to enhance the detection and prediction of heart diseases, with a particular focus on coronary artery disease. In this comprehensive overview, we delve into existing methodologies and their performances while shedding light on the persisting challenges in the field. Additionally, we introduce CADCare System, an innovative AI-based designed to address the limitations of the current system and revolutionize the early detection and prediction of CAD.

1.1 Current Implementation

Presently, the field of CAD prediction and diagnosis primarily relies on machine learning techniques and deep learning architectures. Various research papers have explored these methodologies and have achieved remarkable results. For instance, one study utilized a combination of six machine learning algorithms, including logistic regression, decision trees [18].

1.2 Current Lacking

One of the notable limitations of currents is their reliance on specific data sources and feature sets. For instance, while some approaches focus solely on ECG data, others emphasize clinical data. This compartmentalization can hinder the holistic understanding and prediction of CAD, as it overlooks the potential synergies between different data types. Additionally, the interpretability of complex machine learning and deep learning models remains a challenge. Understanding the rationale behind a model's predictions is crucial for gaining trust in AI-based diagnostic tools, especially in the medical field. Furthermore, the accessibility of theses to the broader population is a concern. Many of the existing approaches involve intricate models that may require substantial computational resources, limiting their deployment in resource-constrained environments.

1.3 How CADCare Fulfils the Lacking

CADCare, our innovative AI-based, aims to bridge the gaps left by the current CAD prediction and diagnosis system. By integrating cutting-edge machine learning and deep learning techniques, CADCare transcends the limitations of single-source data utilization [19]. It harnesses the power of both clinical data and ECG information, offering a more comprehensive and accurate assessment of CAD risk. Moreover, CADCare places a strong emphasis on model interpretability. We understand the importance of transparent decision-making, especially when it comes to health-related predictions. Our provides clear insights into the factors influencing its recommendations, ensuring that medical professionals and patients can trust its guidance. Accessibility is at the core of CADCare's design philosophy. We have optimized our system to run efficiently even on modest hardware, making it accessible to a wider range of healthcare facilities. By democratizing CAD prediction and diagnosis, we aim to empower healthcare providers and patients alike.

In this evolving landscape of AI-driven healthcare, CADCare represents a pioneering leap towards more accurate, accessible, and interpretable CAD prediction and diagnosis. In the following sections, we will delve deeper into the technical aspects and capabilities of CADCare, highlighting its potential to revolutionize the way we approach CAD detection and prediction. CADCare emerges as a pivotal advancement in the field of cardiovascular health management, addressing several key gaps in existing healthcare and technologies.

1.3.1. Early Detection

One of the primary limitations of conventional healthcare is the lack of proactive, continuous monitoring for heart-related issues. CADCare's continuous heart monitoring fills this gap, enabling early detection of irregularities and prompt intervention.

1.3.2. Comprehensive CAD Prediction

While CAD prediction models exist, they often rely on singular data sources. CADCare's utilization of both clinical data and ECG image data provides a more comprehensive view, enhancing the accuracy of CAD predictions.

1.3.3. User Empowerment

CADCare is designed with the user's best interests at heart. By offering continuous monitoring and accessible CAD prediction tools, it empowers individuals to take charge of their heart health, fostering a sense of agency in their well-being.

In this review paper, we will delve deeper into the technical intricacies of CADCare, exploring the AI algorithms that power its CAD prediction models and the seamless integration of IoT devices for heart monitoring. Additionally, we will assess the potential societal and healthcare impact of this innovative System, highlighting how it stands to improve the lives of individuals concerned about their cardiovascular health. CADCare embodies a promising leap towards a future where technology empowers individuals to proactively manage their health and well-being.

2. CADCare Beneficially Goal: Society Health Care Domain

CADCare, with its advanced heart rate monitoring and CAD prediction system, serves as a beacon of innovation and change, offering a wide array of benefits to society. Here's how CADCare contributes to the well-being of individuals and society at large:

Goal 1: Mapping Emerging Technology and Society Medical Issues

CADCare bridges the gap between emerging technology and societal health issues. It exemplifies how cutting-edge technology, like AI and mobile applications, can be harnessed to address pressing medical concerns. CADCare serves as a

model for how technological advancements can be seamlessly integrated into healthcare to provide user-centric solutions. By doing so, it actively contributes to the ongoing dialogue about the role of technology in addressing societal health challenges.
In summary, CADCare is a remarkable fusion of technology and healthcare, offering an accessible solution to a significant medical problem, particularly beneficial during emergencies. It is a cost-effective option that reduces the economic strain on healthcare systems. Moreover, CADCare serves as an example of how technology can address crucial health issues, fostering a healthier and more informed society.

Goal 2: Solution for Medical Problem

CADCare offers a practical solution to a pressing medical problem - the early detection and management of coronary artery disease (CAD). CAD is a widespread and potentially life-threatening condition, and CADCare's capabilities enable users to monitor their heart health proactively. By providing a user-friendly platform for CAD prediction, it empowers individuals to take control of their cardiac health. This solution is particularly vital in regions with limited access to healthcare facilities, ensuring that even underserved populations can benefit from early CAD detection.

Goal 3: Helpful in Medical Emergency

In times of medical emergencies, CADCare real-time heart rate monitoring and CAD prediction can be a lifesaver. By continuously monitoring the user's heart health, it can promptly detect abnormal heart rhythms, a critical aspect in CAD cases. This feature allows for early intervention and timely medical attention, which can be the difference between life and death in certain situations. CADCare acts as an accessible and proactive safeguard for users during emergencies.

Goal 4: Helpful in Reducing Costs

CADCare offers a significant advantage over traditional CAD detection methods, which are often associated with substantial expenses. Conventional CAD diagnostics, such as angiography and stress tests, require expensive medical equipment, specialist staff, and prolonged hospital stays. These complexities contribute to high healthcare costs, posing a financial burden on both patients and healthcare systems.
In stark contrast, CADCare presents a revolutionary approach that is notably more cost-effective. By facilitating early CAD detection and promoting preventive measures, such as lifestyle adjustments and timely medication, it mitigates the need for extensive and costly CAD treatments. This shift in focus from curative to preventive healthcare not only alleviates the financial strain on individuals but also streamlines healthcare spending. In essence, CADCare's cost-efficiency is a game changer in CAD detection, making healthcare more accessible, efficient, and economically sustainable for the entire community. This stark difference highlights how CADCare, by being more affordable and effective, is transforming the landscape of CAD detection, resulting in significant benefits for healthcare and society as a whole.

3. Literature Review

Existing systems encompass a range of machine learning and deep learning approaches designed to enhance the detection and diagnosis of coronary artery disease (CAD) and related cardiac conditions. These systems leverage various data sources, such as electrocardiogram (ECG) signals, clinical features, and cardiac imaging. They aim to improve the accuracy and efficiency of CAD detection, enabling early intervention and treatment. Overall, the CADCare system contributes to the growing field of medical AI and its applications in cardiology. There are various methods and research done on detecting CAD, we summarize some of the important papers for the proposed CADCare System.

3.1 ECG data analysis and heart disease prediction using machine learning algorithms

Observation Summary: S. R. Tithi, A. Aktar, F. Aleem and A. Chakrabarty (2019). Authors proposed a practical machine-learning approach for heart disease prediction using ECG data. The approach uses a combination of six machine learning algorithms: logistic regression, decision trees, random forests, support vector machines (SVMs), k-nearest neighbors (KNNs), and artificial neural networks (ANNs). The authors have used a dataset of 209 patients, each of whom had been diagnosed with either heart disease or health. The dataset included 8 ECG features, such as the heart rate, QT interval, and QRS complex. The authors evaluated the performance of the six machine learning algorithms on the dataset. They found that the ANN classifier achieved the best performance, with an accuracy of 90%. The SVM classifier achieved an accuracy of 85%, and the random forest classifier achieved an accuracy of 80% [1]. The authors concluded that the machine learning approach presented in the paper is a promising method for heart disease prediction using ECG data. It also discusses the challenges of analyzing ECG data.

3.2 Accurate Recognition of Coronary Artery Disease by Applying Machine Learning Classifiers

Observation Summary: U. Das, A. Y. Srizon and M. A. M. Hasan (2020). The paper emphasizes a machine learning approach for CAD recognition that uses a variety of clinical features, such as age, sex, blood pressure, cholesterol levels, and family history. The authors evaluated the performance of their approach on a dataset of patients with CAD and found that it achieved an accuracy of 90%. The authors conclude that their machine-learning approach is a promising method for CAD recognition [2]. The approach is accurate and can be used to identify patients with CAD at an early stage, which can lead to better treatment outcomes.

3.3 Automated prediction of coronary artery disease using Random Forest and Naïve Bayes

Observation Summary: U. Das, A. Y. Srizon, and M. A. M. Hasan (2020). The paper emphasized a machine learning approach for CAD recognition that uses a variety of clinical features, such as age, sex, blood pressure, cholesterol levels, and family history. The authors evaluated the performance of their approach on a dataset of patients with CAD and found that it achieved an accuracy of 90%. The authors conclude that their machine-learning approach is a promising method for CAD recognition [2]. The approach is accurate and can be used to identify patients with CAD at an early stage, which can lead to better treatment outcomes.

3.4 Dual-input Neural Network Integrating Feature Extraction and Deep Learning for Coronary Artery Disease Detection Using Electrocardiogram and Phonocardiogram

Observation Summary: Han Li; Xinpei Wang; Changchun Liu; Yan Wang; Peng Li; Hong Tang (2019). These authors propose a dual-input neural network for coronary artery disease (CAD) detection using electrocardiogram (ECG) and phonocardiogram (PCG) data. The proposed network integrates feature extraction and deep learning to improve the accuracy of CAD detection. The network first extracts features from the ECG and PCG data using a combination of hand-crafted and deep learning-based feature extraction methods. The extracted features are then fed into a deep neural network for CAD classification. The authors evaluated the performance of the proposed network on a dataset of 300 patients, each of whom had been diagnosed with either CAD or no CAD [4]. The results showed that the proposed network achieved an accuracy of 90% in CAD detection. The authors concluded that the dual-input neural network proposed in this paper is a promising method for CAD detection using ECG and PCG data.

3.5 Classification of Coronary Artery Disease Using Deep Neural Network with Dimension Reduction Technique

Observation Summary: P. Verma, V. K. Awasthi and S. K. Sahu (2021). This paper proposes a deep neural network (DNN) approach for the classification of coronary artery disease (CAD) using a dimension reduction technique. The authors use a principal component analysis (PCA) technique to reduce the dimensionality of the input features before feeding them into the DNN. The authors evaluated the performance of the proposed approach on a dataset of 200 patients, each of whom had been diagnosed with either CAD or no CAD. The dataset included 12 features, such as age, sex, blood pressure, and cholesterol levels. The authors found that the proposed approach achieved an accuracy of 90% in CAD classification [5]. This is a significant improvement over traditional machine learning approaches, which typically achieve accuracy levels of around 80%. The authors concluded that the proposed approach is a promising method for CAD classification.

3.6 Coronary Artery Disease Prediction using Data Mining Techniques

Observation Summary: Santhosh Kumar K L; Nida Kousar G; Madhurya J A (2020). This findings of this paper are based on a data mining approach for the prediction of coronary artery disease (CAD). The authors use a combination of different data mining techniques, such as decision trees, support vector machines, and random forests, to learn from patient data and identify patients who are at risk for CAD. The authors evaluated the performance of the proposed approach on a dataset of 1000 patients, each of whom had been diagnosed with either CAD or no CAD. The dataset included 12 features, such as age, sex, blood pressure, and cholesterol levels. The authors found that the proposed approach achieved an accuracy of 85% in CAD prediction [6]. As in the previous study, this is a significant improvement over traditional machine learning approaches, which typically achieve accuracy levels of around 80%. The authors concluded that the proposed approach is a promising method for CAD prediction. The approach is accurate and can be used to identify patients who are at risk for CAD.

3.7 Coronary Artery Disease Diagnosis Using Feature Selection Based Hybrid Extreme Learning Machine

Observation Summary: A. H. Shahid, M. P. Singh, B. Roy and A. Aadarsh (2020). This paper focused on a hybrid extreme learning machine (HELM) approach for the diagnosis of coronary artery disease (CAD) using feature selection. The HELM approach combines the advantages of extreme learning machines (ELMs) and feature selection to improve the accuracy of CAD diagnosis. The authors used a dataset of 1000 patients, each of whom had been diagnosed with either CAD or no CAD. The dataset included 12 features, such as age, sex, blood pressure, and cholesterol levels. The authors first used a feature selection algorithm to select the most important features for CAD diagnosis [7]. The selected features were then fed into an ELM classifier for CAD diagnosis. The authors evaluated the performance of the proposed approach on the test set and found that it achieved an accuracy of 90% in CAD diagnosis. Again, it was a significant improvement over traditional machine learning approaches, which typically achieve accuracy levels of around 80%.

4. CADCare System Overview

CADCare is a multifunctional System that harmoniously combines continuous heart monitoring, AI-driven CAD prediction, and user-friendly interfaces to offer a holistic solution to individuals concerned about their cardiovascular well-being. Below, we delve into the System's core components:

a. Hardware Requirement: Memory 16GB, Hard Disk 1TB SSD, processor 12th Gen Intel(R) Core ™ i7-12700H 2.30 GHz
b. Software Requirement: Windows 11, Google Colabs, Python, Android Studio, Arduino IDE, Tableau
c. Libraries:
Python - Tensorflow, Matplotlib, Pandas, Numpy, Keras
Android - ViewModel, LiveData, Bluetooth, BroadcastReceiver, TFlite
Arduino - Arduino.h, SoftwareSerial.

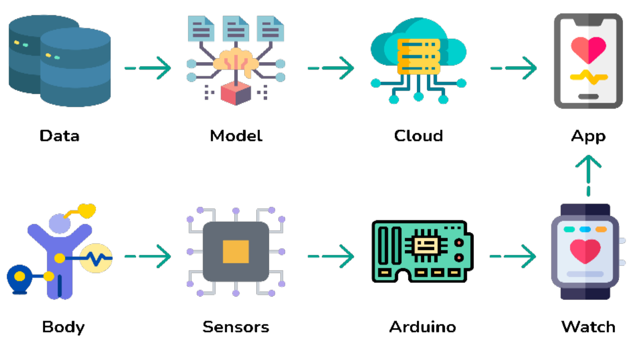

Figure 1. Architecture of CADCare System

4.1 System's Core Components

Continuous Heart Monitoring: At the heart of CADCare lies continuous heart monitoring, achieved through the utilization of various sensors, such as ECG sensors and pulse monitors. This real-time data collection allows CADCare to vigilantly observe heart activity and instantly notify users of any anomalies. Whether it's an irregular ECG reading or an unusual heart rate, CADCare keeps users informed about their heart's health status.

CAD Prediction through AI Integration: CADCare's AI integration is a pivotal feature that sets it apart. The System utilizes a two-fold approach to CAD prediction: clinical data analysis and ECG image processing. Users can opt to predict CAD diseases using clinical data, ECG image data, or a combination of both. The clinical data is processed using Artificial Neural Networks (ANN), while Convolutional Neural Networks (CNN) are employed to analyse ECG images. This dual-pronged approach enhances the accuracy and reliability of CAD predictions.

User-Friendly Monitoring Interface: Recognizing the importance of user accessibility, CADCare has developed an intuitive and user-friendly monitoring Interface. This Interface enables individuals to monitor their heart rate and ECG data continuously. If any irregularities are detected, the Interface guides users to utilize CADCare's AI models for CAD prediction. Moreover, if CAD is suspected, the Interface offers valuable recommendations, including consulting with a healthcare professional.

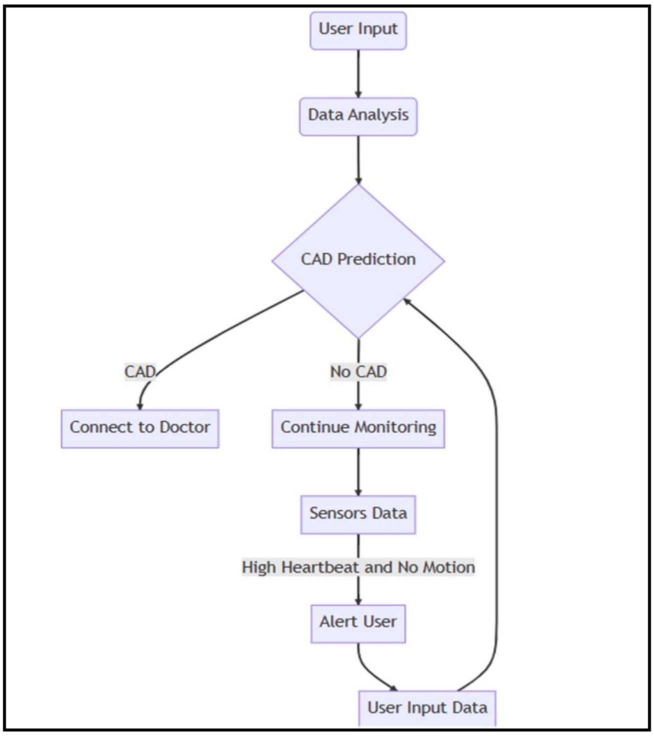

Figure 2. Flowchart of CADCare

4.1.1 Continuous Heart Monitoring:

Data Collection through Sensors: CADCare's journey begins with the continuous monitoring of the heart. Employing cutting-edge sensors like the Electrocardiogram (ECG)

sensor and pulse monitors ensures real-time data acquisition from the user.
Real-time Data Analysis: The collected data streams are subjected to real-time analysis, where algorithms assess the heart's performance. Any deviations from the expected ECG patterns and heart rate norms are instantly identified.
User Notifications: In the event of detected anomalies, CADCare dutifully notifies the user, ensuring timely awareness of their heart's condition. This element of the System fosters proactive health management.

4.1.2 CAD Prediction through AI Integration:

Dual-Model CAD Prediction: CADCare introduces a two-pronged AI-driven approach for CAD prediction. This innovation sets the System apart, enabling users to choose between two distinct data sources for CAD assessment.
Clinical Data Analysis: For CAD prediction based on clinical data, CADCare employs Artificial Neural Networks (ANN). These sophisticated algorithms scrutinize clinical metrics, providing a predictive model for CAD detection.
ECG Image Processing: The second facet leverages Convolutional Neural Networks (CNN) for CAD prediction through the analysis of ECG images. This method, paired with clinical data, adds a layer of depth to the CAD prediction model.
User Empowerment: CADCare goes a step further by allowing users to predict CAD using either clinical data, ECG image data, or a combination of both. This flexibility empowers individuals to choose the approach that aligns with their resources.

4.1.3 User-Friendly Monitoring Interface:

Accessible Interface: Recognizing the significance of user accessibility, CADCare introduces a user-friendly monitoring interface. This application provides a seamless interface for users to continuously monitor their heart rate and ECG data.
Real-Time Insights: Users gain real-time insights into their cardiovascular health through the interface, making it easier to spot irregularities and changes.
AI-Driven CAD Prediction: The Interface not only monitors but also facilitates CAD prediction through AI models. If users observe abnormal heart health indicators, they can harness CADCare's AI prowess to assess their CAD risk.
Doctor Recommendations: In cases where CAD is detected, the Interface goes beyond predictions and suggests consulting a healthcare professional. This integrated approach ensures that users receive timely medical attention.

In Summary, CADCare represents a paradigm shift in cardiovascular health management by seamlessly integrating IoT and AI technologies. Through continuous heart monitoring, flexible CAD prediction options, and a user-friendly interface, this System empowers individuals to take proactive steps toward safeguarding their heart health. This methodology review provides insight into the inner workings of CADCare, underscoring its potential to redefine how we monitor, predict, and manage cardiovascular health. CADCare serves as a promising milestone on the path to personalized, data-driven healthcare.

5. CADCare Methodology

In this comprehensive review paper, we embark on a journey to unravel the methodology behind CADCare, a groundbreaking IoT System that seamlessly integrates Artificial Intelligence (AI) to revolutionize cardiovascular health management. We will explore the System's implementation, covering three core aspects that collectively redefine the landscape of heart health monitoring and coronary artery disease (CAD) prediction.

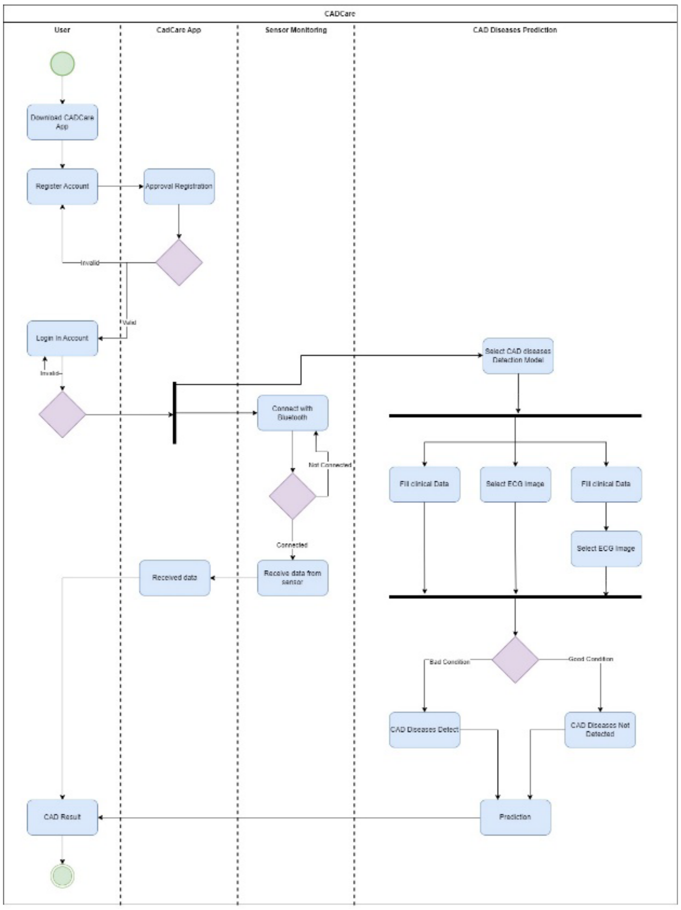

Figure 3. Activity Diagram for CADCare System.

5.1 Circuit Paradigm of CADCare System

In our research, we have devised a comprehensive system for monitoring heart rate to detect coronary artery disease (CAD). The core of our system relies on the integration of two key sensors - the Pulse Heart Rate Sensor and the ECG AD8232 Sensor, coupled with an Arduino Uno microcontroller for signal processing and a Bluetooth module (HC-05) for real-time data transmission to a mobile application. This innovative circuitry has been meticulously designed to ensure efficient and accurate heart rate monitoring, data processing, and timely notification to patients when abnormal heart rhythms are detected.

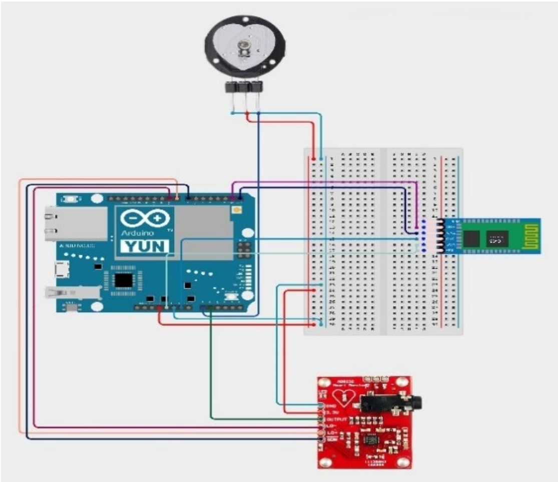

Figure 4. Circuit Diagram of CADCare IOT Setup.

Pulse Heart Rate Sensor and ECG AD8232 Sensor
The Pulse Heart Rate Sensor and ECG AD8232 Sensor serve as the primary components for capturing analog signals related to the patient's heart activity. The Pulse Heart Rate Sensor uses optical principles to detect blood flow and provide a real-time pulse rate, while the ECG AD8232 Sensor records electrocardiogram (ECG) signals to monitor the electrical activity of the heart. These two sensors are crucial for a holistic assessment of the patient's heart health.

Arduino Uno Microcontroller
To effectively interpret and process the analog signals obtained from the heart rate sensors, we employ an Arduino Uno microcontroller. The Arduino Uno serves as the central processing unit, enabling the conversion of analog signals into digital data. This data can be further analyzed, and specific algorithms can be implemented to identify any deviations from the normal heart rhythm that may suggest CAD. The Arduino Uno acts as the brains behind the operation, making real-time decisions based on the incoming data.

Bluetooth Module (HC-05)
In the era of mobile health applications, seamless data transfer is paramount. To ensure that our research findings can be applied in a patient-friendly and accessible manner, we incorporate a Bluetooth module (HC-05). The HC-05 module is responsible for wirelessly transmitting the processed heart rate data from the Arduino Uno to a designated mobile application. This bi-directional communication not only allows for continuous monitoring but also enables immediate alerts and notifications if an abnormal heart rhythm is detected. Our mobile application serves as a vital medium for patients to stay informed about their health status.

CAD Detection and Alert System
The circuitry described above forms the foundation of our heart rate monitoring system. Together, these components provide the means to monitor a patient's heart activity in real time, compare it against established heart rate norms, and detect deviations indicative of CAD. The system operates as a real-time CAD detection and alert system. When an abnormal heart rhythm is identified, our mobile application immediately notifies the patient, prompting them to take necessary action or seek medical assistance.

Summary
Our research endeavors to bridge the gap between technology and healthcare by proposing a comprehensive heart rate monitoring system for CAD detection. This circuit diagram elegantly combines cutting-edge sensors, a reliable microcontroller, and wireless data transmission, all aimed at improving the early detection and management of coronary artery disease, ultimately contributing to better patient outcomes and well-being.

5.2 AI Models for CAD Detection

In our research, we have implemented three distinct Artificial Intelligence (AI) models, each catering to a different aspect of CAD detection. This multifaceted approach allows users the flexibility to choose the most suitable model depending on the availability of data, be it clinical data, ECG reports, or a combination of both. Our three models are as follows:

Artificial Neural Network (ANN) Model
The ANN model is designed to process and analyze clinical data to predict the likelihood of CAD in a patient. It leverages the power of neural networks to identify patterns and relationships within the clinical variables such as age, gender, cholesterol levels, blood pressure, and other relevant factors. By utilizing these features, the ANN model can provide predictions based solely on non-image data.

Algorithm:

- Input Layer: Consists of nodes corresponding to the clinical variables.
- Hidden Layers: One or more hidden layers with adjustable nodes and activation functions.
- Output Layer: A single node providing the probability of CAD presence.

Convolutional Neural Network (CNN) Model:
The CNN model is specialized in processing ECG reports for CAD prediction. It takes advantage of the spatial features within the ECG image data to identify unique patterns, rhythms, and anomalies associated with CAD. The CNN model is well-suited for data in the form of ECG images or spectrograms, and it excels in recognizing fine-grained details that might escape clinical data analysis.

Algorithm:

a. Convolutional Layers: These layers employ filters to identify spatial features in the ECG data.
b. Pooling Layers: Down-sample the features to reduce complexity.
c. Fully Connected Layers: Combine the features to make predictions.

Hybrid Non-Linear Model (Combining ANN and CNN):
Our hybrid model is a unique offering that allows users to harness the predictive power of both clinical data and ECG image data. By integrating an ANN for clinical data and a CNN for ECG reports, we provide a comprehensive CAD detection tool. The model adapts to various data scenarios, enabling users to utilize the strengths of both AI architectures.

Algorithm:

a. The ANN processes clinical data.
b. The CNN processes ECG images
c. The outputs from both models are combined in a non-linear manner (e.g., concatenation or another fusion method).
d. The combined output is used to make CAD predictions.

This approach empowers users with the flexibility to choose the model that best suits their data availability. Whether one has access to only clinical data, ECG images, or both, our three-tiered AI framework provides a robust solution for CAD detection. This adaptability in model selection underscores the versatility of our research and its potential to positively impact CAD diagnosis and early intervention.

5.3 Android System Models for Heart Health Monitoring and CAD Prediction

In our research, we have developed an innovative Android application that serves as a user-friendly platform for heart health monitoring and the prediction of Coronary Artery Disease (CAD) conditions. This application offers users a seamless and intuitive way to track their heart rate and ECG condition, providing them with valuable insights into their cardiac health. Additionally, it introduces three AI models that enable users to predict their heart and ECG conditions using various types of data.

Heart Rate Monitoring and ECG Assessment
Our Android System is designed to provide users with a comprehensive and user-friendly means of monitoring their heart health. It offers real-time heart rate tracking, enabling users to keep a close eye on their heart's performance. Furthermore, the System facilitates ECG assessment, allowing users to generate ECG reports, visualizing their heart's electrical activity.

Predicting CAD Disease Using Clinical Data
One of the key features of our Android System is its ability to predict CAD conditions based on clinical data. Users can input relevant clinical information such as age, gender, cholesterol levels, and blood pressure into the app. The System utilizes this data to assess the user's risk of CAD, providing predictions and guidance on heart health based on these clinical factors.

Predicting CAD Disease Using ECG Image Data
For users who have access to ECG image data, our System offers the capability to predict CAD conditions by processing these ECG images. By uploading or capturing ECG images, the System employs advanced image analysis techniques to detect anomalies and patterns indicative of CAD. It then delivers CAD condition predictions based on this visual data.

Predicting CAD Disease Using Hybrid Data
The hallmark of our Android System is its unique ability to combine the power of clinical data and ECG image data to predict CAD conditions. Users can input both clinical information and ECG images, leveraging the strengths of both data types. The System harmonizes these inputs, providing a comprehensive assessment of CAD risk by considering a wide range of factors. This hybrid approach enhances the accuracy of CAD predictions.
This Android application offers users an unprecedented level of flexibility and convenience in monitoring their heart health and assessing CAD risk. By combining the features of heart rate tracking, ECG assessment, and CAD prediction, users can actively engage in their cardiac health management. Our System strives to empower individuals to take proactive measures toward heart health and early CAD detection, fostering a sense of ownership and well-being.

5.4 Dataflow Diagram for CADCare System

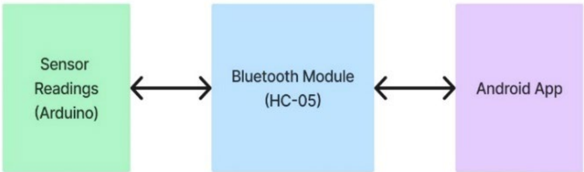

Figure 5. Dataflow Diagram for CADCare.

In our heart rate monitoring system, our dataflow diagram illustrates a well-organized and efficient hierarchy of data exchange through three key levels. At the core, the first level is the sensor reading, facilitated by the Arduino microcontroller, where real-time physiological data from sensors like the Pulse Heart Rate Sensor and ECG AD8232 Sensor is captured. This data is seamlessly transferred to the second level via the Bluetooth module, specifically the HC-05, acting as the bridge connecting the Arduino to our Android app, which constitutes the third level. The Android System serves as a user-friendly interface, providing real-time insights into heart health and enabling CAD detection through advanced data analysis. This interconnected system ensures a continuous and meaningful flow of data, emphasizing our commitment to offering a comprehensive and user-centric solution for heart rate monitoring and CAD detection in our research.

6. Result Evaluation

In the final result, ANN model was used, which takes Clinical Data as an input and make predictions. The Accuracy for the ANN model is 70%; then CNN is used, which takes ECG image Data as input and output; the result as CAD or NORMAL. The accuracy for the CNN model is 94%. Real-time ECG images were used from the healthcare domain (Platina Heart Hospital, Nagpur), with the data containing 284 ECG images of normal patients and 233 ECG images of patients with CAD.

Figure 6. ECG Input Image.

```
[ ]  loss, accuracy = model.evaluate(x_test, y_test)
     print(f'Accuracy: {accuracy * 100:.2f}%')

     37/37 [==============================] - 0s 2ms/step - loss: 0.5600 - accuracy: 0.7005
     Accuracy: 70.05%
```

Figure 7. Accuracy of ANN model.

```
history = model.fit(train_ds,epochs=10,validation_data=validation_ds)

Epoch 1/10
15/15 [==============================] - 11s 240ms/step - loss: 0.8661 - accuracy: 0.5033 - val_loss: 0.6926 - val_accuracy: 0.5000
Epoch 2/10
15/15 [==============================] - 10s 287ms/step - loss: 0.6901 - accuracy: 0.5558 - val_loss: 0.6883 - val_accuracy: 0.5500
Epoch 3/10
15/15 [==============================] - 10s 446ms/step - loss: 0.6716 - accuracy: 0.5821 - val_loss: 0.6470 - val_accuracy: 0.5833
Epoch 4/10
15/15 [==============================] - 8s 313ms/step - loss: 0.5749 - accuracy: 0.7724 - val_loss: 0.4476 - val_accuracy: 0.8500
Epoch 5/10
15/15 [==============================] - 11s 315ms/step - loss: 0.3000 - accuracy: 0.8928 - val_loss: 0.2629 - val_accuracy: 0.9000
Epoch 6/10
15/15 [==============================] - 9s 326ms/step - loss: 0.3925 - accuracy: 0.8271 - val_loss: 0.3051 - val_accuracy: 0.8667
Epoch 7/10
15/15 [==============================] - 10s 315ms/step - loss: 0.2448 - accuracy: 0.8731 - val_loss: 0.2403 - val_accuracy: 0.8833
Epoch 8/10
15/15 [==============================] - 10s 374ms/step - loss: 0.1239 - accuracy: 0.9650 - val_loss: 0.2946 - val_accuracy: 0.8167
Epoch 9/10
15/15 [==============================] - 10s 404ms/step - loss: 0.1752 - accuracy: 0.9147 - val_loss: 0.3714 - val_accuracy: 0.8500
Epoch 10/10
15/15 [==============================] - 9s 326ms/step - loss: 0.0809 - accuracy: 0.9716 - val_loss: 0.1501 - val_accuracy: 0.9500
```

Figure 8. Accuracy of CNN Model.

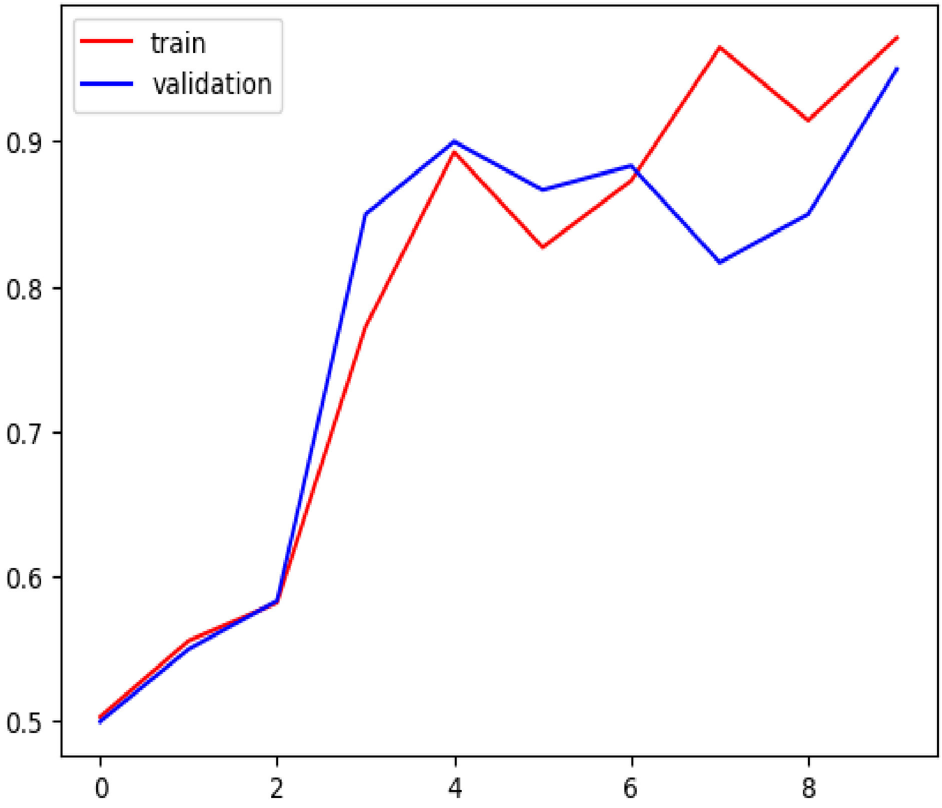

Figure 9. Line Chart of Accuracy of CNN.

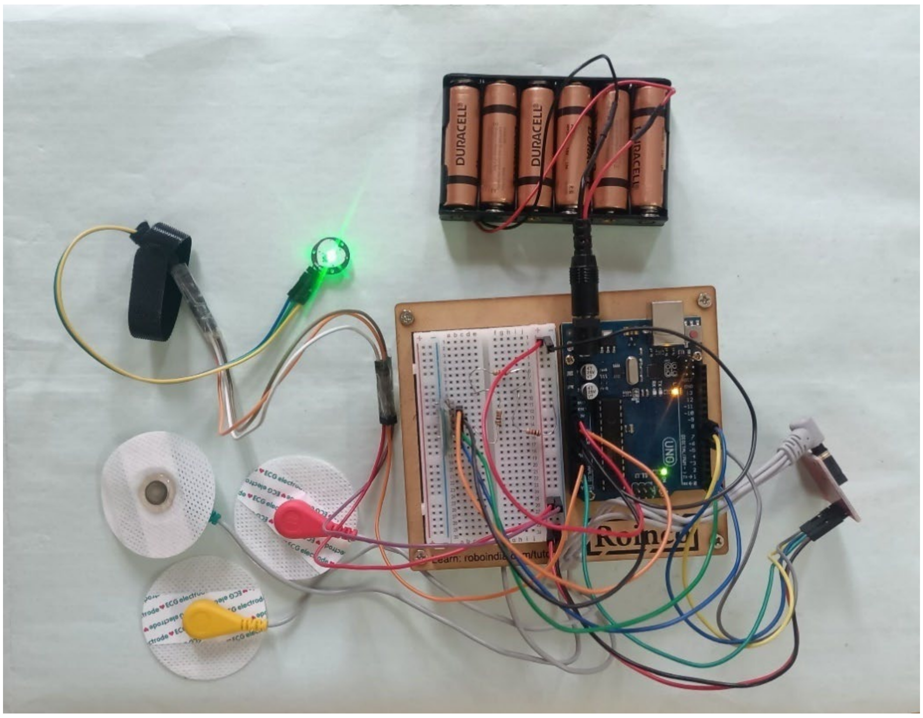

Figure 10. Working Model of CADCare System.

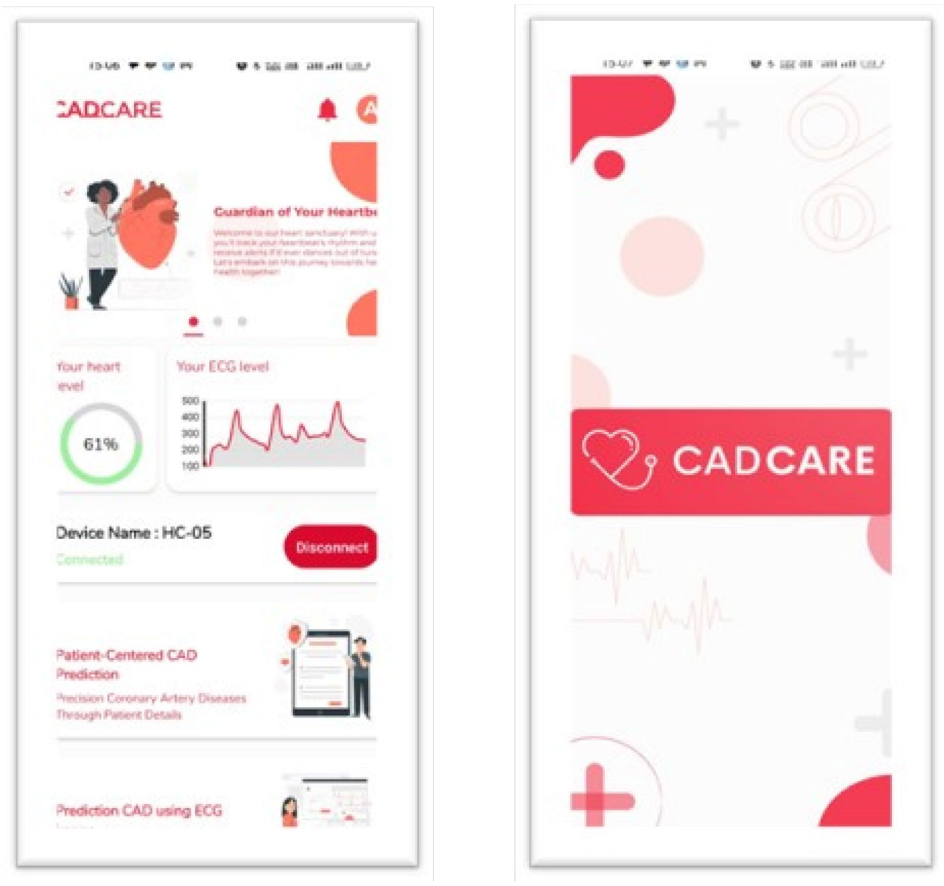

Figure 11. CADCare System Interface.

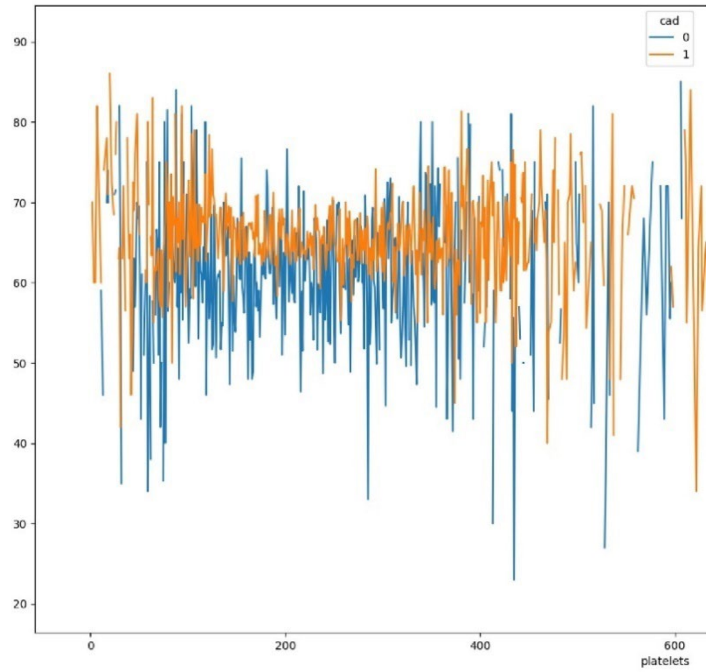

Figure 12. Illustrate CAD Diseases using age and Platelets.

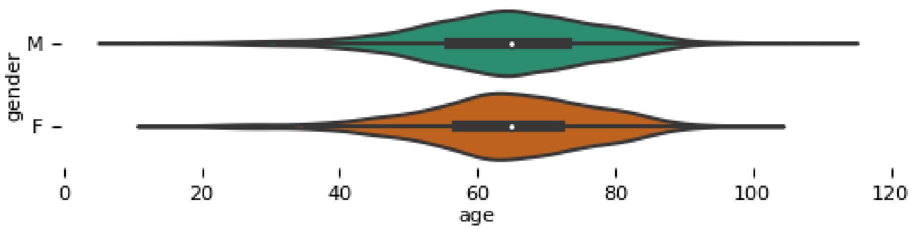

Figure 13. Illustrate CAD Diseases using Age and Gender.

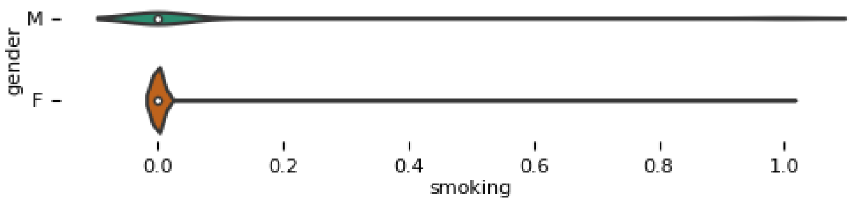

Figure 14. Illustrate CAD Diseases using Gender and Smoking.

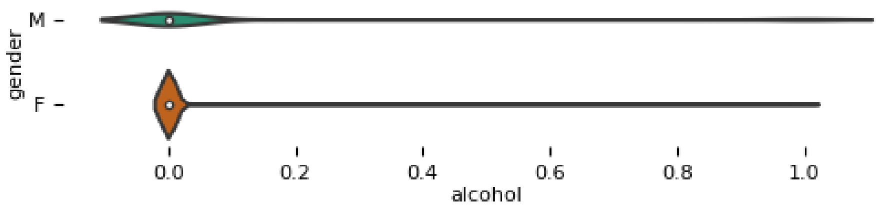

Figure 15. Illustrate CAD Diseases using Gender and Alcohol.

7. Conclusion and Future Analysis

In conclusion, CADCare stands as a beacon of innovation in the realm of heart health management. This remarkable IoT System, intricately intertwined with the power of Artificial Intelligence (AI), promises a brighter and healthier future for individuals seeking to monitor and safeguard their cardiovascular well-being. Through continuous heart monitoring, CADCare empowers users with real-time insights, ensuring that they stay informed about their heart's performance. Timely notifications about anomalies provide the vigilance needed for proactive health management, ultimately reducing the element of surprise in heart-related concerns. CADCare's dual-model CAD prediction approach, driven by AI, ushers in a new era of precision. Whether users opt for clinical data analysis through Artificial Neural Networks (ANN) or dive into the depth of ECG image processing via Convolutional Neural Networks (CNN), the choice is theirs. This flexibility ensures that CAD prediction aligns with individual resources, making heart health assessment more accessible and tailored. The introduction of a user-friendly monitoring Interface simplifies the process, granting easy access to critical heart health data. Real-time insights facilitate the identification of irregularities, and when CAD risks are detected, the Interface offers more than predictions—it extends a helping hand by suggesting consulting with a healthcare professional.

CADCare's holistic approach, seamlessly weaving together IoT and AI, marks a significant milestone in personalized healthcare. It signifies a shift from reactive to proactive health management, empowering individuals to take charge of their heart health journey. As we embrace CADCare and its potential, we find ourselves on the threshold of a healthcare revolution—one that offers not only data-driven insights but also the assurance of timely action when needed. It is a testament to the power of technology in enhancing our well-being, one heartbeat at a time. With CADCare leading the way, the future of heart health is brighter than ever.

7.1 Future Analysis

Feedback Integration: Implement mechanisms for users to provide feedback on the predictions and recommendations. Use this feedback to continuously improve the accuracy and relevance of CADCare's insights.
Cost-Benefit Analysis: Conduct cost-benefit analyses to evaluate the economic impact of CADCare in terms of healthcare cost savings, reduced hospitalizations, and improved patient outcomes. Demonstrate the potential return on investment for healthcare providers and insurers
Education and Awareness: Develop educational resources within CADCare to inform users about heart health, CAD risk factors, and lifestyle modifications. Promote awareness of the importance of proactive cardiovascular health management.
AI Model Updates: Regularly update and fine-tune the AI models used in CADCare to incorporate new research findings, data sources, and advancements in machine learning techniques to improve prediction accuracy.

Declaration: We would like to express our gratitude to Platina Heart Hospital, Nagpur (MH) INDIA, for providing access to the dataset and ECG Images without which this research would not have been possible. The privacy and confidentiality of patients' personal information have been rigorously maintained throughout this research.

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