# An AI-Driven, Context-Aware Approach to Detect Early Onset Heart Attacks and other Cardiovascular Diseases (CVDs)

Rayyan Minhaj[1†], Mahmood ul Hassan[2], Syed Ayaan Danish[1†], Hamad Ali Abosaq[3], Ayihan Ul Haq[1†], Mohammad Alsulami [3], Muhammad Farrukh Shahid[1*], Mohammed Al Yami[4], Tariq J. S. Khanzada[5]

[1*]FAST School of Computing, National University of Computer and Emerging Sciences, Street, Karachi, 100190, Sindh, Pakistan.
[2]Department of Computer Skills, Deanship of Preparatory Year, Najran University, Street, Najran, 61441, Saudi Arabia.
[3]Computer Science Department, College of Computer Science and Information Systems, Najran University, Street, Najran, 61441, Saudi Arabia.
[4]Department of Information Systems, College of Computer Science and Information Systems, Najran University, Street, Najran, 61441, Saudi Arabia.
[5]Department of Information Systems, King Abdulaziz University, Jeddah, 21589, State, Saudi Arabia.

*Corresponding author(s). E-mail(s): mfarrukh.shahid@nu.edu.pk;
Contributing authors: rayyan20021@gmail.com; mahmood.mscs@gmail.com; ayaandanish7@gmail.com; haabosaq@nu.edu.sa; ayihanhaq@gmail.com; mmalsulami@nu.edu.sa; mmzmanan@nu.edu.sa; hanzada@kau.edu.sa;
†These authors contributed equally to this work.

**Abstract**

As stress, cholesterol, diet-related issues, and smoking among middle-aged generations become increasingly alarming, signs of early onset heart attacks are becoming more and more evident. Health monitoring devices like smartwatches and fitness bands, through the use of Internet of Things (IoT), have shown to play a pivotal role in preventive health care measurements and early intervention. Using AI-driven health monitoring systems, individuals can proactively track their cardiac health and detect early signs or symptoms of a potential heart attack. Real-time monitoring of vital parameters, such as respiratory or heart rate, blood pressure, oxygen saturation levels, Electrocardiogram (ECG) readings and blood glucose readings, enables AI to identify any abnormalities or irregular patterns, prompting the user to seek immediate medical attention before a full-blown cardiac event occurs. By leveraging the pre-existing ecosystem of interconnected devices that possess the capability to monitor these vitals, such as smartwatches and fitness bands among other medically advanced sensor-enabled devices, we propose an autonomous self-aware system which can detect anomalies and irregularities through continuous monitoring and data analysis to detect potential red flags prompting the user about their well-being and consult medical authorities and physicians. A framework consisting of multiple sequential modules is proposed, namely Future Vitals Prediction, Anomaly Detection, Self-Awareness, and Risk Assessment. The primary metrics used to evaluate the models were accuracy for classification and mean squared error for regression, among others. We demonstrate a maximum accuracy of **99.96%** for Anomaly Detection and **96.59%** for Self-Awareness, as well as MSE values from **0.01** to **0.04** for Future Vitals Prediction and a best MSE of **0.00000314** for Risk Assessment.

**Keywords:** Context-Awareness, Artificial Intelligence, Cardiovascular Diseases, Heart Attacks, IoT, Deep-Learning

# 1 Introduction

Early intervention of cardiovascular diseases (CVDs) has been a challenging subject to interpret due to the sensitive nature of medical data [1], often unraveling when paired with AI-driven frameworks despite numerous research and accompanying research papers being conducted in the past few decades. There has been even fewer research that tackle integrating frameworks in existing ecosystem to provide solutions, such as utilizing IoT capabilities in sensor-equipped medical devices which has led to a "gray area" between medical challenges and AI based solutions that our framework aims to target. In healthcare, a key distinguishing factor is almost always the effective monitoring of patient's personalized vitals, which, when utilized correctly, can provide great insights into how measures can be taken for early intervention [2].

The impact of the Coronavirus Disease of 2019 brought an increased demand in health monitoring systems despite government measures (social distancing, mandated wearing of masks, and management of COVID patients in hospital wards) being imposed on anyone and everyone. The pandemic was hailed as one of the most serious problems facing the modern era 21st century by many and its severity raised the growing need of remote health monitoring more than ever. The pandemic was coupled with the underlying health issues people vulnerable with CVDs and other chronic conditions suffered from, and therefore, these individuals found themselves at the forefront of

suffering from threatening conditions and devastating consequences as a result. CVD symptoms often go unnoticed until a cardiac event occurs, or conditions are severely deteriorated. Medical IoT devices have played a crucial role in the past few years in the development of health monitoring systems bridging the gap between patient and early diagnosis. These, however, came with their own set of drawbacks mainly the inaccuracy met with global medical standards and the cost ineffectiveness to build them. CVD symptoms are sensitive in terms of time and accurate pattern identification which were unable to be achieved through traditional data storage systems and required modern sensor-based systems, doubling down on the need for data size, speed, and amplitude. Despite the changing environment variables like patient vitals, IoT-based health monitoring systems show immense potential to decrease the widespread effects of late CVD detection through deep learning for automatic feature extraction and representation [6][7][8].
Context or self-awareness is a separate domain where context refers to "any information that can be used to characterize the situation of an entity" [3]. An entity refers to a user, place, or item that is relevant to the user interaction and the application [4]. A vast portion of our research stems from integrating self-awareness with AI-driven decision-making capabilities, thus eliminating any human factor delays that occur as a failure of early interventions of cardiac events. As the IoT ecosystem continues to show immense growth potential from larger and larger social networks, sensors, and mobile devices, the need for contextually aware devices and recommendations has grown enormously [5]. Additionally, self-aware AI has the ability to assess different situations and adapt to the user's requirements or vital patterns by sensing the context and movement and controlling the environment (AI-driven system) [6]. Self-awareness is the concept that provides the AI with dynamic adjustability, reliability and optimality given the conditions of its environment. One such prominent architecture for self-awareness is the Observe-Decide-Act (ODA) loop [6] which through sensors, observes the external data being collected (Observe), next, it assesses the best configuration for the system (Decide) and finally based on a set of requirements to improve system operations, the program reacts (Act). Another approach, the Modified Repeated Incremental Pruning to Produce Error or MRIPPER technique has been used to analyze and classify the data [7]. A rule-based machine learning method is used for analyzing datasets in order to make predictions about heart diseases in the MRIPPER approach. Our approach, however, enables individuals to actively monitor their heart health. By continuously monitoring vital parameters like respiratory rate, oxygen saturation levels, ECG readings, heart rate and glucose levels in real-time, the system can detect irregularities and anomalies, indicating potential early signs of a heart attack. This heightened self-awareness empowers users to promptly seek medical attention long before a full-fledged cardiac event occurs.
The ultimate objective here is to establish an autonomous self-aware system that utilizes diverse machine learning algorithms and deep learning techniques to continuously analyze data, identifying potential red flags in an individual's well-being. By combining AI algorithms with health data, this technology can swiftly recognize deviations from the norm and promptly alert the user to consult medical authorities or physicians. Such early intervention is pivotal in mitigating the risk of heart attacks, particularly

among younger age groups, ensuring timely medical assistance. Using historic patient vital data recorded over long periods of time, the system will be able to predict future vitals over fixed intervals [8]. Vital signatures and patterns differentiate from person to person, hence, ensuring accuracy over prediction rates and minimal mean errors is crucial. Next, the predicted vitals will be accurately differentiated from normal and abnormal based on irregular ranges for the vitals and their respective deviance from them. If detected as abnormal, the self-aware system (SAS) is engaged to determine any physical interference or external activity that may impact vital deviance or aid in the abnormality. If the SAS is unable to pinpoint the source of external interference, the system uses risk-assessment where user's preexisting medical conditions are taken into account to produce probability of the likelihood of a cardiac event occurrence in near future. The deviance are accumulated as a result of the Early Warning Sign (EWS) [8] which our system will refer to as the Life Index Score (LIS). Combined all the individual module components to produce the LIS visible to the user as a quantitative measure of their heart health.

Embracing AI-driven health monitoring devices as proactive tools for cardiac care presents a transformative solution [3]. These solutions through the implementation of our framework aim to:

- Propose a dynamic approach to managing heart health conditions using different Machine Learning Algorithms to facilitate early prevention and intervention.
- Empower individuals to take control of their cardiac health through an existing interconnected ecosystem of smartwatch users.
- Achieve a unique advancement in early onset heart attack detection using prediction algorithms tailored to individual users.
- Integrate AI-driven health monitoring devices with IoT technology aimed at smartwatch users.

With the alarming rise in cardiac risks observed among middle-aged individuals [S], the fusion of readings from various sources holds the promise of reversing the trend and building a healthier, more resilient future. The following sections will cover the approach we have devised to tackle the complexity of early CVD detection starting with a detailed description of the problem, the methodology we have implemented, and our results that support the hypotheses.

The remainder of the paper is organized as follows. Section 2 describes the research problem being tackled by this work, Section 3 delves into the methodology adopted for the study by giving an overview of the proposed framework as well as each module individually, Section 4 outlines the datasets used to train the models at each stage of the proposed framework, Section 5 presents the results of our experiments for each module, and finally, Section 6 concludes our work and suggests some future directions that this research could adopt.

## 2 Research Problem

Cardiovascular diseases or CVDs, particularly heart attacks, have been the leading cause of mortality worldwide in recent years [10]. Lifestyle factors prevalent in middle-aged generations such as improper diet patterns, hypertension, cholesterol, and physical inactivity significantly contribute to the prevalence of heart attacks [11]. The Center for Disease Control and Prevention (CDC) claims that a diet rich in different types of fats (trans, cholesterol and saturated) paired with not enough activity, drinking alcohol, and tobacco usage are linked with heart diseases and CVDs like atherosclerosis [12]. In [13], it is claimed by the director of the Preventive Cardiology Program at UT Southwestern Medical Center that obesity, diabetes, high blood pressure, cholesterol and lack of exercise are "the usual 5 suspects" but labels stress as "the overarching nemesis" in people aged 40-50 who have suffered from heart attacks due to their lack of prioritizing self-care. Representing 32% of all global deaths, heart attacks stand at the forefront of lethal CVD statistics claiming 17.9 million lives annually [14]. Among these deaths, 85% are attributed to heart attacks and strokes, with one-third occurring prematurely in individuals under 70 years of age [14]. The World Health Organization (WHO) underscores the severity of the issue, noting a 29 percent increase in total deaths related to heart diseases in Pakistan over a span of just three years [15]. This increase amounts to approximately 406,870 deaths annually in Pakistan, ranking the country 30th worldwide for its death rate of 193.56 per 100,000 people [15].

Despite these alarming statistics and existing knowledge about the risk factors associated with heart diseases, there is a pressing need to develop technologically advanced and AI-enabled solutions to improve diagnostic methods. These solutions should predict patient outcomes and exterminate the noise external interference cause while determining the onset of heart attacks in their early stages. By addressing lifestyle factors, preexisting conditions and implementing context-awareness protocols integrated with IoT networks (as seen in Figure 1), we aim to reduce the significant burden caused by heart attacks and cardiovascular diseases globally.

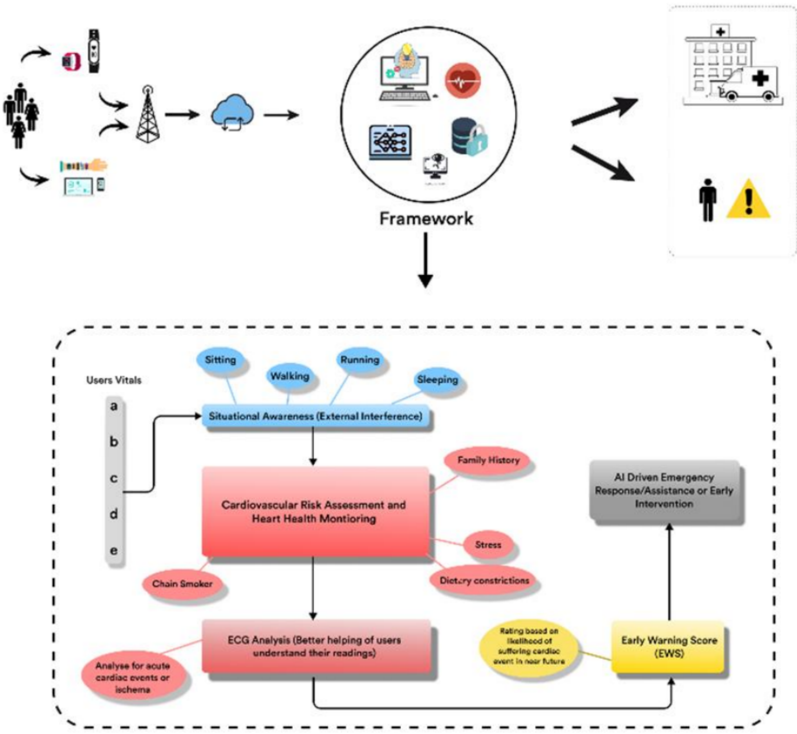


**Fig. 1**: A high-level overview of the proposed framework

## 3 Methodology

The high-level overview of the proposed framework is displayed in Figure 1. The framework stages are as follows. Firstly, the future vitals of the patient are predicted using a deep LSTM (Long Short-Term Memory) Neural Network. LSTM layers are used here due to their ability to capture temporal dependencies, which allows it to forecast future values of time-stamped data [16]. The constants set for measuring the patient vitals and the corresponding vital ranges can be seen below in Table 1 and Table 2 respectively. It is important to note that the data sets used in evaluation of models for the aforementioned stage(s) have been explained in the upcoming sections. The synthesis of medically informed data requires extensive research and referencing due to its sensitive nature making it difficult to properly simulate real-world scenarios. However, despite the scarcity, the data used for each of the modules will be explained in greater detail along with their motivation.

The following subsections outline the experimental methodology adopted for each module of the framework. All of these modules make use of the aforementioned datasets and as a rule of thumb, the output of one module generally feeds into, or determines the use of, the next stage.

**Table 1**: Table of Constants for targeted individual ranges.

| Constant | Value |
|---|---|
| Age Group | 40-50 Years |
| Gender | Male |
| Weather | 26-32°C |
| Body Mass Index (BMI) | 21.0-29.0 |
| Activities | Sitting, Walking, Running, Sleeping |

**Table 2**: Ideal Vital Ranges.

| Vital | Ideal Range |
|---|---|
| Systolic Blood Pressure | 90-120 mmHg [20] |
| Diastolic Blood Pressure | 60-80 mmHg [20] |
| Blood Sugar Level | 81-130 mg/dL [21] |
| Respiratory Rate | 12-20 breaths/min [22] |
| Blood Oxygen (SpO2) | 95% - 100% [23] |
| ECG | Normal Sinus Rhythm |
| Heart Rate | 61-100 bpm [24] |

## 3.1 Future Vitals Prediction

As mentioned, the initial module involves predicting what the patient's vitals will be 15 minutes into the future. For this purpose, a deep neural network consisting of 3 LSTM Layers was adopted. First, the Comma-Separated Value (CSV) file containing the synthetic timestamped data is read into a data frame. The data is then scaled using Min-Max Scaling.

Next, the feature and target data frames are partitioned with a train-test split of 80-20. Crucially, the shuffle parameter is kept False here as this is time-series data and its sequence must be preserved at all times. Time Series Generators are then created for the training partition and the testing partition, both with a time slice window of 3 timestamps and a batch size of 32. Finally, the architecture for the LSTM Neural Network is defined and compiled, with the loss function defined as mean squared error, optimizer defined as Adam with default learning rate, evaluation metrics defined as mean absolute error. The network (seen in Figure 2) is then trained on the train generator for 50 epochs. The trained model is then evaluated, and a vector of predictions is generated once the results are satisfactory. This process is then repeated for each other vital sign as the target, and the remaining vitals as features.

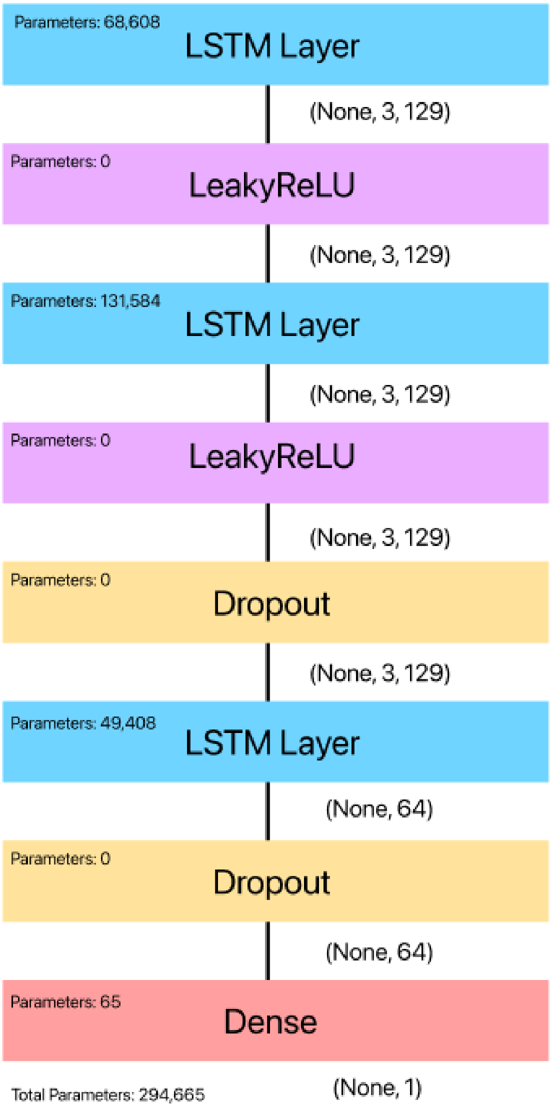


**Fig. 2**: Architecture of the LSTM Model

### 3.2 Abnormal Vitals Detection

The second module is for analyzing the future vitals being predicted by the previous module and detecting abnormalities of any kind in any of the features. If any one feature presents an abnormal value, then that row is classified as abnormal. The methodology for this module is as follows. Firstly, the dataset for this module is read into a data frame, and Exploratory Data Analysis (EDA) is performed on the dataset to uncover some key insights. During EDA of the data, a large imbalance in class distribution was detected, with only 11.4% of values labelled as normal and the remaining labelled as abnormal. To mitigate the bias this would likely bring to the model after training, the class distribution was rectified by over-sampling/augmenting the scarce class and under-sampling the abundant class using the Synthetic Minority Oversampling Technique – Edited Nearest Neighbor (SMOTE-ENN) [17]. This was achieved using the Imbalance Learn Python library provided by Scikit-Learn. The SMOTE-ENN technique successfully rectified the class imbalances, resulting in a new distribution of 54.4% abnormal datapoints and 45.6% normal datapoints (Figure 3).

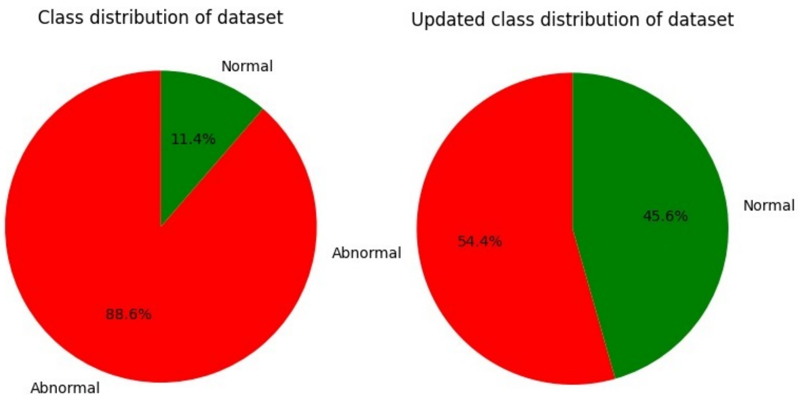


**Fig. 3**: Class distribution of Abnormal Vitals dataset

### 3.3 Self-Awareness Module

The experimental methodology used for this module remains largely the same as the previous one, with the difference that this is now a multi-class classification problem instead of binary. The selection of models tested are the same as previous, with the addition of the Random Forest Classifier [18], as the smaller size of this dataset made it computationally more tractable than before. The dataset for this module is first read into a data frame, and EDA is performed by plotting a correlation heatmap and kernel density plots. The sampling technique from the previous module was also applied to this dataset to ensure a non-biased distribution of classes. One insight unveiled from the kernel density plots was that the vital sign values for the Sitting class and the No Activity class are quite similar (See Fig. 5), which makes intuitive sense. Due to this, the prognosis was that this similarity between the two would result in a minor loss in accuracy for the models as they might struggle to distinguish between the two classes. Regardless, the dataset was split into feature and target classes and a train-test split of 60-40 was made again. The models used for this module remain the same as the last module, with the addition of the Random Forest Classifier as well. Training and evaluation were done in the exact same manner as before, with a Grid Search and 10-Fold Cross Validation. The experimental results are mentioned later in the paper.

### 3.4 Risk Assessment Module

As stated earlier, the goal of this module was to arrive at a probability score from 0 to 1 that could quantify the likelihood of a cardiac event occurring in the near future. For this purpose, various risk factors about the patient that are known to contribute to heart disease are determined. These risk factors include Cholesterol, Diabetes, Family History, Hypertension, and Physical Inactivity. The extent of each factor is determined by asking the patient to rate the severity of each on a 5-point scale from Least Severe to Moderately Severe, to Most Severe. For computation purposes that will soon become clear, the values of each point on the scale range from -2 to 2, with 0 being the midpoint. Additionally, since not all risks are equally impactful on heart health, each risk factor is assigned a weight based on the extent to which it contributes to heart disease. The weights for each risk factor are mentioned in Table 3.

**Table 3**: Risk Factor and corresponding weights

| Risk Factor | Weight |
|---|---|
| Cholesterol | 3 |
| Diabetes | 4 |
| Family History | 2 |
| Hypertension | 4 |
| Physical Inactivity | 3 |

To calculate the probability, we will implement Equation 1 to determine a Risk Score.

$$Risk\ Score = \frac{1}{1 + e^{-(\frac{3C+4D+2F+4H+3P}{8})}} \tag{1}$$

Where C represents cholesterol, D diabetes, F family history, H hypertension, and P physical inactivity. The prediction of likelihood scores was treated as a regression problem and was performed using a shallow neural network. First, the dataset is loaded into a data frame, and the feature and target variables are separated. Then, a train-test split of 80-20 is created. In this research three different models have been tested and the results compared. The three neural networks have a simple architecture consisting of a single hidden layer of 64 neurons. The way in which they differ is the activation function used in the output layer. The three activation functions that are compared are the linear activation function, which simply multiplies the input with an identity and introduces no non-linearity, the sigmoid activation function which applies the logistic function to the input, and a custom implementation of the sigmoid activation function that normalizes the values before applying the logistic function, in the same way as the formula used to calculate the risk scores. The thought process behind implementing our own activation function here is that restraining the output values to the same function that was used to generate the dataset should theoretically result in the least error in predictions. Once the three models are defined, they are compiled with the optimizer specified as Adam with the default learning rate, and the loss function is defined to be mean squared error. All three models are then trained for 50 epochs with a validation split of 20%. The prediction results are discussed in the coming sections.

### 3.5 ECG Analysis

Finally, the ECG analysis aims to classify, using the ECG waves of a person, the type of cardiovascular disease that may be hindering the vital parameters in the first place. To achieve the visualization of individual ECG waves of a single person across various locations of the body, the PhysioNet Physikalisch-Technische Bundesanstalt (PTB) Diagnostics ECG Database [25] was used. More information regarding the dataset can be found in the following sections. The dataset was visualized using a MATLAB script, which allowed for a clearer understanding on how Convolutional Neural Networks (CNNs) [26] could be used to classify the type of arrhythmia being detected.

Following the visualizations, the next step involved training five different convolutional neural networks on two famous datasets in heartbeat classification: the MIT-BIH Arrhythmia Dataset and the PTB Diagnostics ECG Database. This dataset included the images of six different types of classes captured across the aforementioned patient data collected for usage of PhysioNet users. The CNNs used include InceptionNet, ResNet50, MobileNetV2, VGG16, and VGG19.

Being able to classify the dataset accurately meant that a person suffering from heartbeat irregularities could have a more accurate diagnosis based off his vitals or more importantly the ECG captured through a smartwatch or a medical device.

### 3.6 Life Index Score

To conclude the findings, we have then used a derived formula based on the score collected from the Risk-Assessment stage and the severity of the ECG class determined by the ECG Analysis stage to determine a quantitative score on a range of 1-12 termed the Life-Index Score (LIS). The formula used to calculate the LIS is shown in Equation 2.

$$Life{-}Index\ Score = [(Pre{-}Existing\ Score\,\% * 0.4) + (ECG\ Class\ Severity\,\% * 0.6)] * \frac{12}{100} \tag{2}$$

This formula prioritizes the ECG class and its severity while also taking into consideration the affects that pre-existing conditions have on one's cardiovascular health. The LIS is further categorized into one of 3 stages: The Health Heart Zone (1-5): This stage represents individuals with minimal to mild indicators of heart health issues. Scores in this range suggest good heart health and overall well-being.
Warning Zone (6-8): Scores in this range serve as a warning sign that attention to heart health is needed to prevent further deterioration. Critical Condition (9-12): Scores in this range suggest a critical need for immediate medical attention and intervention to address significant heart health concerns

- **The Healthy Heart Zone (1-5):** This stage represents individuals with minimal to mild indicators of heart health issues. Scores in this range suggest good heart health and overall well-being.
- **Warning Zone (6-8):** Scores in this range serve as a warning sign that attention to heart health is needed to prevent further deterioration.
- **Critical Condition (9-12):** Scores in this range suggest a critical need for immediate medical attention and intervention to address significant heart health concerns

# 4 Datasets

The architecture of the proposed framework consists of a number of different modules, each of which makes use of the patient data to rule out more and more possibilities and arrive at a concrete score about the patient's current heart health. However, one major point of contention for the training of the machine/deep learning models involved in each module has been the availability of appropriately labelled training data.
Due to the widespread unavailability of real-world data that would be well-suited to training the proposed models, the decision was made to resort to alternative methods of obtaining data. For this reason, the datasets used for the training and evaluation of some of the models have been synthetically generated in accordance with carefully decided constraints that are kept constant for all datasets. Special care was taken to ensure that the synthetic data closely mimics the distribution of real-world data for accurate results. The specific vital sign features that have been generated consist of Systolic and Diastolic Blood Pressure, Heart Rate, Respiratory Rate, Blood Oxygen Saturation (SpO2), and Blood Sugar Levels. After generation of values, random noise was added to the dataset using a technique called perturbation, which increased the realism and stochastic nature of the dataset.
Each generated datapoint was then labelled according to the needs of the module. The details of the datasets used for the individual models are outlined in the following subsections.

## 4.1 Future Vital Predictions

This first module of the framework involves predicting the vital signs of the patient over the next 15 minutes, using an LSTM Neural Network. The dataset used for training of the LSTM Network was synthetically generated using the techniques above, with the addition of timestamps for each row since this module required time-stamped data. For this purpose, the timeframe used was a period of 10 days, with time slices of 15 minutes over the course of these 10 days. This resulted in a time-series dataset of 960 rows. Additionally, during generation, artificial patterns relating to the vital signs were induced into the data by varying the vital generation ranges for different times of the day. These patterns recur daily throughout the 10-day period.

## 4.2 Abnormal Vitals Detection

The second module makes use of the output of the first module, i.e., the predicted vital signs for the next 15-minute time slice and classifies the vitals to detect any abnormality in them. For this purpose, a dataset consisting of the aforementioned features was generated using the technique stated. After the generation of values, noise was randomly added to cause them to randomly deviate to varying extents from the base value, resulting in a random number of values that fall outside normal ranges. The resulting datapoint was then automatically labelled as abnormal and normal with respect to medically defined standards for what is considered to be a normal and safe value for each vital. Approximately 35,000 datapoints were generated and labelled, and the results were written to a CSV file. Figure 4 below illustrates the distribution of each class in the dataset using Kernel-Density-Estimate (KDE) Plots.

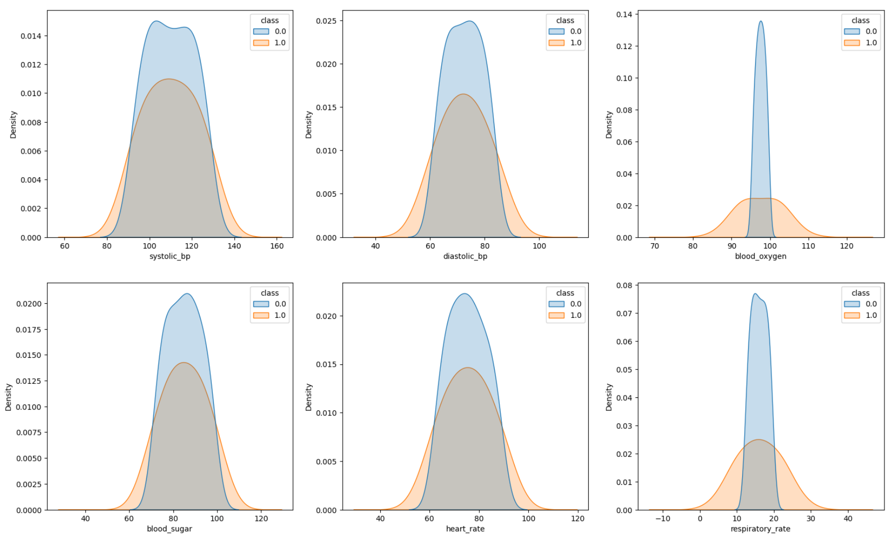


**Fig. 4**: Kernel-Density-Estimate Plots for Abnormal Vital dataset

## 4.3 Self-Awareness Module

The self-awareness module, being the most novel aspect of the framework, requires a carefully generated dataset. The class labels of this dataset are select physical states/activities that are classified by the models, which are used to rule out false alarm abnormal vital readings due to the variation in vital signs that these activities can bring. The classes include sitting, walking, running, and sleeping. A fifth class is also included, which covers the case where none of the aforementioned physical activities are detected, indicating that a potential health issue might exist. The approach adopted here was similar to the previous module, with the appropriate vital sign range defined for each class. For each class, samples are randomly generated within the defined ranges and rounded to 2 decimal places. Each new value is then appended to a Pandas data frame, and the finished dataset is written to a CSV file. The KDE Plots in Figure 5 showcase the distribution of each class in this dataset.

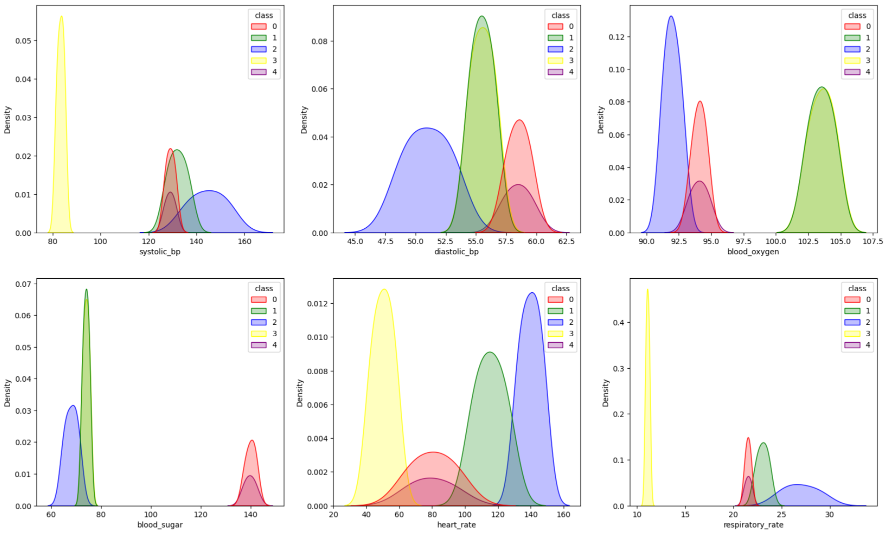


**Fig. 5**: Kernel-Density-Estimate Plots for Self-Awareness dataset

## 4.4 Risk-Assessment Module

The data used in the risk assessment module was a continuous value ranging from 0 to 1 that represents the likelihood score for heart disease existing, given that the previous modules have not already ruled it out. The scores are generated from five risk factors, namely Cholesterol, Diabetes, Family History, Hypertension, and Physical Inactivity. The value for each risk factor is a scale that can range from no severity (-2) to high severity (+2). Each risk factor is assigned a weight based on the magnitude of risk that it contributes towards heart disease. To generate this dataset, all possible combinations of risk severity values were generated, and the risk score was calculated for each using the mentioned formula, resulting in a dataset suitable for training of a regression model that can take as input risk factor values, learn the appropriate weights, and output the correct score based on its learning from the training data.

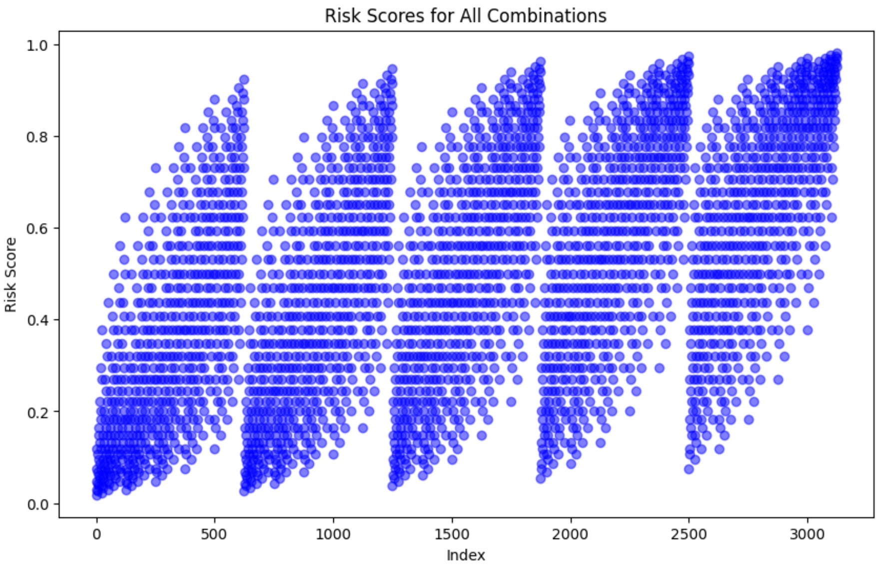


**Fig. 6**: Possible combinations of risk factors

## 4.5 ECG Analysis

The PTB Diagnostics ECG Database [25] used in order to visualize individual patient ECG waves through provided millivolt measurements in numerical format. It was developed by the National Metrology Institute of Germany and has provided this compilation of digitized ECGs for research, algorithmic benchmarking or teaching purposes to the users of PhysioNet. The ECGs were collected from healthy volunteers and patients with different heart diseases by a professor at the Department of Cardiology of University Clinic Benjamin Franklin in Berlin, Germany.
The ECGs in the dataset were collected using a non-commercial PTB prototype recorder with the following specifications [25]:

- 16 input channels (14 for ECGs, 1 for respiration, 1 for line voltage)
- Input voltage: ±16 mV, compensated offset voltage up to ± 300 mV
- Input resistance: 100 Ohms (DC)
- Resolution: 16 bit with 0.5 micro-Volts/LSB (2000 A/D units per mV)
- Bandwidth: 0 - 1 kHz (synchronous sampling of all channels)
- Noise voltage: max. 10 micro-Volts (pp), respectively 3 micro-Volts (RMS) with input short circuit
- Online recording of skin resistance
- Noise level recording during signal collection

Figure 7 and 8 showcase the images provided by PTB Diagnostics ECG Database and the visualized part of the ECG using MATLAB respectively.

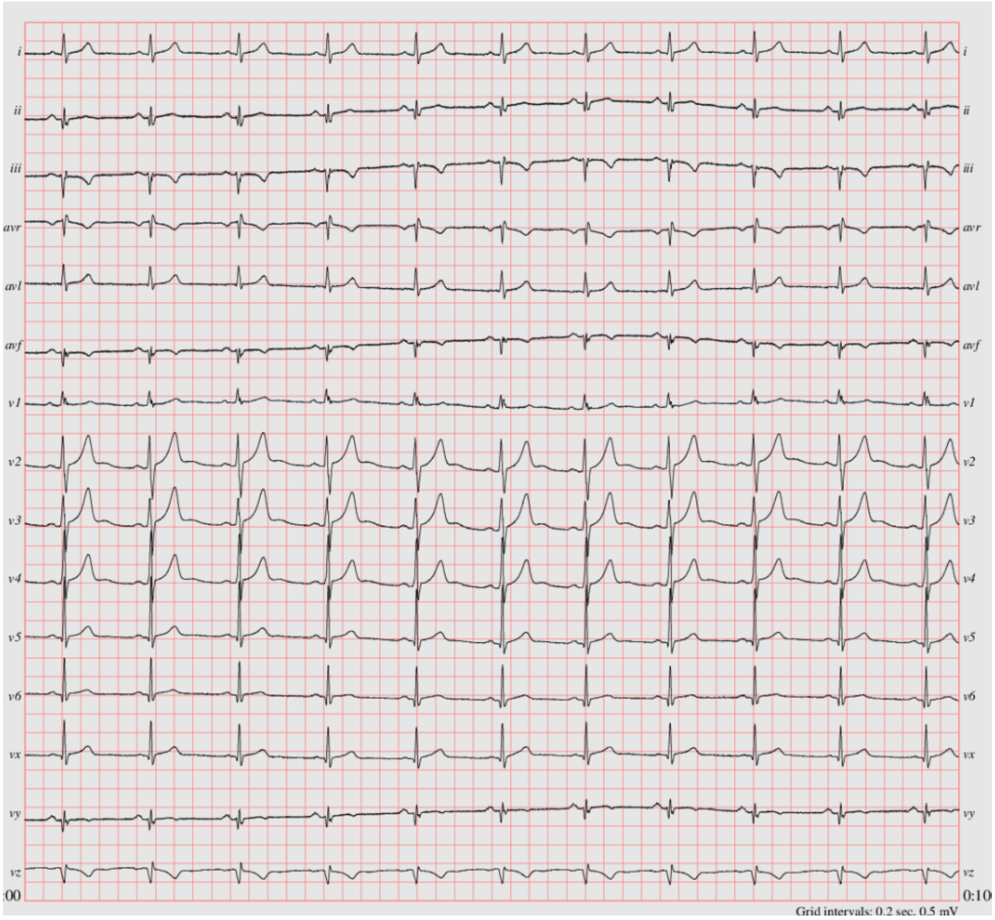


**Fig. 7**: Sample output of Patient 22 from PhysioNet Databank [25]

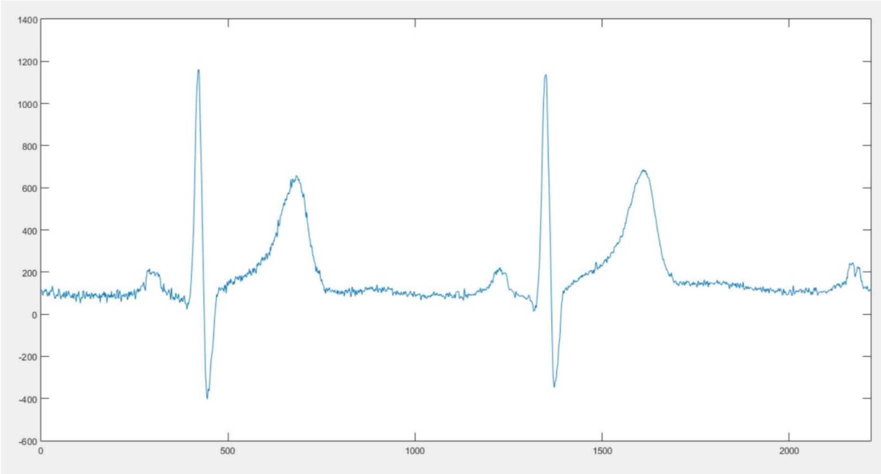


**Fig. 8**: ECG Waves visualized using MATLAB

Similarly, for the classification models, the MIT-BIH Arrhythmia + PTB Diagnostics ECG Dataset was used. This dataset was divided into six of the following classes:

- M - Pacemaker
- N - Normal
- Q - Unclassifiable
- S - Supraventricular/Premature Beat
- V - Premature Ventricular Contraction
- Q - fusion of V and N

Figure 9 displays a sample image from all of the six classes from the dataset.

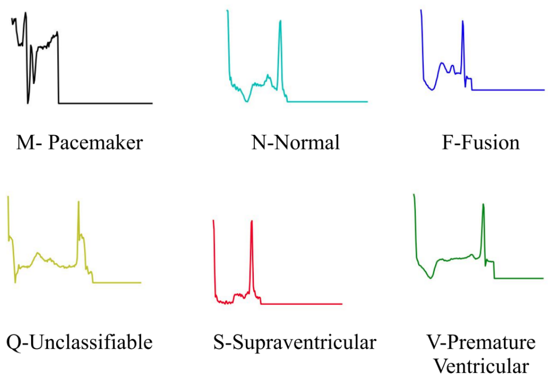


**Fig. 9**: MIT-BIH Arrhythmia and PTB ECG Diagnostics dataset classes

# 5 Experimental Results

In this section we outline in detail the results obtained for each module of the framework.

## 5.1 Future Vitals Prediction

The evaluation metrics used to judge the accuracy of the predicted values were Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error as seen in Table 4.

**Table 4**: Results for Future Predictions

| Vital Sign | Mean Absolute Error | Mean Squared Error | Root Mean Squared Error |
|---|---|---|---|
| Heart Rate | 0.0962 | 0.01564 | 0.12508 |
| Diastolic BP | 0.11768 | 0.02290 | 0.15133 |
| Systolic BP | 0.09719 | 0.01456 | 0.12067 |
| Blood Sugar | 0.16747 | 0.04419 | 0.21023 |
| Blood Oxygen | 0.23761 | 0.07459 | 0.27312 |
| Respiratory Rate | 0.16161 | 0.04382 | 0.20933 |

## 5.2 Abnormal Vitals Detection

As mentioned, the models in this module were evaluated using the Average 10-Fold Accuracy, Precision, Recall, and F1 Score. The metric values for each model are displayed in Table 5. Additionally, the confusion matrices for each model can be seen in Figure 10. The results show an extremely strong performance by the Decision Tree and Histogram Gradient Boosting Classifiers. However, Decision Tree would take the edge here due to ease of computation and slightly higher metrics.

**Table 5**: Results for Normal/Abnormal Vital Classification

| Model | Average Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Decision Tree | 99.9651% | 99.9768% | 99.9735% | 99.9752% |
| Histogram GB | 99.9466% | 99.9262% | 99.9372% | 99.9317% |
| K-NN | 97.4120% | 97.4481% | 97.9507% | 97.6446% |
| Gaussian NB | 96.6603% | 96.2730% | 96.2730% | 96.5134% |

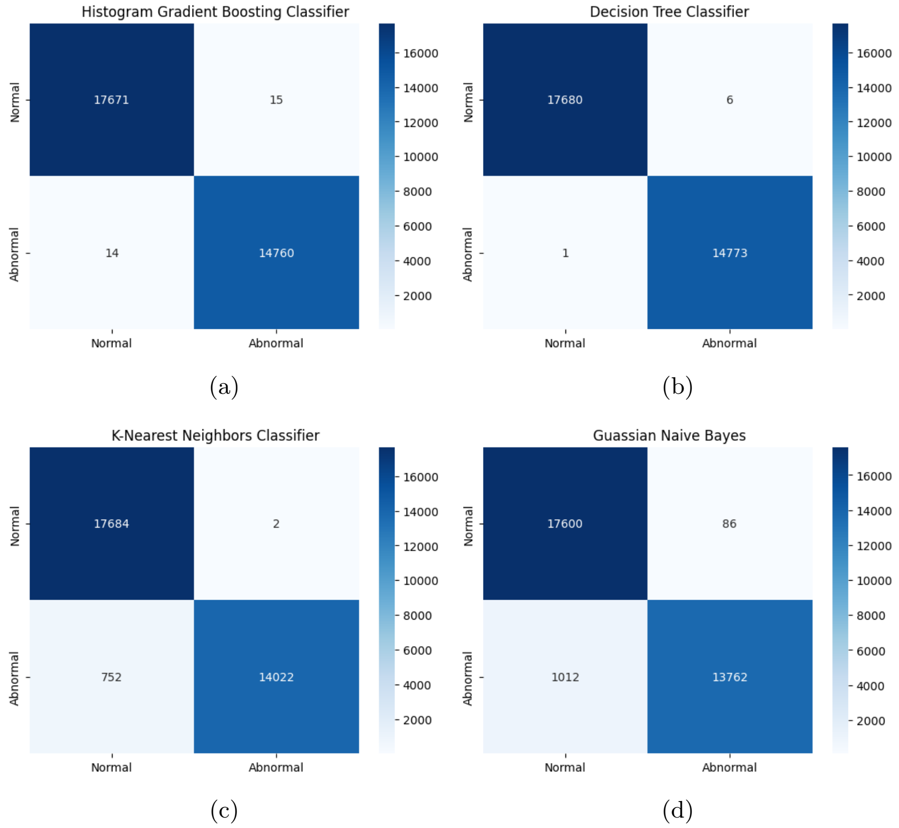


**Fig. 10**: Confusion Matrices for Abnormal Vitals Detection Module

### 5.3 Self-Awareness Module

The Self-Awareness classification models were evaluated much like the previous module, with the same metrics. The results for each model are displayed in Table 6.

**Table 6**: Results for Self-Awareness Module

| Model | Average Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| K-NN | 96.5945% | 93.0820% | 94.7569% | 93.6997% |
| Histogram GB | 95.3119% | 86.6958% | 87.9742% | 87.0419% |
| Random Forest | 95.0464% | 86.4526% | 88.4190% | 86.8528% |
| Gaussian NB | 94.7144% | 86.1649% | 88.0432% | 86.5321% |
| Decision Tree | 94.2067% | 84.5883% | 84.6699% | 84.6252% |

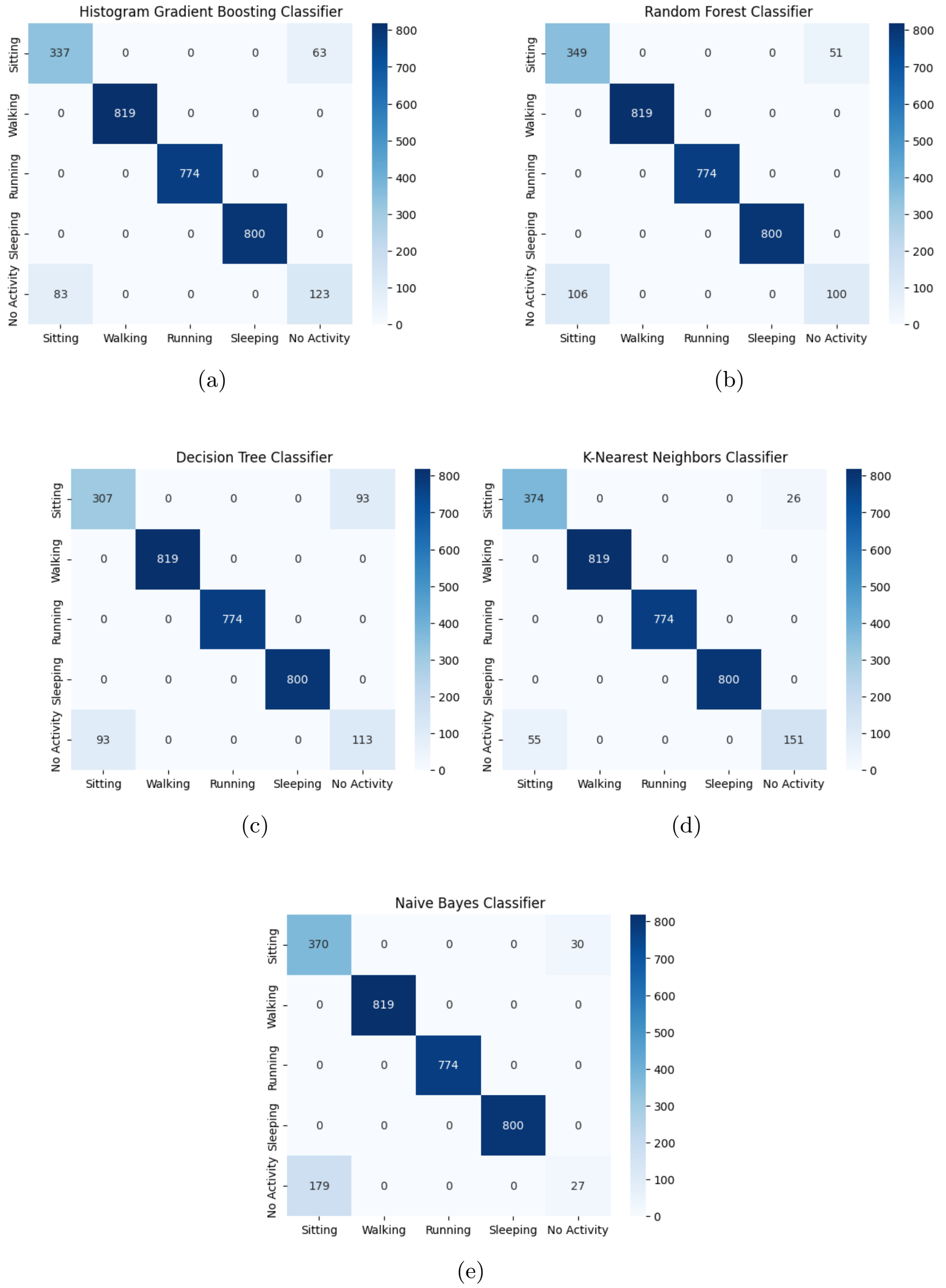


**Fig. 11**: Confusion Matrices for Self-Awareness Module

The minute difference between the “No Activity” class due to being mistaken for “Sitting” showcases the similarity between the two. It is important to note that the “No Activity” class is further assessed for potential heart related issues. The following confusion matrices obtained for each model are displayed in Figure 11.
The matrices obtained for each show that KNN Classifier performs the best at distinguishing all classes. The results also confirm the expected difficulty in distinguishing between the No Activity and Sitting classes. Work can be done in the future to rectify these misclassifications, such as by gathering additional training data, tuning hyper-parameters further, or even potentially restructuring the classes of physical activities that are being analyzed; however, for the time being the results are satisfactory.

## 5.4 Risk Assessment Module

Since this module involved a regression problem, the evaluation metrics used are the same as the first module. The results for each model are shown in Table 7. Similarly, Figure 12 visualizes the regression plot for all three different activation functions used.

**Table 7**: Risk Assessment Scores Results for Each Model Used

| Model | Mean Absolute Error | Mean Squared Error | Root Mean Squared Error | Cosine Similarity |
|---|---|---|---|---|
| Linear | 0.01329 | 0.00028 | 0.01702 | 0.99360 |
| Sigmoid | 0.00339 | $1.04563 \times 10^{-5}$ | 0.00441 | 1.00000 |
| Custom Sigmoid | 0.00139 | $3.14537 \times 10^{-6}$ | 0.00178 | 0.99999 |

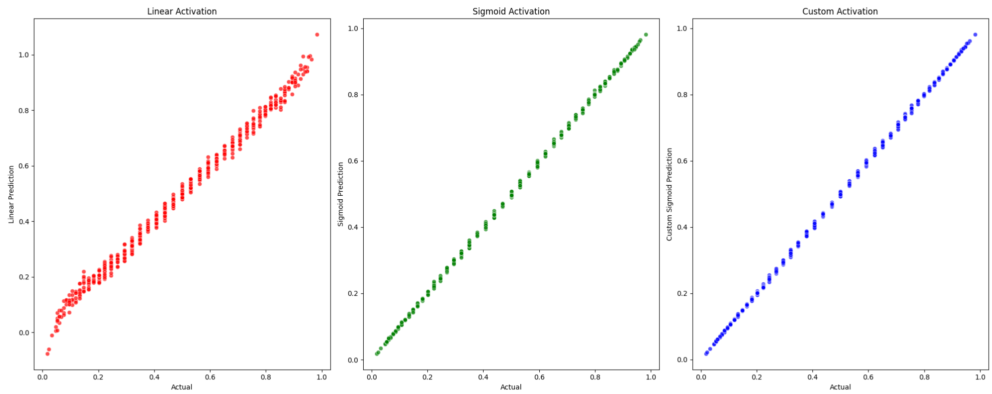

**Fig. 12**: Regression Plot of the three different activation functions used

## 5.5 ECG Analysis

For the ECG Analysis module, below are the results of five popular CNN architectures, tested using accuracy, precision, recall, and ROC curve AUC.

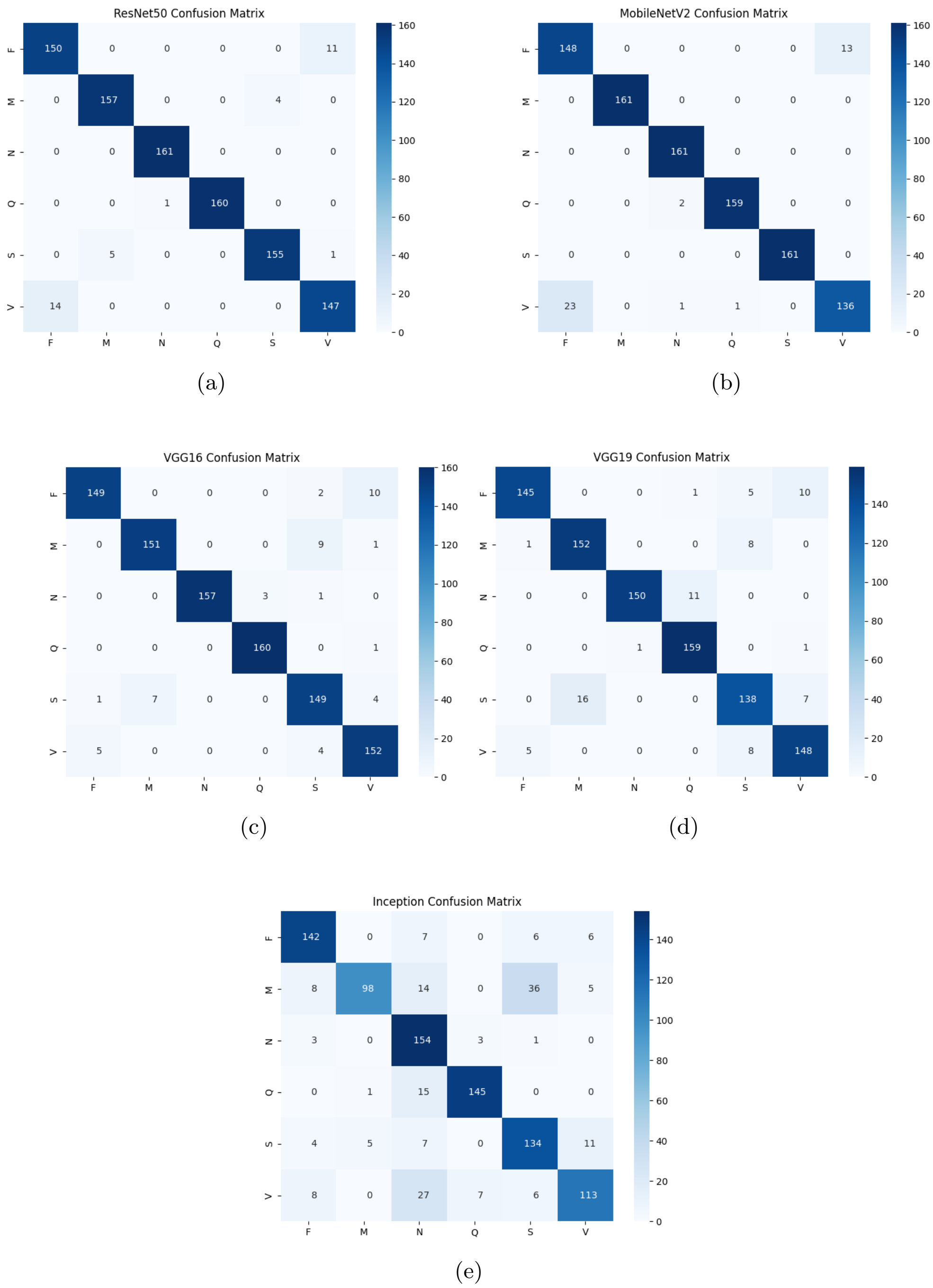


**Fig. 13**: Confusion Matrices for the CNN Models used

**Table 8**: ECG Analysis Results for Each CNN Used

| Model | Test Accuracy | Precision | Recall | ROC Curve AUC |
|---|---|---|---|---|
| InceptionNet | 81.37% | 82.04% | 80.85% | 0.9459 |
| ResNet50 | 96.27% | 96.27% | 96.27% | 0.9978 |
| MobileNetV2 | 95.86% | 95.86% | 95.86% | 0.9979 |
| VGG16 | 95.03% | 95.89% | 94.10% | 0.9971 |
| VGG19 | 92.34% | 93.33% | 91.30% | 0.9934 |

Of the used CNNs, the best result was given by ResNet50 followed by the MobileNetV2 architecture as shown in Table 8. Additionally, the confusion matrices for the models are displayed in Figure 13.

# 6 Conclusion and Future Directions

The paper presents a novel framework designed to utilize the potential of wearable IoT devices within the existing ecosystem to establish a contextually aware smart health monitoring system capable of detecting early signs of impending cardiac events. Through a series of AI-powered modules, the framework accurately predicts patients' vitals for the next 15 minutes and applies various classifications to identify abnormalities, while considering external factors that may influence interference in vital signs. By integrating key risk factors associated with heart disease severity, the system computes a probability score for the likelihood of a cardiac event occurring in the near future. Rigorous testing of multiple machine and deep learning methods across various hyperparameters was conducted to ensure optimal accuracy and minimize false positives or negatives, crucial in medical applications where outcomes directly impact individuals' well-being. Decision Tree, Random Forest, K-Nearest Neighbors, Histogram Gradient Boosting, and Naïve Bayes were among the classification models evaluated, with Decision Tree proving most effective for abnormality detection and KNN Classifier for self-awareness. Regression tasks utilized a deep LSTM neural network for time-stamped prediction, with multiple shallow neural networks employing different activation functions compared for efficacy. Evaluation metrics such as Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, and Cosine Similarity demonstrated the superiority of modified sigmoid activation function in minimizing error metrics across all regression models.
As for the future works that could potentially improve the results of this study even further and lead to an even more comprehensive understanding of heart health monitoring, we restate the importance of training, testing, and evaluating the AI models of each module on appropriately collected and labelled real life patient data to robustly demonstrate the capabilities of each model, as opposed to the use of synthetic data which may often be too idealistic or unrealistic. Additionally, we reiterate that the self-awareness module could see even further improvement in results with the appropriate measures such as redefining the physical activity classes that are being evaluated to create a distinction between the No Activity class and others being detected, further tuning hyperparameters, improving quality of training data, and testing diverse ensembles of models to overcome the shortcomings of individual models.

Finally, we suggest a future direction that an extension of this framework may adopt in the form of AI-powered ECG Analysis, which is often considered to be one of the strongest indicators of heart disease [16]. Applying machine and deep learning methods to the analysis of ECG waves can lead to even more refined results and enable a greatly reduced margin of error in cardiac disease detection.

# 7 Acknowledgment

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# 8 Data Availability Statement

All data associated with this study are available within the document. The data used for training and evaluation of the AI models was synthetically generated in accordance with carefully decided constraints to ensure realistic simulation. Specific datasets used include synthetic time-stamped data for vital predictions, abnormal vital detection data, self-awareness module data, and risk assessment data. The ECG analysis data was obtained from the PhysioNet PTB Diagnostics ECG Database, which can be accessed at PhysioNet. For any additional information or access to the synthetic data generation methods, please contact the corresponding author.

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