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Detecting Heart Attacks Using Learning Classifiers

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Abstract: Cardiovascular diseases (CVDs) have emerged as a critical global threat to human life. The diagnosis of these diseases presents a complex challenge, particularly for inexperienced doctors, as their symptoms can be mistaken for signs of aging or similar conditions. Early detection of heart disease can help prevent heart failure, making it crucial to develop effective diagnostic techniques. Machine Learning (ML) techniques have gained popularity among researchers for identifying new patients based on past data. While various forecasting techniques have been applied to different medical datasets, accurate detection of heart attacks in a timely manner remains elusive. This article presents a comprehensive comparative analysis of various ML techniques, including Decision Tree, Support Vector Machines, Random Forest, Extreme Gradient Boosting (XGBoost), Adaptive Boosting, Multilayer Perceptron, Gradient Boosting, K-Nearest Neighbor, and Logistic Regression. These classifiers are implemented and evaluated in Python using data from over 300 patients obtained from the Kaggle cardiovascular repository in CSV format. The classifiers categorize patients into two groups: those with a heart attack and those without. Performance evaluation metrics such as recall, precision, accuracy, and the F1-measure are employed to assess the classifiers' effectiveness. The results of this study highlight XGBoost classifier as a promising tool in the medical domain for accurate diagnosis, demonstrating the highest predictive accuracy (95.082%) with a calculation time of (0.07995 sec) on the dataset compared to other classifiers.

Keywords: Cardiovascular diseases (CVDs), Machine Learning (ML), Forecasting techniques, Heart attacks, Decision Tree, Support Vector Machines, Random Forest, Extreme Gradient Boosting (XGBoost), Adaptive Boosting, Multilayer Perceptron, Gradient Boosting, K-Nearest Neighbor, Logistic Regression.

1 Introduction

Heart disease refers to a form of cardiovascular disorder that impacts the proper functioning of the heart and leads to obstructions in the blood vessels responsible for supplying oxygenated blood to the heart [1, 2, 3, 4, 5, 6, 7].

One major concern is that individuals often do not experience symptoms of illness until the later stages of the disease when the damage is already irreversible [8, 9]. Heart failure (HF) patients commonly encounter symptoms such as difficulty breathing, weakness, and swollen feet [6]. The prevalence of HF is on the rise worldwide, attributed to factors such as stress, high blood pressure, and family history [10]. Additionally, diabetes resulting from undetected high levels of glucose in the blood can lead to severe conditions like heart attacks and kidney disease [11].

The rapid and accurate diagnosis of Heart Diseases (HDs) followed by early treatment has been identified as a significant challenge by many medical practitioners [7, 8, 12]. This process heavily relies on physicians' advanced knowledge and experience in diagnosing patients with similar symptoms [9]. According to the American Heart Association (AHA), medical diagnosis of HDs is difficult due to the similarity of symptoms with other diseases, such as chest pain, sleep problems, shortness of breath, palpitations, nausea, leg swelling, weight gain (1-2 kilograms per day), chronic cough, and increased heart rate [14]. Bridging the gap between accuracy in diagnosis through knowledge and the lack of experience in the field of Cardiovascular Disease (CVD) is a challenge in many countries. Previous research on HDs has often neglected to emphasize the significant attributes used in prediction [9].

In the medical domain globally [6], an experienced practitioner often fails to identify early, minute-to-minute life-threatening cases of HDs [15]. According to medical statistics, HD is one of the leading causes of death worldwide [3, 4, 5, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23]. The World Health Organization (WHO) indicated that heart attacks are progressively increasing every day in several nations, contributing to nearly 30% of deaths [6, 9, 12, 17, 24, 25, 26]. HF is still a stressful and expensive condition, according to Medicare, with 4.4 million yearly hospitalizations

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and a total projected annual cost of more than (11 billion USD) [25].

With 17.3 million deaths worldwide in 2013, HD was the leading cause of mortality. Similarly, HD was responsible for over 17.6 million fatalities in 2016, up14.5 percent from 2006. If nothing is done, the global death toll is predicted to grow to roughly 22 million by 2030, [6, 7, 9, 24] as in Figure 1. According to AHA, nearly half of American adults, or 121.5 million people, have CVDs. Figure 2 shows that the early death rate differs between high-income and low-income countries, ranging from 7% in high-income countries to 43% in low-income ones [17]. HD is one of the three leading causes of mortality in Korea, accounting for about half of all fatalities in 2018 [4] as expressed by Figure 3. Associated HD is on the rise, according to the latest WHO study. Every year, 17.9 million people die. Also, in the United Kingdom, over 70,000 individuals die each year from HD. Figure 4, indicates that about 1 in 5 men and 1 in 9 women die from cardiac disease and Figure 5 shows that there are 500 deaths per 100,000 in Egypt related to cardiovascular disorders such as acute HD, coronary insufficiency, and stroke [7]. Figure 6 demonstrates that heart failure affects 6.5 million adults in the United States, with 3.6 million (55%) of them being female [25].

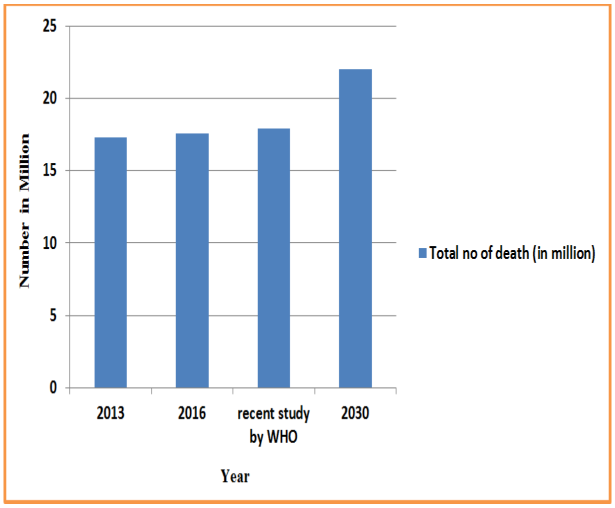

Fig. 1: Total number of heart disease mortality over the world.

Researchers found that patient health records from healthcare sources enormous the growth of structured and unstructured patients' data that offers new opportunities for clinicians to improve HD prediction [27]. Although medical data is so huge, it may be difficult to analyze [26] due to missing data of patients' records contained in the databases [27, 28, 29]. To avoid human errors in diagnosis, recently, professionals designed various intelligent healthcare frameworks based on Machine Learning (ML) [24, 30]. These helpful frameworks analyze medical data via various data cleaning and preprocessing tools to assist physicians to automatically classify new patients and improve decision of diagnosis and may prevent CVD with early detection [16, 19, 20, 27, 31, 32, 33, 34]. Also, this advancement in technology helps patient to accurately know if he/she has a heart attack or not.

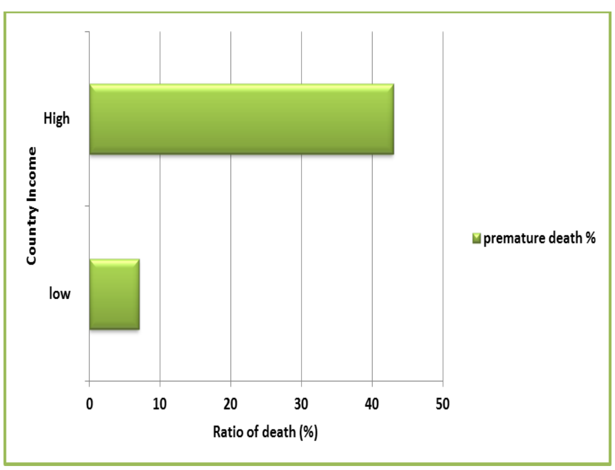

Fig. 2: Ratio of premature heart disease death based on country income.

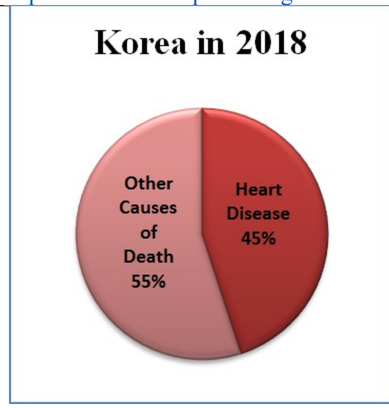

Fig. 3: Heart disease mortality in Korea '2018'.

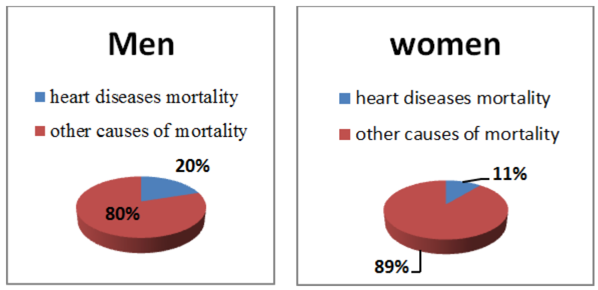

Fig. 4: Heart disease mortality > 70,000 case in United Kingdom annually.

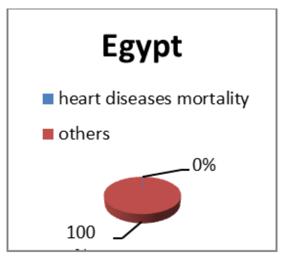

Fig. 5: Heart disease mortality in Egypt annually.

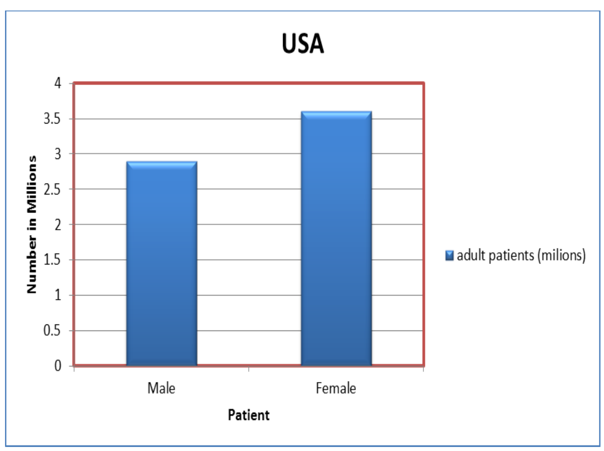

Fig. 6 Number of heart disease adult patients in USA.

The major challenge nowadays is to predict heart attack before it occurs and to take precautions at an early stage to improve symptoms of HF and prolong patients' lives [6, 15, 19, 29, 35]. Predictive analytic provides algorithmic solutions [21] built by ML [36] to potential train data through [15, 26] an accurate automatic classification smart tools that help doctors to perform diagnosis efficiently and accurately to improve the quality of lives [1, 4, 6, 7, 37, 38]. Data Mining (DM) techniques can be used to examine and anticipate human behavior as well as extract information from large datasets [18, 39] that can be transformed into valuable information [40]. By transforming descriptions of medical diagnoses and processes used to locate hidden information and deliver correct findings and speedy identification of diseases, medical data classification saves time for both doctors and patients [10, 41, 42]. Data such as blood sugar, cholesterol levels, and blood pressure can be used to predict HD [29]. ML algorithms were developed in clinical decision making to design smart systems. These computational tools are dissecting the multidimensional medical datasets and generating better insights. With the help of ML methods in the medical field it can generate better insights into optimization, clustering and computation models [31] that help physicians in accurately diagnosis [1, 4, 6] to provide appropriate treatment to patients. What was mentioned above motivates us to have significant motivation for this research. Our objective is to improve the heart attack prediction accuracy with minimum computational time as time is a critical factor in saving patients. The main contribution of this study is to conduct an empirical investigation of various ML classifiers for predicting heart attacks based on the relevant HD parameter. we used a reference data set of Kaggle to predict heart disease. It consists of 14 different parameters. We have evaluated the performance metrics of a set of ML classifiers such as Decision Tree (DT), Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), Multilayer Perceptron (MLP), Gradient Boosting (GB), K-Nearest Neighbor (K-NN) and Logistic Regression (LR) for heart attack prediction. The results show that XGBoost is the best classifier that can predict heart attack with high accuracy and the shortest time which helps doctors to assess heart attack risk and save the patient. Reduced salt intake, consumption of fruits and vegetables, regular physical activity, and abstinence from cigarette and alcohol use can all help minimize HD risk and death [4, 17].

The remaining sections of the paper are organized as follows: Section 2 presents a review of previous work related to the prediction of heart attacks. In Section 3, we describe the dataset used in this study, which is the 'Heart Attack Analysis and Prediction Dataset 2020' obtained from Kaggle. Section 4 provides an overview of the problem to be addressed, followed by the introduction of the nine classifiers. Section 5 presents the parameter settings, measured parameters, evaluation, and results. The discussion of the results is presented in Section 6, while Section 7 concludes with the main findings and recommendations for future research.

2 Literature review

In this section, we provide a concise overview of recent studies that are pertinent to the prediction of HDs, focusing on the utilization of different datasets and ML algorithms.

With the purpose of reducing the number of required examinations to take a patient, Bhatla and Jyoti [43] did research on decreasing the number of features used in detecting HD. They proposed a system based on DT and Naive Bayes (NB) using fuzzy logic, as well as a multi-criteria decision-making technique that addresses the uncertainty of inaccuracies and ambiguities caused by consistent priority measures of different disease symptoms, in order to assist patients and clinicians in determining whether they have heart failure. Srinivas et al. [42] presented a hybrid classifier of CVDs using the multi-layered associative and perceptual classifier. The Cleveland, Hungary, and Switzerland datasets were used in the study, and performance was assessed using 85% right ratings for a limited number of attributes. Chauhan et al. [44] used Weighted Association Rule to extract the data from the electronic records through automation processes and predict patient's risk of having coronary disease with accuracy 60.4%. To train an appropriate collection of features and increase performance, Xu et al. [45] suggested using a deep neural network categorization of ECG signals. Sivaranjani and Yuvaraj [17] introduced a cardiac function prediction system based on the computational model of a deep learning approach to help the user enter clinical features and learn about the current state of patient health at the lowest treatment cost. The classification which has been performed by Buettner and Schunter [46] using the RF algorithm, which has been validated in the Cleveland dataset. Using the Kaggle Cardiology dataset, it aims to compare the performance of three ML classifiers: K-NN, DT methods, and RF for diagnostic purposes. Khourdifi et. al [47] used SVM technology for diagnosing HD, age, blood pressure, and blood sugar levels are all factors to consider in patients with diabetes and obtained a prediction accuracy of 94.60%. Also, Priyatharshini and Chitrakala [48] developed an ambiguous, rule-based, self-learning system for predicting HD, with a 90.7% overall accuracy. Mohan et. al. cite mohan2019effective presented a mixed random forest with a linear model that finds significant features for predicting CVD with an accuracy level of 88.7%. In a recent study by Kumar et. al. [2], various ML algorithms were used. They used RF, DT, LR, SVM, and K-NN are some of the ML classifiers to predict CVD. The RF classifier had a higher accuracy of 85%, a ROC AUC value of 0.8675, and a 1.09 second execution time. Posonia et. al. research [11] applied Decision Tree J48 to forecast 768 diabetes patients' data. It gave more efficiency with less processing time.

Fitriyani et al. [4] proposed a clinical decision support system for HD prediction model that consists of a density dependent spatial ensemble of applications with noise to detect and eliminate outliers, a hybrid artificial minority sampling technique modified near neighbors to balance training, and a hybrid artificial minority sampling technique modified near neighbors to detect and eliminate outliers. For predicting HD, data distribution and XGBoost were used. The accuracy of proposed model was 95.90% for the Statlog data set and 98.40% for the Cleveland data set, according to the findings. Purnomo et al. [49] used feature selection in the form of reverse deletion of NB to improve cardiology classification accuracy from 84.29% to 89.45%. Erdogan and Guney [14] proposed a method for determine weight coefficient of the patients data according to their effects on the success rate then the presence of HDs were determined by using ML algorithms. The proposed method achieved a success rate of 86.90% by analyzing the features of 10 different patients. Siddique and Sivabalakrishnan[50] used the random walk memetic algorithm in standardized cardiology datasets from the UCI repository. It aids doctors in diagnosing a patient's ailment at an early point so that additional therapy can be started. It has a 95% accuracy rate. The approximation clustering feature selection module and the fuzzy rule-based classification module, as well as the adaptive genetic algorithm to refine the resultant rules and predict HD, were referenced by Reddy et al. [23] for early-stage HD diagnosis. Rajdhan et. al. [51] used UCI Cardiology datasets to apply NB, DT, LR, and RF algorithms to forecast the likelihood of developing HD and identify a patient's risk level. When compared to other classifiers, the RF algorithm had the highest accuracy of 90.16%, according to the findings of the testing. Shankar et. al. [52] predicts whether an individual is at risk for HD. This prediction will be implemented by applying a Convolutional Neural Networks (CNN) algorithm to real-life structured and unstructured hospital data. The accuracy ranges between 85 and 88%. Khan [8] also suggested an IoT cardiac framework that uses a modified deep CNN to categories sensor data into normal and pathological with a 98.2%. But, Ali et al. [53] used the RF approach and attained 100% accuracy, sensitivity, and specificity. Later, Al-Yarimi et. [36] depicted dynamic feature optimization through discrete feature-relationship weights for supervised learning performance and label the specific patient record as being at risk for HD or not with the least amount of false alarm. The accuracy of the proposed model was 92.062%. Karadeniz et al. [38] proposed classifier for predicting HD based on distance sequence randomization analysis. They used the Spectf medical data set. In addition, the Graph Lasso and Ledoit Wolf contraction-based classifier was developed for the Stat log dataset that is the UCI data. These two algorithms provide relatively good accuracy results: 88.7% and 88.8% for Spectf and Statlog, respectively. Ketu and Mishra [21] suggested that the paper presents an empirical analysis of several ML classifiers, K-NN, SVM, Extra Tree, Bagging, RF, LR, DT, and AdaBoost, in case of imbalance and balanced class models. For diagnosis, on the EKG-based arrhythmia data set. The majority class has more accuracy than the minority class in a two-tier balancing problem. Magesh and Swarnalatha [30] introduced a block-based DT learning approach with RF classifier that was evaluated using Cleveland core samples from the UCI repository. The significant features were determined by entropy and the radio frequency in predicting HD. The classifier has a prediction accuracy of 89.30% and a 9.70% error rate. Martins et. al. [5] cited the application of DM techniques to diagnose CVD. Improved DT, RI, RF, and DL classifiers were used. The improved DT is the best model that achieved 73.54%, 75.82%, 68.89%, 78.1% and 0.788 in terms of accuracy, precision, sensitivity, specificity and AUC, respectively. Nandy et. al. [28] used a swarm artificial neural network to predict CVD, which generates predetermined numbers of neural networks at random for training and evaluation. The proposed model has an accuracy rate of 95.78%.

Mehmood et. al. [22] suggest a method to help HD based on CNN to predict CVD with 97% accuracy while Boukhatem et al. [1] found that the performance of the SVM model was better with an accuracy of 91.67%. Rani et. al. [35] The authors developed a feature selection algorithm-based hybrid decision support system for CVD prediction that combines genetic algorithm, recursive feature cancellation and various ML methods, such as, SVM, naive cells, LR, and SVM, and AdaBoost algorithms. The system was tested on a Cleveland cardiology dataset available at UCI and the RF classifier achieved the best accuracy of 86.6%. Jothi and Karthikeyan [20] suggested an evolutionary feature selection of genetic algorithm and linear discriminant analysis with hybrid ensemble approach to enhance the prediction of CVD. The classification accuracy of the model was 93.65% for the stat log dataset, 82.81% for the SPECTF dataset, and 84.95% for the coronary HD dataset. Recently, Vincent et al. [3] have suggested a deep learning classification model for HD prediction based on BP-NN with mRmR feature extraction. It has a sensitivity accuracy of 98.21%, a value of 97.85%, an accuracy value of 98.41%, a recall of 97.43%, and an accuracy of 97.09%. Modak et. al. [29] investigated on modulated variance for infinite feature selection, and they developed a multi-layered model for HD prediction. The Cleveland, Hungary, Switzerland, Long Beach, and Statlog datasets were used to test the model. The accuracy was 87.70%, the *F*-1 degree was 87.21%, the sensitivity was 88.50%, and the specificity was 87.02%, and precision of 86.05%. While Truong et al. [54] established a framework for detecting congenital cardiac disease utilizing the RF algorithm, with a sensitivity of 0.85% and a specificity of 0.88%. El-Shafiey et. al. [6] used a hybrid genetic algorithm model, particle swarm optimization, and random forest to find the best features for improving HD prediction accuracy, which was 95.6% in the Cleveland data set and 91.4% in the Statlog data set, respectively.

It is important to note that many studies in this field have provided unbiased assessments of the suitability of various ML algorithms for making informed decisions regarding patient cases. Several comparisons have been made between different ML algorithms and applied to heart attack datasets. However, previous studies on HD prediction have not utilized an appropriate classifier to effectively enhance the classification performance of HD.

3 Dataset Description

Different researchers use the "Heart Attack Analysis and Prediction Dataset 2020[1]," which may be found in ML archives of Kaggle's online community of data scientists and ML practitioners. Table 1 Benchmarking our proposed model based on the Kaggle dataset. This data set was utilized to develop a framework for heart attacks, and it was then categorized and processed in Python using ML. The Kaggle heart attack dataset contains 303 instances with 10 features extracted from medical parameters such as age, sex, chest pain kind, blood sugar levels, cholesterol levels, resting blood pressure, and so on, with the extracted data set having (303*10) feature matrices. To diagnose a heart attack, more relevant autonomous information functions and target yield markers are extracted and applied. The objective class is divided into two categories: those who have had a heart attack and those who haven't. The dataset's dictionary is displayed below.

Table 1: 303 examples of 10 data set features are described in this data collection.

Feature	Desrciption	Type	Domain
Age	The patient's age	Numeric	29:77
Sex	The patient's gender	Binary	A value of 0 denotes **female** and 1 for **male**
Exang	Angina caused by exercise	Binary	A value of 0 denotes **no** and 1 for **yes**
Ca	Fluoroscopy has colored a large number of significant vessels	Nominal	Values: 0, 1, 2, 3, 4.
Cp	Chest Pain Types	Nominal	Values: typical angina, atypical angina, nonanginal pain, asymptomatic.
Trestbps	The measurement of resting blood pressure is expressed in millimeters of mercury (mm/Hg).	Numeric	94:200
Chol	Cholesterol in mg/dl as measured by BMI sensor	Numeric	126:254
Fbs	Blood sugar levels exceeding 120 mg/dL after a period of fasting indicate elevated levels of glucose in the bloodstream.	Binary	A value of 0 denotes **false** and 1 for **true**
Rest ecg	electrocardiographic findings at rest	Nominal	Values indicating abnormal cardiac conditions include ST-T wave abnormalities (such as T wave inversions and/or ST elevation or depression greater than 0.05 mV) and the presence of left ventricular hypertrophy as determined by Estes' criteria.
Thalach	heartbeats maximal	Numeric	71:202
Target	The output that represents the chance of heart attack.	Binary	A value of 0 denotes **a less chance** and 1 denotes **more chance.**

4 Methodology

Based on the literature review presented above, Figure 7 illustrates a comparison between the related studies and the current research. The objective of this study, as mentioned earlier, is to evaluate multiple ML classifiers for effectively classifying patients with HD and individuals without HD, aiming to predict the likelihood of a heart attack occurrence. As Figure 8 depicts, the methodology consists of four stages: (i) Dataset collection, data pre-processing & Transformation phase, (ii) ML tool, (iii) ML algorithms, and (iv) Evaluation prediction model of diabetes. During processing the four phases in a conceptual model, to clean, integrate, convert, and standardize the data, this study starts with data collecting, data preparation, and data filtering. Following that, the required fields for ML are picked based on the programming language. The data was converted into a file format that the ML software could read. Using the Python programming language, different ML techniques based on binary class or multiclass datasets were investigated.

[1] https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction

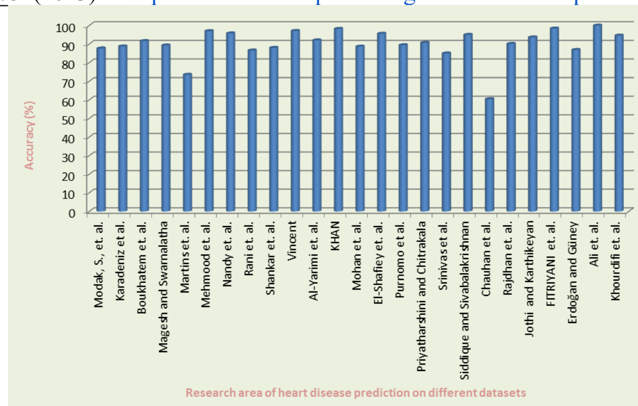

Fig. 7: Studies on applying ML algorithms to detect cardiac disease.

4.1 Preprocessing heart disease data.

In this step, the dataset goes through a number of processes, including data cleaning, data filtering, data integration, and data scaling. The information gathered was saved as Excel spreadsheets or text documents. The cleansing step is essential in order to examine the data using the classifier algorithms that have been chosen. Missing values are removed, inconsistencies are addressed, outliers are identified, and duplicate data is removed. The information was represented by numbers and saved as a CSV or text file for submission to the DM tool. Holdout approaches are used in a lot of experiments. We separated the dataset into two sets using the holdout technique: a training set that contains 80% of the dataset; Train the final model on the entire dataset to get a model that can better generalize to the unseen or future dataset, and a test set containing 20% of the dataset. For assessment, the performance measures are calculated for the actual cardiology categories and categorized between the testing phases. The processed data was tested using nine models; our best performer was the XGBoost models with a constrained accuracy of over 95%.

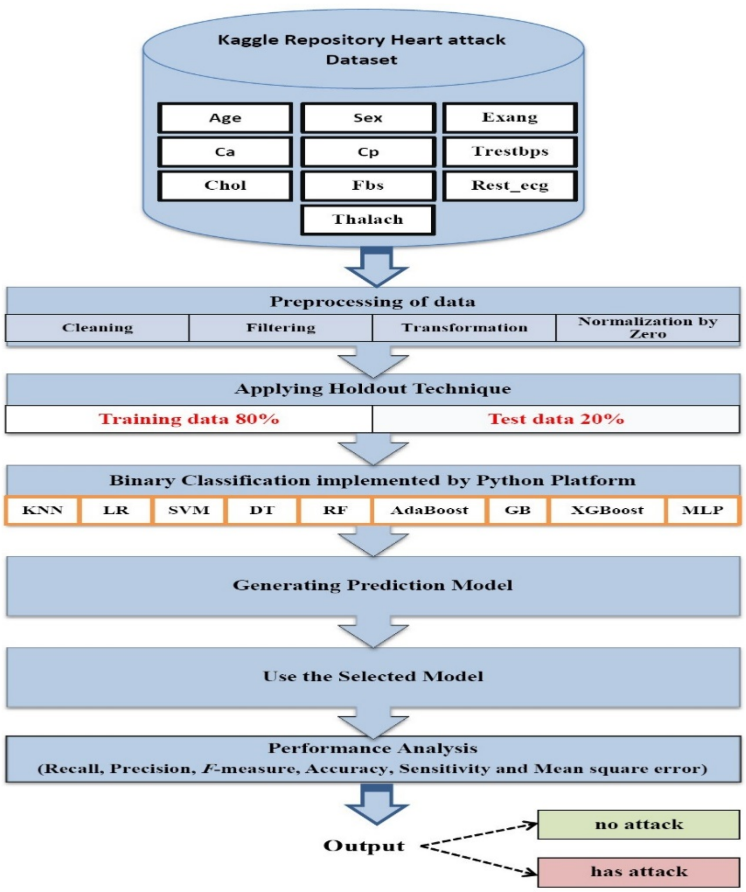

Fig. 8: The current study's proposed framework.

4.2 Classification

Model functions, representations, standard preferences, and algorithms distinguish ML techniques. Classification algorithms use a lot of hidden information in databases and derive useful patterns from predicting future trends using new data [55]. Different companies use different classifiers to analyze data. However, the method used depends on the characteristics of the data set. The technology you use can have an impact on the quality of your data, which can have a big impact on your outcomes [56]. The following is a brief overview of the classification algorithms employed in this paper.

4.2.1 Decision Tree classifier

DT is one of the classification algorithms. It has the ability to deconstruct a complex decision-making process into a series of straightforward decisions [55]. As a result, the solution is simple to understand. The first phase in this learning process is to train DT using the observations from the predictions in the previous step and information from the recording devices from the current and previous periods. DT then generates the decision rules that are included in the decision criterion that selects the best prediction algorithm and checks whether the selection is the best option [57].

4.2.2 Random Forest classifier

In 2001, Breiman proposed the RF algorithm, which joins the results of multiple DT during training and forms the pattern of classes or average prediction for individual trees. It chooses the samples and the predictors randomly [58, 59, 60]. Values of hyperparameter effects on RF, as when we use optimized values of hyperparameters the accuracy of prediction increases [61]. Booststrap sampling method is the basic idea of the RF algorithm. It generates randomly and repeatedly N samples from the training dataset. It builds a robust classifier by integrating weak DTs. This classifier is adapted to build a number of DTs [62, 63, 64]. 2/3 of the original data size will use for each training sets cluster and 1/3 for test sets. The features were selected randomly to split DTs. Continuous Gini gain classification up to 1, and only 1, this method is continued to build new trees since the load consumption pattern is present in the node (leaf node) [65]. RF helps to relieve the overfitting problems and enhance the capability of generalization by choosing the input and predictors randomly [58]. The strengths of RF are that the learning effect for integrated RF is regularly larger than the sum of the learning effects for parts. RF is suitable for large volumes of data, it can estimate missing values effectively, it can balance errors in unbalanced sets for population, it estimates the greatest important features in classification, produced forests can use with other datasets whether in classification or regression problems [66], improves prediction accuracy without a significant increase in computation [62]. It tends to have a good performance in predicting stock prices [66]. It has many applications in bioinformatics, DM, big data, and additional domains [58].

4.2.3 Support Vector Machine classifier

Vapnik and Cortes [67, 68, 69] first proposed SVM for classification of linear and non-linear problems [70]. It is one of the well-known supervised binary classifiers [67, 71, 72] that builds a model by grouping data into two classes [70, 73]. It plots a boundary called it hyperplane to separate the training dataset (a decision surface) in the input space by maximizing the isolation edge between positive and negative examples [67, 69, 70]. Extensive studies have been conducted on SVM can optimize the performance either by altering the used manner to train the classifier, or by decreasing training sets size [74]. SVM applied in extensive applications in ML, statistic, object recognition, text categorization, speaker identification and health care [69].

4.2.4 Extreme Gradient Boosting classifier

XGBoost is a hierarchical boost-based DT suite designed to be highly scalable with modifications in regularization, loss function and column sampling. Resembles tilt boost, XGBoost minimizes the loss function and builds additional extensions to the objective function. It is a classification and regression ML technique [75]. Given that XGBoost focuses only on DT as a basic classifier, the waste function variant is used to control the complexity of the tree. XGBoost executes many techniques to accelerate the DTs training which is not directly concerning the ensemble accuracy. It concentrates on lowering the computational complexity of reaching the best divisions, which is the most time-consuming part of DT building.

4.2.5 Gradient Boosting classifier

GB is a method for creating new models and applying them to error prediction. The final prediction is the summation of scores. The gradient descent method reduces the degree of loss when creating new models. The performance of the model is measured by the objective function. It consists of training loss and modifications in regularization which penalizes the model complexity and prevents overfitting [76].

4.2.6 Adaptive Boosting classifier

The adaptive boosting algorithm is known as Adaboost. It has the advantages of being fast, simple to operate and simple to program. No need to adjust any parameters except for the number of iterations. Weak learning can be flexibly combined with any method to find weak hypotheses, even without prior knowledge. A week of learning with enough data and reliable intermediate precision can provide a set of theoretical learning guarantees. Rather than trying to design an algorithm that is accurate across space, the focus is on finding methods of learning that are weaker than random predictions [77]. AdaBoost employs the concept of boosting, which is an ensemble strategy for improving the performance of underperforming students. The classifier is first trained on the original dataset in this algorithm. The classifier is then trained several times, with each copy attempting to fix the error made by the preceding copy. The classifier is trained on a new subset of data for each copy. By giving weights to data objects, many subsets of the dataset can be generated. Because it is awarded a larger weight, an erroneously categorized instance has a better probability of being selected for the following subset. Multiple models are trained in this manner, one after the other. Then, using a cost function, these weak classifiers are joined to create a strong classifier. Higher-accuracy classifiers are given greater weight in the final prediction. The Adaboost algorithm can be given a weak classifier to which boosting should be performed as a parameter. DT is Adaboost's default classifier for boosting [35].

4.2.7 Logistic Regression classifier

For binary classification tasks, LR can predict the variable Y value that has two possible values: 0 or 1. When Y has more than two possible values, it can also be used for multi-classification problems. The following logistic regression equation calculates the likelihood that input X should be classified as class 1:

$$\boldsymbol{P(x)} = \frac{\boldsymbol{exp}\,(\beta_0 + \beta_1 \boldsymbol{X})}{\boldsymbol{1+exp}\,(\beta_0 + \beta_1 \boldsymbol{X})} \tag{1}$$

Here in Equation (1), β_0 is bias and β_1 is the weight that is multiplied by input X [35].

4.2.8 K-Nearest Neighbour classifier

K-NN is common unsupervised learning methods which recognize unseen data patterns. It is a centroid-based technique [72], executed by classifying hidden objects according to the closest point of its neighbors by training in the attribute space via using various distance measurements between 2 points like Manhattan, Euclidean, maximum dimension distance, and so on. For the hidden instance, the class obtained by determining the most common class in its nearest K examples [70]. K-NN has high flexibility and efficiency to deal with various scenarios that have different complexities. But the drawbacks of K-NN that it required specific experience to estimate the natural clusters beginning number to obtain efficient result, may be in particular cases the resulted set of a cluster not optimal [72].

4.2.9 Multilayer Perceptron classifier

When an Artificial Neural Network (ANN) consists of multiple hidden layers and utilizes backpropagation, it is known as a Multilayer Perceptron (MLP), where the number of layers exceeds three, including the input and output layers. A feed-forward network, which does not form cycles between connections, can be classified as an MLP. It functions by receiving input from other perceptron's, assigning weights to each node, and transmitting the data to the hidden layer. The output layer then receives the output from the hidden layer [26].

5 Experimental Results

The obtained results, as well as a description of the simulated results, are both included in this section. These tests were carried out on a Lenovo laptop running Windows 10 with the following requirements: 1 core processor with a clock speed of 2.40 GHz and 16 GB of RAM. The algorithms were created and tested using Jupyter notebook, which is the greatest tool for implementing Python Programming scripting languages with a wide range of libraries and header files for precise and accurate work.

5.1 Parameters Settings

In this study, the prediction of heart attacks is conducted using nine ML algorithms, namely Decision Tree (DT), Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), Multilayer Perceptron (MLP), Gradient Boosting (GB), K-Nearest Neighbors (K-NN), and Logistic Regression (LR). Table 2 presents the overall configurations for all algorithms, including the specific parameter values for each algorithm. The experiments in this paper were implemented using Python programming language.

5.2 Performance Measures

The comparative analysis for this study was performed and be judged by some essential performance measures. The Recall, Precision, F-measure, Accuracy, Sensitivity and Mean Square error were defined as follows, (TP , TN , FP , and FN represent True Positive, True Negative, False Positive, and False Negative respectively) [55, 79]:

Table 2: Parameter settings

Classifier	Used parameters
K-NN	n neighbors=4
LR	random state=65 , max iter=1000
SVM	kernel=”rbf”, C=.5, gamma = 0.1 , random state = 65
DT	random state=10, criterion=”gini”,max depth=100
RF	n estimators=300, criterion=”gini”, random state=5, max depth=100
AdaBoost	learning rate= 0.15, n estimators= 25
GB	random state=10, n estimators=20, learning rate=0.29, loss=” deviance”
XGBoost	objective=’binary:logistic’, learning rate=0.1, max depth=1, n estimators = 50, colsample bytree = 0.5
MLP	random state=48, hidden layer sizes=(150,100,50), max iter=150, activation = ’relu’, solver=’adam’

5.2.1 Accuracy

Accuracy is used to quantify how well the algorithm matches the measured values. Equation (2) defines accuracy as the percentage of true predictions out of a total number of guesses.

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \quad (2)$$

5.2.2 Recall

Recall is another metric that is used to determine how well the proposed algorithm matches the ground truth. Recall, sensitivity, or TPR is a metric that measures the number of true positives based on the sum of true positives and false sounds (True Positive Rate). Recall is the percentage of properly detected items in everything you need to see, which is calculated by TP divided by $TP + FN$, as shown in Equation (3):

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

5.2.3 F1-score

The (F_1) scores of sensitivity and specificity (i.e., harmonic mean) are metric that measures how well we were able to discriminate between the foreground and background of the ground truth., which is shown in Equation (4):

$$\boldsymbol{F_1} = \frac{\boldsymbol{Recall*Precision}}{\boldsymbol{Recall+Precision}} \quad (4)$$

5.2.4 Precision

Precision, which equals TP divided by $TP + FP$, is expressed as in Equation (5):

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5)$$

5.2.5 Mean Square Error

After generating the expected values for the training data set, supervised learning is used to train the models. The coefficients (or weights) into the models are plugged in using the test data as evaluated by the mean square error (MSE) in Equation (6) to see if the estimations are still accurate for the test data. When the fit is judged to be 0, it also means that the fit is ideal [55, 80].

$$MSE = \sum_{i=1}^{D}(x_i - y_i)^2 \quad (6)$$

(where, D means number of data points)

5.2.6 Training Time

Training time refers to the time spent developing the classifier. This depends on how the algorithms are implemented. The emphasis here is on comparing metrics such as accuracy and training time to determine which method is best suited for a certain dataset type.

5.3 Comparisons between classifiers based on Kaggle Dataset

According to the previous classifiers mentioned within the previous section, these techniques are applied to heart attack data sets so that a comparison study can be done. To evaluate the recommended model's classification performance, the results of its experiments were compared to those of other state-of-the-art methods in terms of heart-disease prediction. Several standards can be used in analysis, including accuracy, precision, recall, F_1-Score, Mean Square Error, and time to create the model per second, but the most important are accuracy and time to build the model. The models were mostly created with the help of the Python software and the ML tool. Nine classifiers (DT, SVM, RF, XGBoost, AdaBoost, MLP, GB, K-NN and LR) were applied to the dataset. The dataset was split into two parts once it was deployed: a training set that was used to train the model of the actual dataset for 80% of the time, and a test set that was used for the remaining 20% of dataset. It was used as a model's training set. The heart attack dataset's results are listed below. The comparisons between different classifiers in terms of classification accuracy and training duration are shown in Table 3. It shows that the XGBoost achieve a better value of accuracy at 95.082%, followed by K-NN (when the Values of K = 4), MLP and AdaBoost, which is the value of the accuracy at 93.443%. At the same time, SVM and Random Forest brought accuracy values at 91.803%. However, Logistic Regression achieves the accuracy to around 90.164%, followed by Gradient Boosting achieving accuracy at 88.525%. Finally, the DT has the lowest accuracy, with an accuracy rating of 80.328%.

Table 3: Comparisons of different classifiers

Classifier	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**MSE**	**Time (s)**
XGBoost	**95.082 %**	**0.968**	0.938	**0.952**	**0.049**	0.07995
K-NN	93.443 %	0.938	0.938	0.938	0.066	0.01199
LR	90.164 %	0.882	0.938	0.909	0.098	0.01199
SVM	91.803 %	0.886	**0.969**	0.925	0.082	0.00402
DT	80.328 %	0.794	0.844	0.818	0.197	**0.00298**
RF	91.803 %	0.935	0.906	0.921	0.082	0.54767
AdaBoost	93.443 %	0.967	0.906	0.935	0.066	0.07001
GB	88.525 %	0.903	0.875	0.889	0.115	0.026
MLP	93.443 %	0.938	0.938	0.938	0.066	0.93447

6 Discussion

In the Heart attack diseases, as shown in Table 3, a comparison between nine different ML classification algorithms, which are XGBoost, AdaBoost, MLP Classifier, Random Forest, Gradient Boosting, Logistic Regression, SVM, K-NN and DT will use a variety of binary-classification and regression criteria to assess the algorithms' performance. The chart in Figure 9 highlights the differences in the performance between the 9 classifiers. The maximum accuracy value was 95.08% for the XGBoost method, while the lowest accuracy value was 80.32% for DT technique. So clearly, the boosting algorithms have dominated the accuracy when it comes to the model comparison.

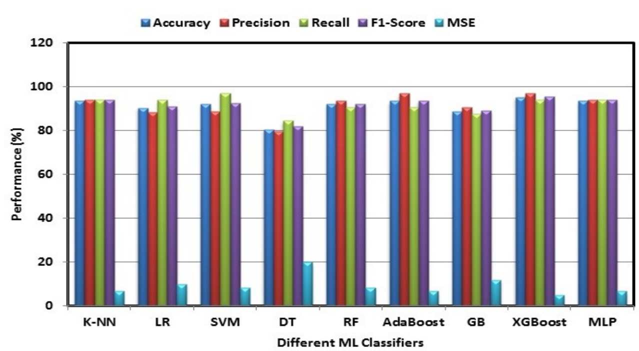

Fig. 9: Comparisons of 9 ML techniques in terms of accuracy, precision, specificity and sensitivity.

The quality of classifiers was evaluated via numerical measures of the confusion matrix, which is the middle output of the classifiers within the Python tool. The confusion matrix checks the accuracy of the classifiers by measuring four different potential classes; TP, TN, FP and FN mainly concentrated on the prediction of heart attacks. The confusion matrix for the accuracy measure for DT, SVM, RF, XGBoost, AdaBoost, MLP, GB, K-NN and LR classifiers as in Figure 10,11. The efficiency of classifiers is usually assessed using the confusion matrix which comprises of data about actual classification and the predicted classification achieved by a model used for classification.

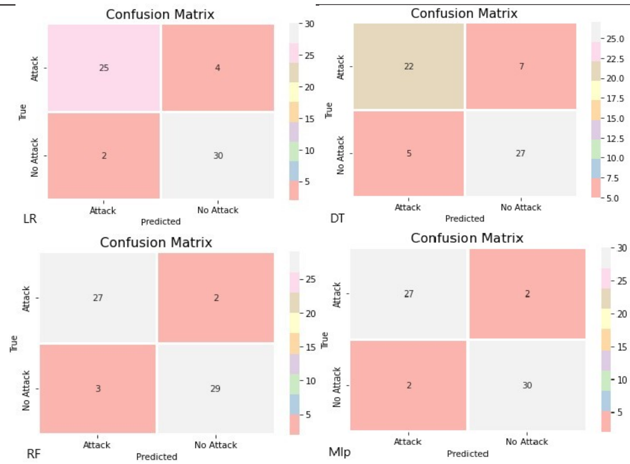

Fig. 10: The Corresponding Confusion Matrices of the Classifiers (DT, LR, MLP and RF)

When it comes to the execution time, DT is again at the bottom (which is a good thing this time) and is the fastest algorithm. Figure 12 shows the comparison between different ML classification algorithms execution times. Finally, ML was applied to help attain the maximum accuracy in the various classification algorithms for heart attack disorders. The XGBoost algorithm, which had the greatest accuracy of 95.082% with an execution time of 0.07995 seconds, was found to be the best classification algorithm that suits our dataset. Due to the difficulty in diagnosis of CVD and the similarity of symptoms with other diseases.

Also, according to the discussions in Section 1, doctors encounter a lot of challenges while diagnosing HD, it requires sufficient knowledge and doctors experience. Researchers proposed that health care centers and hospitals should have forecasting techniques to ensure high-quality heart attack prediction. Many applications of ML algorithms have been proposed to predict heart attack occurrence. Nonetheless, no current research has similar experimental analysis results as our article, among all the used models on the dataset, K-NN gave the best results with 93.44% accuracy. In our paper used nine algorithms based on ML to compare their performance and improve prediction quality. We used 10 features to predict heart attacks with 95.082% accuracy. The comparative analysis performed in section 5, using the bench- mark Kaggle dataset, indicate that the XGBoost classifier has proven effective, and achieved an overall accuracy of 95.082% (as shown in Tables 9). Apart from better accuracy XGBoost model also exhibited faster convergence behavior and time consumed of 0.07995 sec.

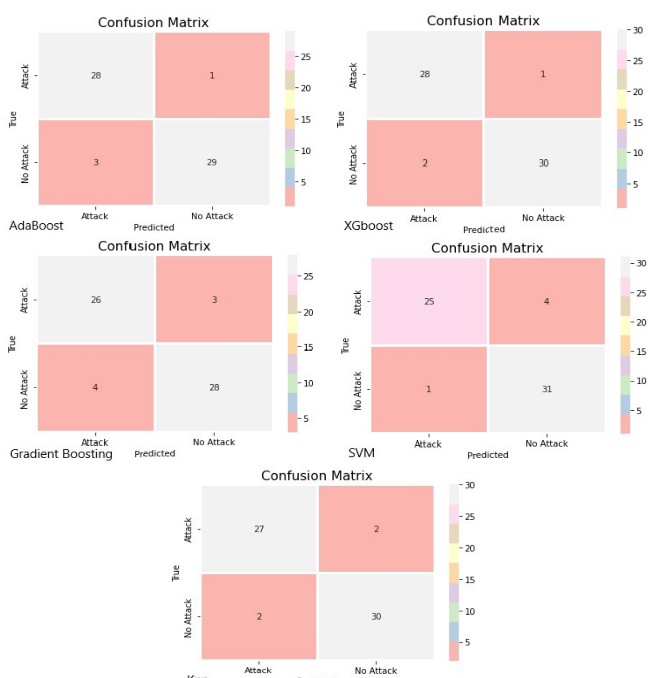

Fig. 11: The Corresponding Confusion Matrices of the Classifiers (AdaBoost, XGboost, Gradient Boosting, SVM and KNN).

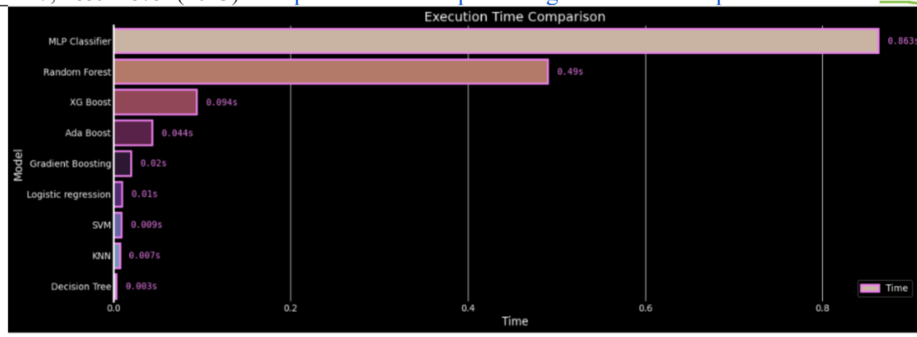

Fig. 12: Time analysis for heart disease dataset.

7 Conclusions and Further Work

Heart Disease is the leading cause of mortality, making the prediction of HD patterns a significant and challenging task in the medical field. To address this, ML techniques can be employed to reduce and comprehend HD symptoms effectively. In this study, we are currently developing a comprehensive framework that aims to enhance the scope of comparative analysis involving nine ML classifiers, including DT, SVM, AdaBoost, MLP, RF, GB, LR, K-NN, and XGBoost.

This research introduces a heart disease prediction framework that utilizes the XGBoost classifier to effectively diagnose normal and abnormal heart functioning and predict heart disease. The framework offers several benefits: Firstly, through a statistical-based analysis, the model's performance was compared to other classification models, demonstrating superior results. Experimental findings confirmed the proposed model's accuracy of up to 95.082% for the Kaggle cardiovascular repository dataset, surpassing state-of-the-art classifiers. Secondly, the model's computational efficiency is noteworthy, completing computations in a mere 0.07995 seconds. This highlights the significance of the XGBoost classifier when compared to other classifiers. Consequently, the proposed framework is expected to provide timely responses in the face of increasing medical data, serving as a practical guideline for healthcare practitioners and potentially benefiting numerous heart disease patients.

In future work, the research can be extended by exploring advanced machine learning techniques or hybrid models to enhance the accuracy and predictive power of heart disease prediction when integrated with fully wearable devices. Additionally, incorporating additional relevant features or data sources, such as genetic information, lifestyle factors, or medical imaging data, can provide a more comprehensive understanding of heart disease prediction. Conducting an in-depth analysis of the interpretability of the machine learning models used in the study can offer insights into the underlying factors influencing predictions. Validating the developed framework on larger and diverse datasets from multiple healthcare institutions or population cohorts will improve the generalizability of the results. Finally, conducting prospective studies and collaborating with medical professionals to assess the real-world impact and clinical utility of the framework will validate its effectiveness for integration into healthcare systems. These future research directions aim to contribute to improved patient care, early detection, and proactive management of heart diseases through advancements in heart disease prediction.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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