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A Detailed Analysis of Detecting Heart Diseases Using Artificial Intelligence Methods

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ABSTRACT

Hearts are crucial for maintaining a healthy lifestyle and are ranked high among the organs that need special care. Globally, heart disease is one of the leading causes of death, posing a considerable public health challenge in low-income countries in particular. Early diagnosis and the identification of risk factors are critical when dealing with these diseases, as early symptoms are often not evident. Heart disease can be caused by several factors, including smoking, poor diet, stress, a lack of physical activity, and excessive alcohol consumption. During the diagnosis process, doctors may encounter various challenges, including vague symptoms, misleading test results, and other medical complications. It is currently possible to diagnose heart disease more accurately and effectively using machine learning algorithms. The present study examines seven different machine learning algorithms on a dataset consisting of 4,238 records and 16 different patient characteristics. Among the classification models, Naive Bayes, Decision Trees, Random Forests, Support Vector Machines (SVM), Artificial Neural Networks (ANNs), K Nearest Neighbors, and Logistic Regressions yielded 78.9%, 79.9%, 83.9%, 70.9%, 83.7%, 83.4%, and 85.5%, respectively.

1. INTRODUCTION

The heart is one of the fundamental organs of the body, and its significance extends beyond physical health. A healthy heart is among the most crucial factors determining an individual's quality of life. Therefore, the heart plays a vital role in sustaining the body's vital functions. Heart disease ranks among the most common causes of death worldwide. A healthy heart is a critical factor in determining the quality of life. Epidemiological data consistently places heart diseases as the primary cause of death for many years. This trend is evident in both developed and developing countries. A significant characteristic of heart diseases is that symptoms in the early stages can be mild or vague, often progressing unnoticed. Hence, the diagnosis, identification of risk factors, and effective treatment methods are of great importance in preventing and managing heart disease. Unhealthy lifestyle habits such as smoking, poor diet, stress, a sedentary lifestyle devoid of physical activity, and excessive alcohol consumption are significant factors that increase the risk of heart disease. Regular health screenings, identification of risk factors, and lifestyle changes are crucial steps in effectively combating heart disease [1-3].

Jagtap et al.'s study is based on data collected from medical research conducted by Kaggle and the Cleveland Foundation (from the University of California, Irvine). Seventy-five percent of the entries in the dataset are used for training, while the remaining 25% are allocated for testing purposes. Among the Support Vector Machine (SVM), Logistic Regression, and Naive Bayes algorithms, it was observed that SVM exhibited the highest accuracy, with an efficiency of 64.4% [4].

Singh & Kumar used machine learning algorithms, specifically KNN, SVM, DT, and LR, in their study to predict heart disease. They utilized the UCI dataset for training and testing. Seventy-three percent of the dataset was used for training, and the remaining 37% was allocated for testing. KNN emerged as the most successful model with an accuracy of 87% [5].

Dutta et al. utilized data from the National Health and Nutrition Examination Survey (NHANES) to predict the

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occurrence of Coronary Heart Disease (CHD) in their study. They employed NHANES data from 1999–2000 to 2015–2016 in their project. Using a Convolutional Neural Network (CNN) architecture, they achieved a classification power of 77% for accurately identifying the presence of CHD in a test dataset and 81.8% for accurately classifying the absence of CHD cases. The balanced accuracy of the model was determined to be 79.5% [6].

Srivastava & Choubey utilized the Cleveland Heart Disease dataset from UCI in their study to detect heart disease. They employed machine learning algorithms, including K-Nearest Neighbors, Support Vector Machines, Decision Trees, and Random Forests. Among these, the K-Nearest Neighbors model achieved the highest accuracy, with an accuracy rate of 87% [7].

Nikam et al. used a dataset comprising 12 rows and 70,000 columns (patient records) in their study. After removing similar records, they utilized the remaining 68,975 patient records. To determine which technique more accurately predicted cardiovascular disease, they employed various algorithms such as Neural Networks, Decision Tree Classifier, K-Nearest Neighbors, Logistic Regression, Naive Bayes, XGB Classifier, and LGBM Classifier. The Decision Tree Classifier yielded the highest accuracy, with a rate of 73.12% [8].

Pasha et al. analyzed various algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors, and Decision Trees in their articles. Among these, Artificial Neural Network (ANN) achieved the highest accuracy, with a rate of 85.24% [9].

Rubini et al. conducted a comparative analysis of machine learning techniques, including Naïve Bayes, Logistic Regression, Support Vector Machine (SVM), and Random Forest (RF), for the classification of cardiovascular diseases in their articles. They demonstrated that Random Forest achieved the highest accuracy at 84.81%, establishing it as the most accurate and reliable algorithm among the tested methods [10].

Garg et al. employed two supervised machine learning algorithms, namely K-Nearest Neighbors (K-NN) and Random Forest, in their articles. The prediction accuracy obtained with the Random Forest algorithm was 81.967%. On the other hand, the prediction accuracy achieved by K-Nearest Neighbors (K-NN), which outperformed Random Forest, was 86.885% [11].

Vayadande et al. utilized the Kaggle heart dataset, which comprises 303 rows with a total of 14 feature attributes, in their study. According to their findings, Logistic Regression, Random Forest, and XGBoost algorithms achieved a higher accuracy of 88.52% compared to other methods such as Naive Bayes (NB), K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), Multi-Layer Perceptrons, Artificial Neural Network, Decision Tree, and Cat Boost [12].

Rindhe et al. used Artificial Neural Network, Random Forest, and Support Vector Machine in their project to predict heart disease in patients. They utilized the UCI dataset consisting of 303 samples and 14 input features. With the Support Vector Classifier, they achieved an accuracy of 84.0% [13].

This section comprehensively covers the topic of heart disease. Additionally, it focuses on how artificial intelligence techniques, particularly machine learning methods, can be applied to the classification and diagnosis of heart diseases. Throughout this section, numerous studies and research findings related to recent developments in the field of cardiology are referenced. Table 1 includes previously published studies on heart diseases.

Tablo 1. Summary of Previously Published Studies on Heart Diseases.

Methods	Dataset size	Accuracy	References
Support Vector Machine	303 samples and 14 features	%64.4	[4]
K-Nearest Neighbor	303 samples and 14 features	%87	[5]
Convolutional Neural Networks	37079 patients	%79.5	[6]
K-Nearest Neighbor	303 samples and 14 features	%87	[7]
Decision Tree	68,975 patient records	%73,12	[8]
Artificial Neural Network	-	%85.24	[9]
Random Forest	14 features	%84.81	[10]
K-Nearest Neighbor	303 samples and 14 features	%86.885	[11]
Logistic Regression, Random Forest, XGBoost Algorithms	303 samples and 14 features	%88.52 %88.52 %88.52	[12]

2. Materials and Methods

There are various algorithms for the classification [14, 15] process of heart disease detection, and the results can vary for different datasets. Therefore, selecting the most suitable classifier based on the used data is crucial for obtaining accurate classification results. For the detection of heart disease, models were trained using Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbor, Logistic Regression, and Artificial Neural Network algorithms. The steps used throughout this project are outlined in Figure 1.

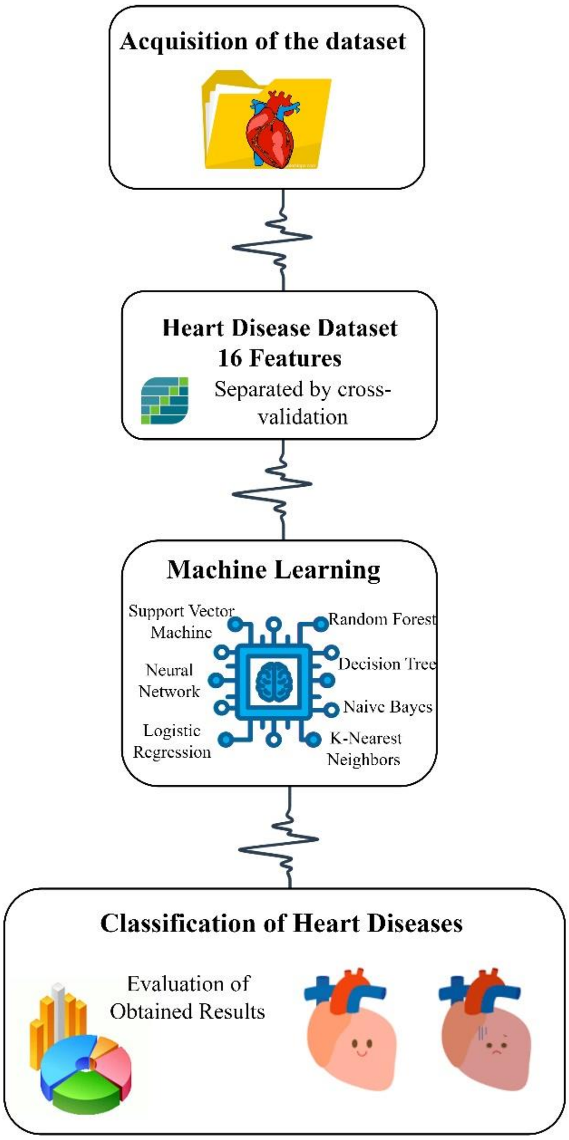


Figure 1. General flow diagram of the project.

2.1. Dataset

The dataset is named "Heart Disease Dataset," and it has been obtained from Kaggle. Originally published by Mirza HASNINE [16], this dataset comprises 16 different patient features. In total, it consists of 4,238 records. The values and value ranges of the features in this dataset are presented in Table 2. The dataset provides a concise overview of heart disease, covering its definition, symptoms, statistics, risk factors, cardiac rehabilitation, a quiz, public health initiatives, and additional resources. Key points include the prevalence of conditions like Coronary Artery Disease, symptoms of heart attacks and heart failure, alarming statistics, crucial risk factors, the importance of cardiac rehabilitation, and efforts by organizations like the CDC. The information is sourced from reputable institutions like the American Heart Association and the National Heart, Lung, and Blood Institute.

2.2. Performance Metric and Confusion Matrix

The confusion matrix is a matrix used to evaluate the performance of classification algorithms [17]. This matrix visually represents correct and incorrect classifications by comparing the values predicted by a model with the actual values. The confusion matrix assists in calculating important metrics for a model in classification problems, such as precision, specificity, accuracy, and F1 score. It is used to understand how accurately the model predicts each class and identify the types of errors made, providing guidance for improving the model [18]. A binary classification problem can be expressed as shown in Table 3 [19]:

Table 2. Values and value ranges of features in the dataset.

Features	Values	Features	Values	Features	Values
Gender	Male/Female	Blood Pressure Medications (BPMeds)	0/1	Systolic Blood Pressure (SysBP)	83.5-295
Age	32-70	Prevalent Stroke	Yes/No	Diastolic Blood Pressure (DiaBP)	48-142.5
Education	Graduate postgraduate Primaryschool Uneducated Empty	Prevalent Hypertension	0/1	Body Mass Index (BMI)	15.54-56.8
Current Smoker	0/1	Diabetes	0/1	Heart Rate	44-143
Number of Cigarettes Per Day	0-70	Total Cholesterol	107-696	Glucose	40-394
Heart Stroke	Yes/No				

TN represents the number of True Negatives, which is the number of data points that the model correctly predicts as negative. FP represents the number of False Positives, which is the number of data points that the model wrongly predicts as positive when they are actually negative. FN represents the number of False Negatives, which is the number of data points that the model wrongly predicts as negative when they are actually positive. TP represents the number of True Positives, which is the number of data points that the model correctly predicts as positive.

Table 3. Confusion matrix

Predicted Class		Actual Class	
		Positive	Negative
	Positive	TP	FP
	Negative	FN	TN

Performance metric is a measurement tool used to assess the effectiveness and success of a system, model, or process [20, 21]. These metrics are employed to evaluate the degree of success of a specific task, compare results, or identify improvement opportunities. The success of the classification methods used in this research was measured with Table 4, which includes performance metrics, formulas, and evaluation conditions. Classification results were assessed according to these criteria, and the effectiveness of the model was evaluated [18, 22].

Table 4. Table of Performance Measurements, Formulas, and Evaluation Conditions.

Performance Metrics	Formula	Description
Accuracy	$(TN + TP)/(TN + FP + TP + FN)$	The summation rate of correct predictions is the number of samples evaluated.
Precision	$TP/(TP + FP)$	It is used to measure positive patterns correctly predicted from the total number of prediction forms in a positive class.
Recall-Sensitivity	$TP/(TP + FN)$	It is used to measure the proportion of correctly classified positive patterns.
F1-score	$(2 * TP)/(2 * TP + FP + FN)$	Represents the harmonic mean between Recall and Precision values.

2.3. Cross Validation

Cross-validation, is a method used to objectively evaluate the performance of machine learning models [23]. The dataset is divided into training and testing data, and the model is trained and evaluated on different subsets of data. This helps identify overfitting issues, assess generalization capabilities, and obtain more reliable results [21]. Cross-validation is a crucial tool in machine learning projects to better predict the real-world performance of a model. [24].

2.4. Machine Learning Algorithms

2.4.1. Naive Bayes -NB

Naive Bayes (NB) classifier is also referred to as the "Independent Feature Model." It is based on Bayes' theorem and serves as a simple probabilistic classifier with a strong independence hypothesis. Essentially, the NB classifier is used to predict the probability of an object or data sample belonging to a specific class. In other words, it assumes that the presence/absence of a specific class feature is independent of the presence of another class feature. NB classifiers typically work in supervised learning and are highly suitable for high-dimensional input situations [25]. The diagram of a Naive Bayesian classifier for two classes, one for being heart disease positive and the other for being negative, is depicted in Figure 2.

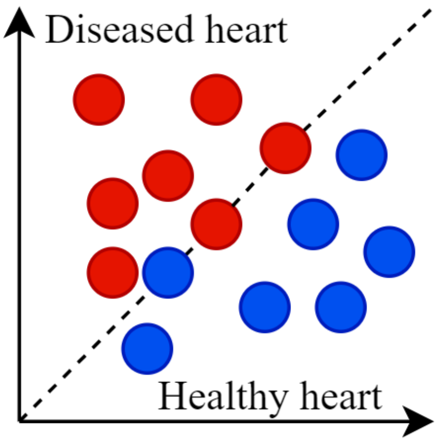


Figure 2. Diagram of a two-class Naive Bayesian classifier.

Step 1: Let's assume D represents the training set, and each record is represented by an n-dimensional feature vector, denoted by $X = (x_1 + x_2 \dots + x_n)$, which implies predicting n measurements from n attributes (let's say from A1 to An).

Step 2: Consider the number of classes m for prediction (denote them as C1, C2, ..., Cm).

According to Bayes' theorem:

$$\boldsymbol{P(C_i|X) = \frac{P(X|C_i) * P(C_i)}{P(X)}} \quad (1)$$

Step 3: Since P(X) is constant for each class, $P(X|C_i) * P(C_i)$ should be maximized for each class.

Step 4: Afterward, conditional independence of class is assumed.

$$\boldsymbol{P(X|C_i) = P(x_1|C_i) * P(x_2|C_i) \dots \dots P(X_m|C_i)} \quad (2)$$

Step 5: To predict class X, $P(X|C_i)P(C_i)$ is calculated for each class (C_i).

Naive Bayes classifier predicts the class label as (C_i) if X is predicted to belong to class (C_i) .

$$\boldsymbol{P(X|C_i)P(C_i) > P(X|C_j)P(C_j)} \quad (3)$$

$$\boldsymbol{for\ 1 \le j \le m, j \ne i} \quad (4)$$

2.4.2. Decision Tree-DT

Decision Tree is a classification algorithm that can handle numerical and categorical data, creating tree-like structures. This algorithm facilitates the analysis of data by representing it in a graphical tree structure. It is a commonly used, simple method, particularly for processing medical datasets [26]. For the training examples of dataset D, trees are created based on high-entropy inputs [27]. These trees are constructed simply and quickly using a top-down recursive divide-and-conquer (DAC) approach. The tree pruning process is applied to remove irrelevant examples from D [28]. A diagram of a Decision Tree classifier is shown in Figure 3.

$$\boldsymbol{Entropy = -\sum_{j=1}^{m} p_{ij} \log_2 p_{ij}} \quad (5)$$

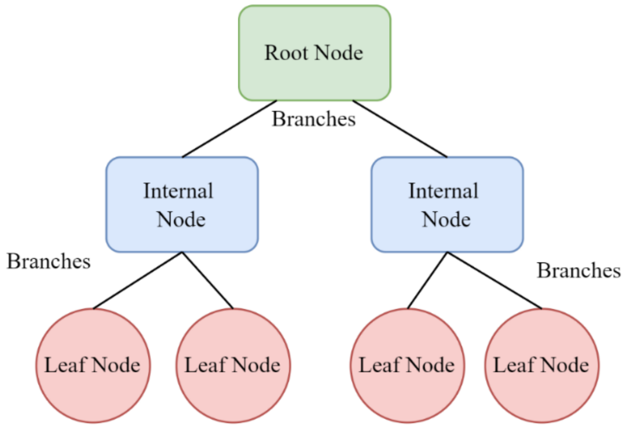


Figure 3. Decision Tree diagram.

2.4.3. Random Forest (RF)

Random Forest (RF) classifier creates multiple decision trees during the training phase and forms a class with an average prediction. Each tree is trained with a subset of examples consisting of independently randomly chosen samples from the training dataset. In this process, trees use randomly selected features depending on the input data. During the classification process, each tree independently votes for the most popular class for the input vector, and the results are combined to make the classification. This method is a logical strategy to achieve more reliable and effective classification results through the combination of different trees. The number of features and the number of trees to be grown are two user-defined parameters required to create a random forest classifier. At each node, only the selected features are considered for the best split [29, 30]. A diagram of a two-class Random Forest classifier, one for being heart disease positive and the other for being negative, is shown in Figure 4.

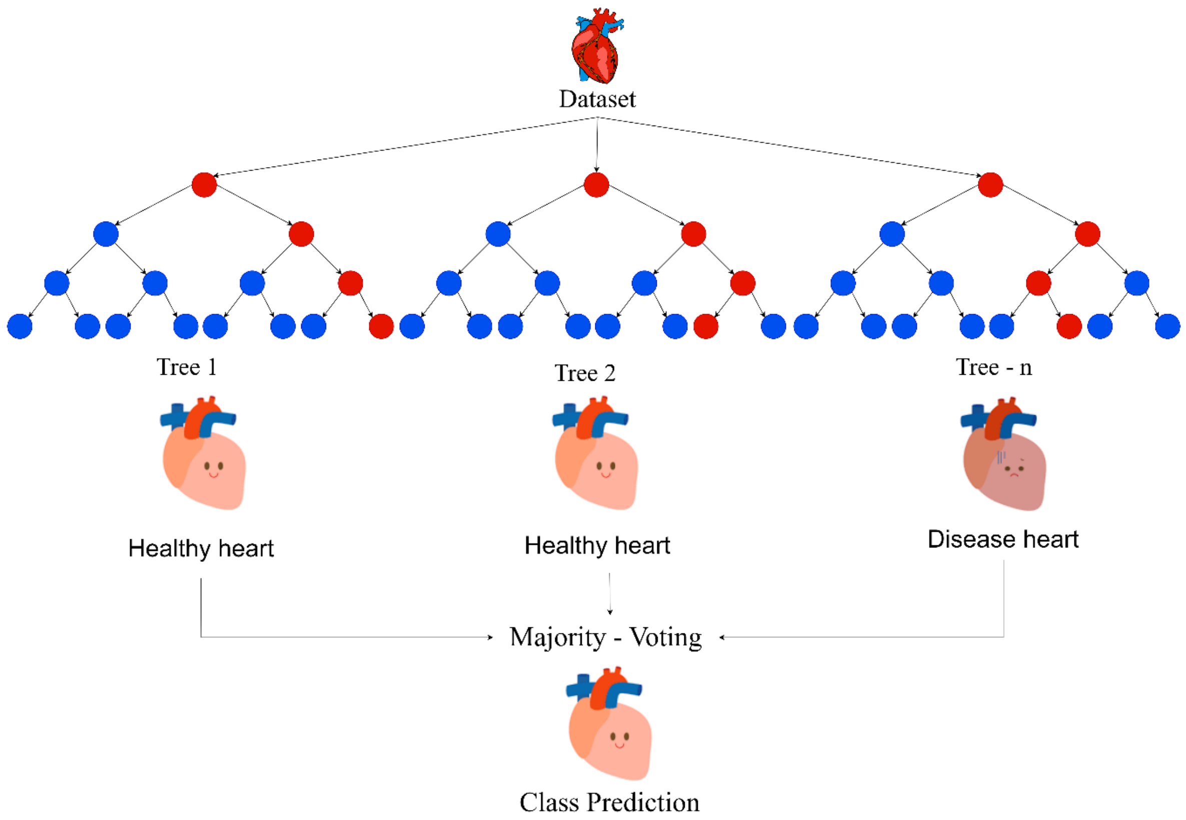


Figure 4. Diagram of a two-class Random Forest.

2.4.4. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning algorithm that performs well, especially with small datasets. Its main objective is to find the separation hyperplane that best separates the data. By representing data points as vectors in space, it seeks to separate classes with the hyperplane that has the widest margin, and support vectors are crucial in this process [31]. Additionally, it successfully classifies non-linear data by mapping them into a high-dimensional feature space using kernel functions, allowing it to handle complex datasets [32, 33]. Figure 5 depicts the structure of a two-class Support Vector Machine.

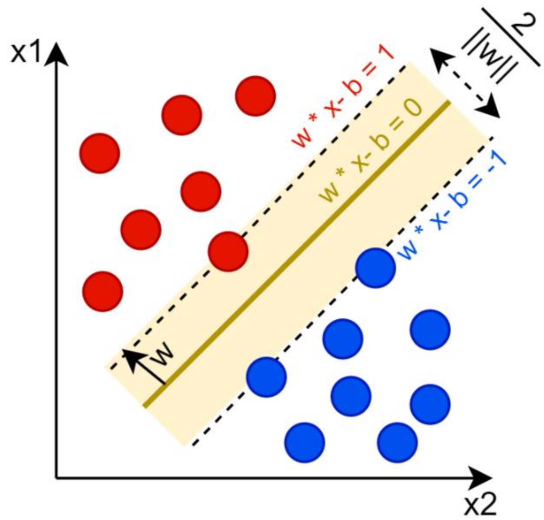


Figure 5. Diagram of a two-class Support Vector Machine.

2.4.5. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) is an artificial intelligence model that mimics the functioning of biological neurons. This structure consists of artificial neurons organized in layers. It performs tasks such as data processing, pattern recognition, and prediction. Input data is multiplied by weights, processed using activation functions, and produces the output [34]. Figure 6 illustrates the diagram of a two-class artificial neural network.

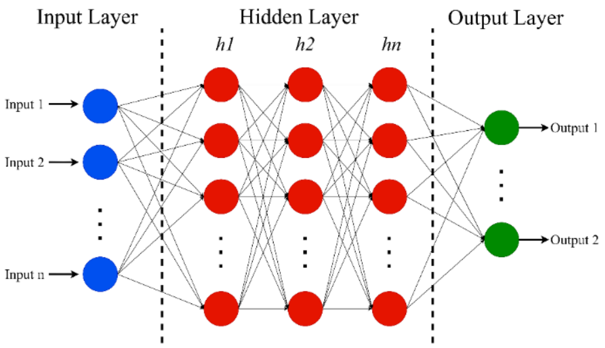


Figure 6. Diagram of a two-class Artificial Neural Network

2.4.6. K-Nearest Neighbor (KNN)

The K-Nearest Neighbors (KNN) algorithm is a simple and popular learning method used in the field of machine learning for classification and regression problems [35, 36]. In the case of classification, the algorithm determines the k nearest sample data points using features representing the data points in space to classify a new data point, predicting the class based on the majority class of these k neighbors. In regression, it predicts the target value of a new data point by taking the average of the target variables of the k nearest neighbors. KNN is preferred due to its simple implementation and low cost, but its performance may decrease with large datasets and high-dimensional data. Additionally, performance should be optimized with the proper choice of k value and data preprocessing methods [37, 38]. The diagram of a two-class K-Nearest Neighbors classifier used to distinguish individuals with and without heart disease is shown in Figure 7.

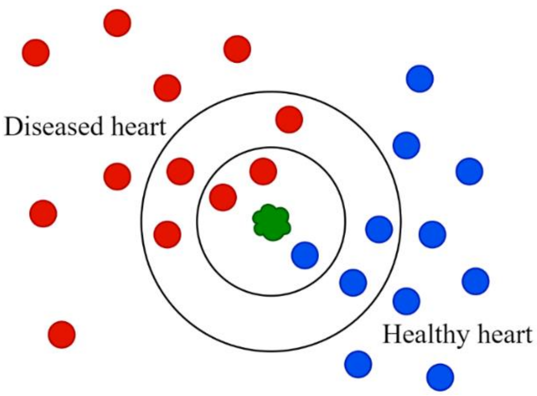


Figure 7. Diagram of a two-class K-Nearest Neighbors.

2.4.7. Logistic Regression (LR)

Its main goal is to use a logistic function to separate data points into two or more classes. The logistic function predicts class labels by transforming input data into a probability value range, typically between 0 and 1. The algorithm is trained using feature vectors and their corresponding class labels. During the training phase, the model attempts to approximate a logistic function that fits the sample data points representing the dataset and iteratively updates the model parameters [39]. After training is complete, the logistic function is used to predict the class of a new data point, and class labels are assigned based on probability values above a threshold (usually 0.5). Logistic Regression is not only a simple and effective classification method but also performs well with high-dimensional data and is preferred for its interpretability. However, it may not be sufficient on its own for linearly inseparable data and can be extended with kernel methods to address nonlinear problems [40, 41]. For illustrative purposes, a typical two-class logistic regression is provided in Figure 8.

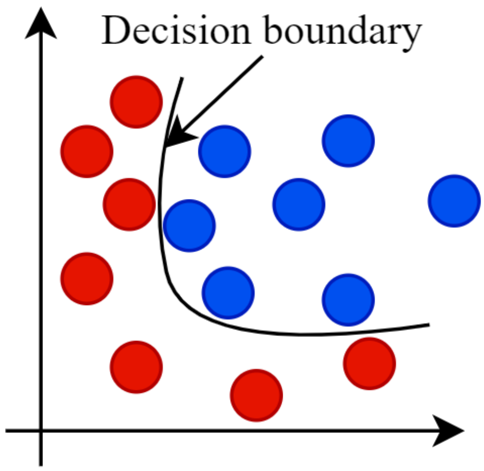


Figure 8. Diagram of binary logistic regression.

3. Experimental Results

In this section, the results obtained with the Naive Bayes, DT, RF, SVM, ANN, KNN, and LR classification methods on a dataset with a total of 4238 records and 16 different patient features are presented. The confusion matrices for all models used are provided in Table 5.

Table 5. Confusion matrices of classification models

Algorithms			Confusion Matrix – Predicted Class: Healthy Heart Patient	Confusion Matrix – Predicted Class: Diseased Heart Patient
Actual Class	Naive Bayes	Healthy Heart Patient	3111	483
		Diseased Heart Patient	411	233
	DT	Healthy Heart Patient	3244	350
		Diseased Heart Patient	503	141
	RF	Healthy Heart Patient	3509	85
		Diseased Heart Patient	596	48
	SVM	Healthy Heart Patient	2865	729
		Diseased Heart Patient	505	139
	ANN	Healthy Heart Patient	3483	111
		Diseased Heart Patient	579	65
	KNN	Healthy Heart Patient	3474	120
		Diseased Heart Patient	582	62
	LR	Healthy Heart Patient	3573	21
		Diseased Heart Patient	594	50

The confusion matrices in Table 5 shape the main findings of this research. The confusion matrix allows us to evaluate the performance of classification models in detail. In Table 5, the highest TP value is 3573, belonging to the LR model. The lowest TP value is 2865, associated with the SVM model. TP and TN values are of great importance in disease detection. These values are the primary determinants of success. It is expected that the ratio of these values to the entire data is at the maximum level. Table 6 displays the performance metrics of the classification models.

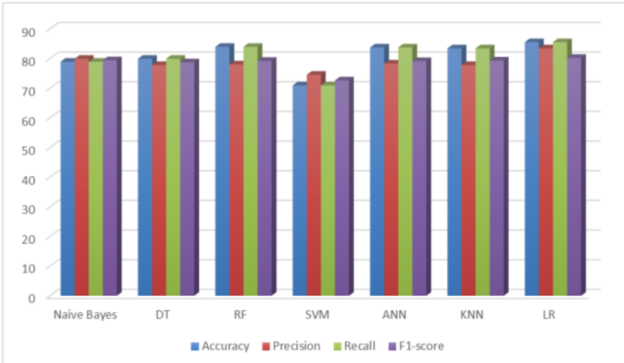
Table 6. Performance measurement results of the models.

Performance Metrics	Naive Bayes	DT	RF	SVM	ANN	KNN	LR
Accuracy	78.9	79.9	83.9	70.9	83.7	83.4	85.5
Precision	79.9	77.8	78.0	74.5	78.3	77.8	83.4
Recall	78.9	79.9	83.9	70.9	83.7	83.4	85.5
F1-score	79.4	78.7	79.2	72.6	79.1	79.3	80.2

According to Table 6, the highest classification accuracy value belongs to the LR model. The lowest classification accuracy value is attributed to the SVM model. Other performance metrics also parallel the classification accuracy values of the classification models. The comparative display of all model performances is shown in the graph in Figure 9.

According to Figure 9, the highest classification accuracy is for the LR model, while the lowest classification accuracy is for the SVM model. Due to the different learning styles of each algorithm based on the data, there may be variations in performance metrics. The rankings of classification accuracies of classification models may vary depending on the data. The rankings shown in Figure 9 were obtained for this dataset.

Figure 9. Performance table of models used in the diagnosis of heart disease



4. Results and Findings

The obtained results are important in evaluating the performance of various machine learning algorithms used for the diagnosis of heart disease. This study examines the effectiveness of these algorithms through classification experiments conducted on a large dataset with 4,238 records and 16 different patient features. The results indicate that different algorithms achieve different levels of accuracy. The highest accuracy rate, 85.5%, is achieved by the LR (Logistic Regression) model. Other algorithms such as RF (Random Forest) and ANN (Artificial Neural Network) also show good results with accuracies of 83.9%

and 83.7%, respectively. These results demonstrate the potential usefulness of machine learning algorithms in the diagnosis of heart disease and their ability to assist in making accurate diagnoses.

The KNN model has an accuracy of 83.4%, indicating successful classification of the data. However, it has a slightly lower accuracy compared to RF and ANN models. The DT model achieves an accuracy of 79.9%, showing that it classifies the data more successfully than Naive Bayes and SVM models.

The Naive Bayes model has an accuracy of 78.9%. On the other hand, the accuracy of the SVM model is determined to be 70.9%. SVM draws attention with particularly low accuracy on this dataset, indicating a mismatch with certain features of this dataset. Similarly, the Naive Bayes also achieving low accuracy suggests that this algorithm may not be an ideal choice for this dataset. These results highlight that the success of machine learning projects depends on the characteristics of the dataset and the accurate selection of the algorithm.

Acknowledgments

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Data Availability

The dataset can be accessed through the following link: [https://www.kaggle.com/datasets/mirzahasnine/heart-disease-dataset/data].

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