Prediction oh heart diseases by using Supervised Machine Learning

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Abstract

Heart Disease is a complex and life-threatening ailment that poses a significant mortality risk around the world, with nearly a third of global deaths attributable to heart-related conditions. The early prediction and detection of heart disease are of utmost importance in the medical field, as they may lead to saving numerous lives. However, the lack of heart expertise in many countries and the high rates of misdiagnosis highlight the need for accurate and efficient prediction methods. Machine learning-based approaches have the potential to address this need, particularly in handling the large amounts of data generated by medical sectors and hospitals. In this study, the performance and accuracy of several supervised machine learning algorithms were compared for heart disease prediction using a dataset obtained from PhysioNet databases. The classifiers that were applied included Artificial Neural Network (ANN), Gradient Boosting, Decision Tree, Naive Bayes, and Random Forest. Results showed that the ANN algorithm achieved the highest Accuracy of 94.1%, with a sensitivity and specificity of 94.1%. The study thus concluded that supervised machine learning techniques can be utilized with great success to forecast heart disease, displaying exceptional potential for practical application and accuracy.

Keywords

Heart Disease; health-care; Machine Learning (ML); Supervised Learning; Artificial Neural Network.

1. Introduction

In the modern era, individuals are heavily preoccupied with their personal and professional lives, leaving them with insufficient time to attend to their own well-being. This often results in feelings of stress, anxiety, and depression, among other negative experiences. Such factors can lead to illness, including severe conditions like cancer, tuberculosis, and heart disease. The primary cause of death within the medical field is heart disease or cardiovascular disease (CVD) [1], which is responsible for roughly 17 million fatalities annually [2][3]. The heart is a critical organ, and heart disease poses a significant risk to one's health. Due to lifestyle changes and reduced physical activity, these diseases are increasingly common, even among younger age groups. Contributing factors include smoking, lack of exercise, consumption of high-cholesterol and junk food, and unhealthy living habits. The heart pumps blood to all parts of the body, and any dysfunction within the heart can lead to improper functioning of other organs as well. [4].

Machine learning is a rapidly growing field that involves using algorithms to extract useful information from data. This information can be used to make informed decisions and predictions in various fields, including medicine. There are different types of machines learning algorithms, including supervised, unsupervised, and ensemble learning [5], that are used to classify and evaluate the accuracy of datasets. In the diagnosis of heart disease, various machine learning techniques such as decision trees, artificial neural networks, and Naïve Bayes classification are employed [6]. By using machine learning algorithms, models can be created that accurately predict the prominence of heart disease based on patient data, which is particularly useful in the medical diagnosis industry. Machine learning can also be applied to predict other diseases such as liver disease, diabetes, and tumors [7]. The use of machine learning in disease diagnosis reduces manual error and improves accuracy, resulting in highly reliable disease diagnoses. Machine learning has proven to be an effective and promising tool in medicine, finance [8], security, and many other fields.

Early detection and accurate diagnosis of heart disease can be critical in reducing mortality rates and improving patient outcomes. By applying ML techniques to the analysis of large datasets, researchers can develop models that are capable of accurately predicting the likelihood of heart disease in individual patients. These models can also uncover risk factors and shed light on the underlying causes of heart disease, enabling healthcare providers to develop more effective prevention and treatment strategies [7].

In this study, we analyzed the factors contributing to heart disease and attempted to predict heart disease using various ML techniques. The prediction of heart-related disease can make a significant impact on the medical field and people's lives. The following Sections discuss the literature survey and related efforts Section 2, the projected system methodology, and the implementation algorithm Section 3, the results and discussions Section 4, and the conclusion Section 5.

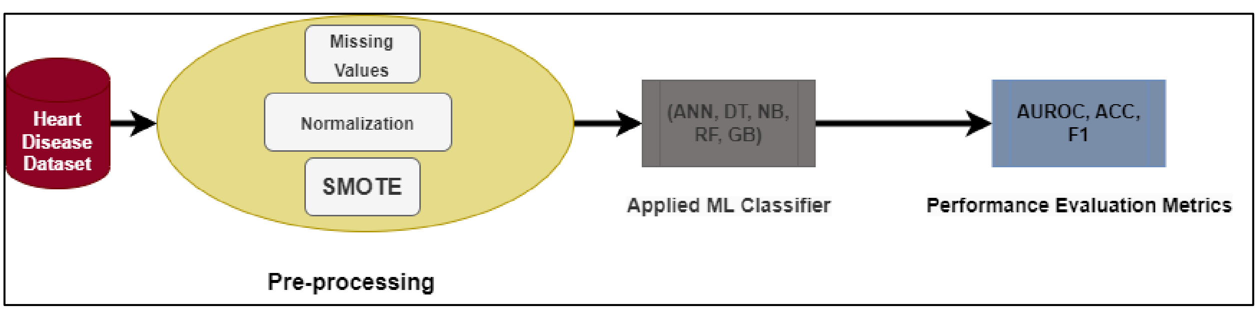

Fig. 1. Experimental methodology.

2. Background Study

In recent years, the application of machine learning techniques has become increasingly popular among researchers seeking to develop accurate and reliable models for predicting heart disease. These methods involve the use of complex algorithms and statistical models to extract meaningful insights from large datasets of medical information, such as patient records, lab results, and imaging data. Many ML algorithms have been researched and assessed for their capacity to accurately predict heart disease, including decision trees, artificial neural networks, and Naive Bayes classification. These models are designed to learn from patterns in the data and make predictions based on historical records of patients who have or have not experienced heart disease.

Researchers have been proposed predictive models based on prescribing data using data mining techniques. And compare the performance of several algorithms to the findings of a number of studies, as done in 2017, František Babič et al. [9] presented the application of various statistical and data mining methods to understand three different medical data sets, and generate prediction models. The study focused on two directions: a predictive analysis based on Decision Trees, Naive Bayes, Support Vector Machine, and Neural Networks, descriptive analysis based on association and decision rules. The algorithms above showed accuracy (68.48% - 89.93%). and in 2017, H. Mansoor et al. [10] A study was conducted to evaluate the effectiveness of Logistic regression and Random forest classification algorithms in estimating the risk exposure of patients with cardiovascular disease. The results indicated that the Logistic regression model performed better than the Random Forest algorithm, achieving an accuracy rate of 89%, whereas RF produced an accuracy rate of 88%. and in another study in 2018, Shiva Kazempour Dehkordi & Hedieh Sajedi [11] Using data mining techniques, a predictive model was developed based on prescription data. The researchers introduced an algorithm called "Skating," which utilized an ensemble approach similar to Boosting and Bagging to enhance the accuracy of the system. The performance of four classification algorithms, including Decision Tree, Naïve Bayes, and kNN, was compared in the study. The results showed that Skating was the most accurate classifier with an accuracy of 73.17%. However, this performance was relatively low compared to other classification algorithms and methods. Recently, researchers have conducted recent studies through which they were able early predict chronic disease, in 2020, Sandeep Kumar Hegde and Monica R. Mundada [12] A new approach for feature selection in conjunction with machine learning algorithms was suggested to forecast chronic disease with high precision. As a result, a new framework for the early prediction of chronic disease was established. The framework's forecasting capability was assessed by comparing it to various algorithms and chronic disease datasets. The performance of the new approach was evaluated using standard metrics such as accuracy, resulting in an accuracy score of 83.7%. and In 2021, M. Kavitha et al. [7] A new machine learning method was suggested to forecast heart disease. The Cleveland heart disease dataset was employed in this approach, which utilized regression and classification data mining techniques. The experiment results demonstrated that the heart disease prediction model achieved an accuracy rate of 88.7%.

In this section, we discuss several research studies that have out to predict outcomes of heart disease using ML techniques. However, the accuracy obtained in each study is currently not considered satisfactory, with certain algorithms performing better than others. In this study, five algorithms were identified that showed satisfactory accuracy through 10-fold cross-validation, demonstrating their potential for use in prediction. Therefore, the aim of the study was to discover classifiers that can efficiently predict heart disease outcomes and can be of practical significance.

Table 1
Descriptions Dataset

#	Feature Name	Feature Description
1	Low blood pressure (mHg).	low blood pressure values from blood pressure signal
2	High blood pressure (mHg).	high blood pressure values from blood pressure signal
3	SpO2	level from the SpO2 signal
4	Rhythm	sinus tachycardia
5	QRS complex width	the activity of the bundle branch in the heart
6	Peak-to-peak	Peak-to-peak regularity
7	ST elevation	myocardial infarction, Prinzmetal's angina, and left ventricular aneurysm
8	Chest pain	No - Yes
9	Shortness of breath	No - Yes
10	Palpitation	No - Yes
11	Patient at rest	No - Yes
12	Chronic Heart Diseases	Normal, Cold-State, Sick, Urgent, Risk

3. Experimental Setup

This Section identifies and describes the Chronic Heart Diseases dataset and the pre-processing stages involved. then apply supervised ML algorithms. In order to determine how effectively the model meets its goals, its performance must be measured by using performance evaluation metrics. This study employed Orange, The Orange platform is a robust tool for conducting data analysis and visualization, enabling users to comprehend data flow and increase their productivity.

3.1. Data Identification

The purpose of this research was to create a model based on a dataset of heart disease patients, which was collected from the PhysioNet databases [13]. The dataset consists of 11 features, and Table 1 provides a breakdown of each one. There was a total of 580 patient records in the dataset, which included individuals with heart disease, those without heart disease, and patients with severe conditions. Table 2 offers additional information about the cases of these patients.

Table 2
Number of Patient Cases

#	Patient Cases	No. Cases
0	Normal	22
1	Cold State	50

2	Risk	66
3	Urgent	151
4	Sick	291

3.2 Data Preprocessing

Data preprocessing plays a critical role in machine learning methods, as it is essential to ensure accurate and reliable results from the data [14]. The effectiveness of machine learning algorithms is greatly influenced by how well the dataset is organized and processed. The initial step in pre-processing is data cleaning, which entails dealing with any missing values present in the dataset. Missing values are a common challenge that requires a specific approach to address them, and there are several methods for handling them, such as replacing them with the mean value, extrapolating values from existing ones, or removing them entirely [15]. The second step is data transformation or normalization, which involves converting the data into a suitable format with a common scale so that each variable contributes equally to the analysis. One successful approach for normalization is the MinMax Scalar [16], which ensures that all features in the dataset range from 0 to 1. After applying these two steps, unbalanced data can be processed by using techniques such as the Synthetic Minority Oversampling Technique (SMOTE) in Python to address any bias in the machine learning algorithms [17]. This step ensures that the algorithms are trained on balanced data and can make unbiased predictions

3.3 Supervised Machine Learning Algorithms

Various supervised ML techniques were utilized in this study. A concise summary of the recommended supervised ML approach for identifying diseases is provided in the next subsection.

3.3.1 Decision tree (DT)

The study utilized a common and well-established machine learning method known as DT to classify data items. DT creates a tree-like structure that assesses and matches results to classify the data. The tree's structure comprises several levels of nodes, including a top-level parent node (root) and child nodes. The internal nodes evaluate input features and have at least one child node that branches off based on the evaluation's outcome. This evaluation and branching process continues until the final leaf node, which represents the decision's outcome. DT is widely considered an easy-to-understand and learn the method and is a crucial component of many medical diagnosis protocols. [18][19].

3.3.2 Artificial Neural Network (ANN)

ANN are a type of machine learning that replicates the functioning of the human brain. ANN are designed to learn from data and can classify and predict the output, much like how neurons in the human brain process information and respond [20]. The structure of an ANN comprises a data input layer, hidden layer(s), and output layer, with multiple nodes that function like neurons. ANN are non-linear statistical models that are effective for solving complex problems. They have become popular in various fields, such as medicine, image recognition, speech recognition, and facial recognition. However, the performance of an ANN for prediction depends largely on selecting the appropriate parameters and activation function [4].

3.3.3 Naive Bayes (NB)

NB algorithm is a supervised learning method that employs Bayes theorem for probabilistic classification of data. The algorithm works by assuming that the features present in one class are independent of the features in other classes[15]. meaning that the presence or absence of any feature does not affect any other feature. This assumption allows the NB algorithm to calculate the probability of each feature independently, which makes the algorithm computationally efficient and straightforward to implement. The NB classifier can be useful in handling missing values and it can work efficiently with large datasets. This algorithm is advantageous due to its fast training and classification times. Additionally, the Naive Bayes model assumes the independence of features which can be beneficial for certain datasets [4].

3.3.4 Random Forest (RF)

RF algorithm utilizes ensemble learning and is based on decision trees [21]. During the training stage, it generates a large number of trees, creating a forest of decision trees [22]. Each decision tree in the forest predicts class labels for individual instances during the testing phase. The final decision for each test data is determined through majority voting, where the class label with the highest number of votes is selected. This process is repeated for all data in the dataset. Random forests are useful for classification tasks in various fields, including medical diagnosis and image recognition [23].

3.3.5 Gradient Boosting (GB)

GB is a ML algorithm used for classification and regression. It is an ensemble method that combines multiple weak learners to create a strong predictor. The algorithm works by iteratively fitting decision trees to the residuals of the current model, with the goal of minimizing the loss function. Each iteration improves the accuracy of the model by focusing on the errors made in the previous iteration. The ultimate forecast is determined by aggregating the predictions made by all the trees in the model [24]. The number of trees, the learning rate, and the complexity of the trees are all hyperparameters that can be adjusted to optimize the performance of the algorithm [25].

3.4 Performance evaluation metrics

To identify the most effective classification algorithm, five different algorithms, namely ANN, RF, DT, GB, and NB, were applied to the dataset, and their accuracy and other statistical variables were compared using a 10-fold cross-validation technique. The algorithms were evaluated based on their performance metrics, and this section provides a brief summary of the evaluation results. To determine the sensitivity, specificity, and accuracy of each algorithm's outcomes, a confusion matrix was generated. The corresponding equations were employed to compute these metrics [26][27]:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

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

$$F1 = 2.\frac{precision.recall}{precision+recall} \quad (4)$$

$$AUROC: \frac{TP}{TP+FN} \quad (5)$$

The confusion matrix generated for each algorithm involved four parameters, true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Sensitivity, specificity, and accuracy were used to evaluate the algorithms. Sensitivity refers to the proportion of actual positives that were correctly identified by the classifier, while specificity indicates the classifier's ability to correctly identify negative outcomes. Accuracy is the percentage of correctly classified instances by the classifier, and it represents the proximity to the target on average. Different statistical measures, such as precision, recall, and F-measure, were employed to compare the performance of different algorithms. Precision measures the percentage of expected positives that are actual positives, recall represents the proportion of positives that are correctly classified, and F-measure balances precision and recall for a classifier. AUROC is a performance metric for discrimination that evaluates the model's ability to distinguish between cases and non-cases. [28][29][30].

To evaluate the model in this study, a K-fold cross-validation approach was used for both training and testing. This technique involves dividing the dataset into K number of groups, or "folds," where K represents the number of groups. K-fold cross-validation is a machine-learning evaluation method, in which the model is trained on (K-1) groups while the remaining group is used to assess the trained model. The model is trained K times in this method, with each fold being used to evaluate the model. In this study, a 10-fold cross-validation technique was used to avoid overfitting in the predictive model. [31].

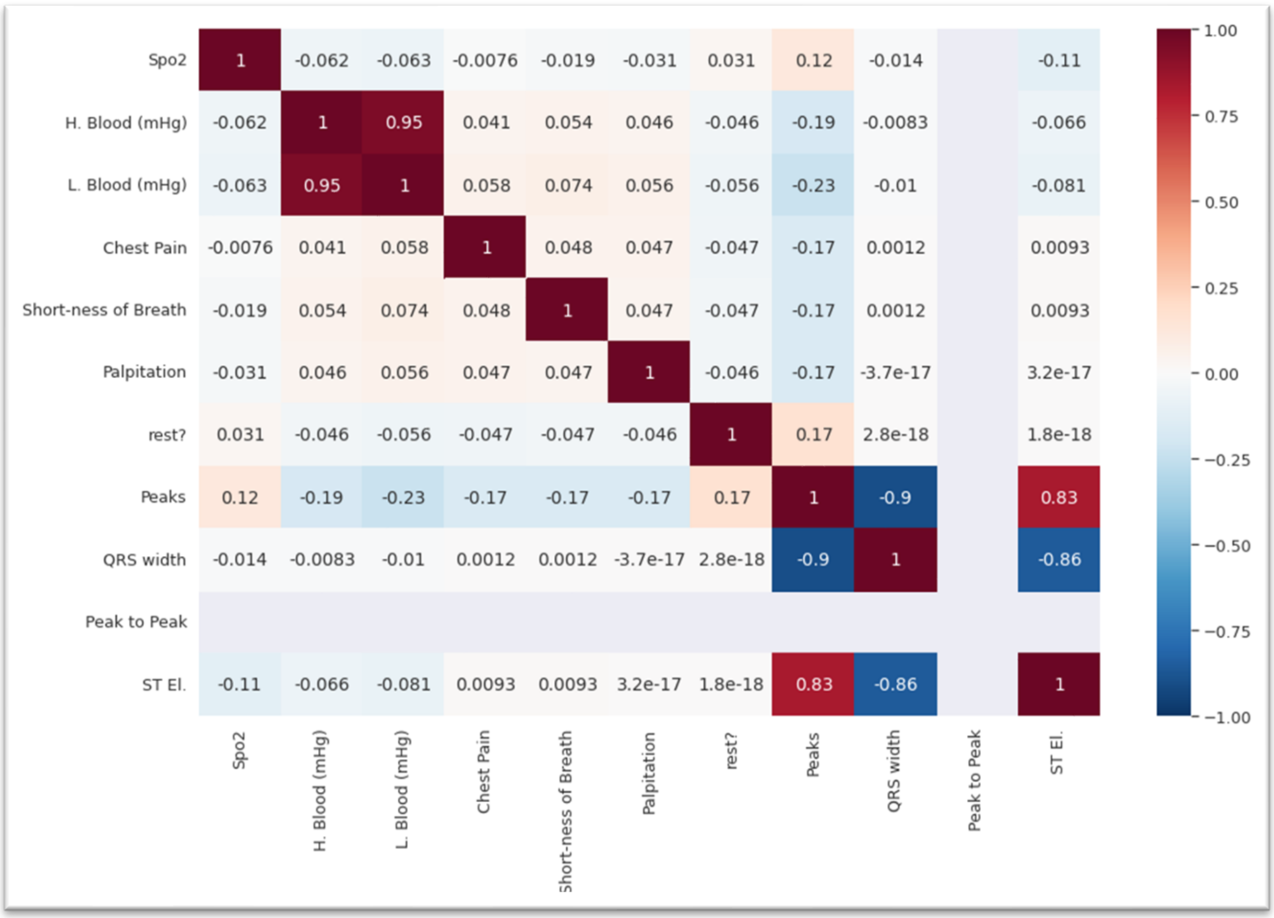

Fig. 1 Heatmap of the dataset.

4. Results and Discussion

4.1 Results of visual data and pre-processing

Data visualization and pre-processing were performed on the dataset to gain a better understanding of its features and identify any correlations between them. A heatmap was created and presented in **Fig 1**, which depicts the correlation between the different features in the dataset. The cells in the heatmap are colored to represent the strength of the correlation between two features, with negative correlations indicated by values less than zero, and zero representing no correlation.

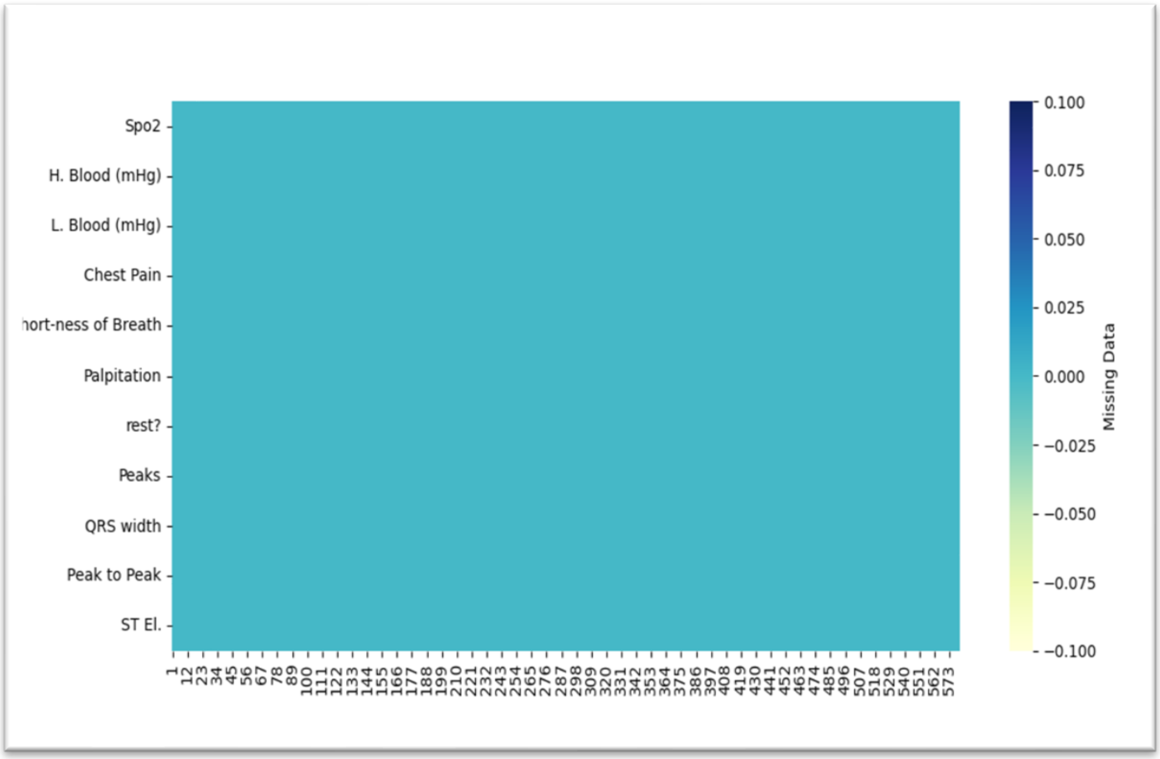

Fig. 2 result of imputing the missing values

Fig. 2 demonstrates the result of imputing the missing values in the dataset after filling in the missing values, effectively transforming the dataset into a complete and usable form. This processed data set will then be used for the remaining pre-processing steps where a MinMax Scaler has been applied to normalize the data and a SMOTE technique has been applied to process the unweighted data, the dataset must be stoichiometric before being adopted in the ML models. It is crucial to perform these pre-processing steps to ensure that the dataset is in a form suitable for analysis and modelling.

4.2 Result of machine learning models

Following the preprocessing of the heart disease dataset, a variety of classification algorithms, including ANN, Naive Bayes, DT, Random Forest, and Gradient Boosting, were applied using 10-fold cross-validation techniques. The performance of each algorithm was assessed using different cross-validation metrics, and the best-performing algorithm was identified. The entire process is shown in **Fig. 1**, and **Table 3** displays the performance results of the classifiers used. The evaluation metrics employed include AUROC, accuracy, F1, precision, and recall, which were chosen to provide a comprehensive assessment of each classifier's performance and ensure a fair comparison between them. The study's results show that ANN provides maximal accuracy, sensitivity, and specificity, followed by Gradient Boosting, which outperformed Decision Tree, Random Forest, and Naive Bayes.

This study identified several ML classifiers with the potential to accurately detect heart disease, which may be valuable to clinicians seeking to predict heart disease occurrence in their patients. However, it should be noted that the dataset used in this study had limited data on heart disease, and further data and analysis are required to establish a more robust prediction model. Despite this limitation, we anticipate that future research will improve our understanding of the strengths and limitations of this approach and that the use of machine learning algorithms in analyzing additional data will lead to highly accurate predictions of heart disease and its related conditions.

Table 3
Evaluation metrics of five supervised ML classifiers

ML classifiers	AUC	Accuracy	F1	Precision	Recall
ANN	0.991574	0.941379	0.941149	0.941452	0.941379
Decision Tree	0.882650	0.743103	0.738877	0.737667	0.743103
Gradient Boosting	0.966494	0.85	0.847661	0.850678	0.85
Random Forest	0.930146	0.787931	0.783868	0.787009	0.787931
Naive Bayes	0.897837	0.746551	0.745020	0.746611	0.746551

5. Conclusion

Heart disease is a severe condition that can cause life-threatening complications, including heart attacks, and even death. Machine learning techniques have the potential to accurately predict the occurrence of heart disease, this study aimed to evaluate the utility of ML approaches in heart disease prediction using a heart disease dataset. The data was pre-processed to address missing values, normalize the data, and correct for imbalance to ensure unbiased machine learning algorithms. The study applied several ML algorithms and found that the classification algorithm ANN performed extremely well with 94.1% accuracy. The objective of the study was to find the most suitable and straightforward ML methods that could deliver good results on the given dataset. Even though the study was in its initial phase of applying ML techniques, the findings indicate that it could be a valuable addition to patient care.

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6.References

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