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Original Article

A Comparative Study Evaluated the Performance of Two-class Classification Algorithms in Machine Learning

Shilan Abdullah Hassan[a], **Maha Sabah Saeed**[b]

[a] Network Department, Computer Science Institute, Sulaimani Polytechnic University, Sulaymaniyah, Iraq.
[b] Network Department, Computer Science Institute, Sulaimani Polytechnic University, Sulaymaniyah, Iraq.

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Corresponding Author:
shilan.abdullah@spu.edu.iq

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Abstract: Worldwide, heart attacks, also called myocardial infarctions, are a leading cause of death. It is critical to detect heart attacks early and predict them accurately in order to provide effective medical intervention and care to patients. Heart attacks can be effectively identified and predicted using machine learning techniques in recent years. The Organization for World Health (WHO) reports that around 17 million individuals worldwide pass away from cardiovascular diseases (CVD), notably heart attacks and strokes, each year. In this study, 1026 patients both men and women are almost equally affected by CVDs. While heart attacks and strokes remain among the leading causes of mortality worldwide, using machine learning to predict heart disease has the potential to prevent premature death. A comparative study evaluated the performance of five well-known two-class classification algorithms: two-class boosted decision trees, two-class decision forests, two-class locally deep SVMs, two-class neural networks, and two-class logistic regression. Among these algorithms, the Two-Class Boosted Decision Tree method demonstrated outstanding prediction ability, achieving a 100% accuracy rating. Its exceptional recall and precision rates highlight its effectiveness in handling challenging classifications. To facilitate the development and deployment of machine learning models, Azure Machine Learning offers a wide variety tools and services. By leveraging Azure Machine Learning's capabilities, researchers and healthcare professionals can analyze large datasets containing patient information and medical records to identify patterns and risk factors associated with heart attacks.

1. Introduction

The disease of heart disease and heart attacks are common throughout the world and can be very dangerous. In addition to extensive research, machine learning approaches have proven effective in enhancing prognosis and treatment. Various disorders that affect the heart and blood vessels are called cardiovascular diseases (CVD), sometimes known as heart disease. Coronary heart disease, valvular heart disease, heart failure, and arrhythmias are some of these ailments (CVD). Researchers have used machine learning algorithms to examine massive datasets, including medical imaging data and electronic health records, to find trends and estimate the probability of having a heart attack [1]. Heart attacks are frequently caused by coronary artery disease. It happens when plaque buildup causes the coronary arteries, which are in charge of Oxygen-rich blood reaching the heart muscle, to constrict or obstruct.

To identify people at high risk, Machine learning techniques have been used to analyze a variety of factors, including age, gender, blood pressure, cholesterol levels, and lifestyle habits, all of which contribute to risk. These algorithms can produce unique risk scores that support early diagnosis and preventive measures [2]. Myocardial infarctions, often known as heart attacks, are caused by an abrupt stoppage of blood supply to a section of the heart muscle. By combining multiple clinical characteristics, genetic data, and biomarkers Heart attack risk can be predicted using machine learning models. These forecasting tools can aid medical personnel in identifying those who are at high risk and putting in place specific actions to stop or lessen the effects of a heart attack [3]. Additionally, the accuracy of diagnosing heart disease and heart attacks has been improved using machine learning algorithms. V

By analyzing medical imaging data, such as electrocardiograms (ECGs), echocardiograms, or cardiac MRI scans, these algorithms can assist in the early identification of abnormalities and provide valuable insights for accurate diagnosis and treatment planning [4]. In addition to diagnosis and risk prediction, machine learning algorithms play a significant role in treatment optimization. They can analyze data from previous patient outcomes to generate personalized treatment plans, recommend suitable medications, and predict the efficacy of interventions such as stenting or bypass surgery. These models enable healthcare professionals to make better selections, resulting in improved patient outcomes. [5].

It is important to note that with machine learning models, healthcare professionals can enhance their ability to assess individual risk, develop targeted prevention strategies, and improve patient results. though, it is crucial. to consider the interpretability and transparency of machine learning algorithms to ensure their responsible and ethical use in clinical practice [6]. Globally, heart disease and heart attacks remain significant health concerns. Our understanding, early detection, and treatment strategies for these conditions can be enhanced by integrating machine learning prediction models with traditional medical knowledge. Machine learning algorithms have the potential to revolutionize cardiac care and improve outcomes for individuals at risk of heart disease and heart attacks.

2. Related works

In the past few years, there has been significant research focusing on utilizing Predicting cardiac disease and heart attack with machine learning algorithms. The related work in this area encompasses both exploratory data analysis and the development of a prediction model based on Machine Learning. According to a paper [7], they examined studies that utilized machine learning techniques to analyses large-scale medical datasets to predict cardiovascular diseases. To gain insight into the use of medical big data in improved risk assessment and patient care, a review has been conducted on the performance and efficacy of various machine learning algorithms for predicting cardiovascular disease. Study [8] focused on creating a prediction model in utilizes machine learning techniques to predict the possibility of heart disease, based on multiple features extracted from the prediction model dataset.

The authors used exploratory data analysis techniques to gain insights into the dataset, identify patterns, and select relevant features. The work [9], tries to predict cardiac disorders accuracy is improved using exploratory data analysis with Tableau and K-means clustering, chest pain is a key sign of heart problems and is a primary cause of disability and early mortality, along with heart stroke and vascular disease. The research work [10], provided a practical primer for utilizing in this work, the writers talk about the potential applications of AI in cardiovascular research, including the collection, analysis, and prediction of data. Clinical decision-making and patient outcomes in cardiovascular disease can be enhanced by leveraging AI techniques. In this paper [11], the use of ML algorithms for predicting cardiovascular illness is growing.

Support Vector Machine (SVM), boosting, and Convolutional Neural Network (CNN) algorithms have shown promise in stroke while boosting and custom-built algorithms are suitable for coronary artery disease. SVM may perform particularly well against heart failure and cardiac arrhythmias. This knowledge can help clinicians choose the right algorithms for their datasets. In the study [12], Machine learning classifiers such as random forest, decision tree, logistic regression, SVM, and K-neighbors nearest (KNN) were used to predict CVD.

The Random Forest classifier beat other classifiers in categorizing CVD patients, has the highest accuracy for cardiovascular illness prediction (85.71%), AUC (Area Under the Curve) ROC (Receiver Operating Characteristics) score of 0.8675, and execution duration of (1.09) seconds. According to the experimental results [13], traditional data mining techniques are outperformed by an AdaBoost Ensemble model for heart disease prediction that makes use of recognized feature patterns. This method employs SMOTE to control noise and class imbalance while improving feature extraction. The highest accuracy was attained with RF-CART, 86.29%, followed by RF-RedEPTree, 85.45%. AdaBoost-RF got the best overall accuracy (95.47%) and the fewest errors. According to the results in the paper [14], Naive Bayes (83.60%), K-nearest neighbor (90.16%), Logistic regression (86.88%), random forest (96.72%), extreme gradient boost (95.08%), and decision tree (77.049%) are the machine learning techniques that were employed. Interestingly, the random forest approach outperformed the other algorithms, with a maximum accuracy rate of (96.72%). the authors in [15] outperform human predictions, which are (85%) accurate, by achieving improved model accuracy of (87.5%) through data screening, logistic regression, and KNN. KNN stands out with the highest accuracy (88.52%). revealed that (44%) of the data set participants were diagnosed with heart disease. Throughout the study [16] SVM outperforms MLP, which only achieves (90.57%) accuracy for two-class heart disease diagnosis. MLP outperforms SVM in five-class classification with an accuracy of (68.86%) compared to (59.01%). This shows that SVM performs better for two-class problems, while MLP performs better for five-class ones.

3. Materials and Methods

Figure 1 depicts the representation stages of the cardiovascular disease prediction system, and despite the existing numerous systems in the following section, determining the best suitable algorithm remains a challenge.

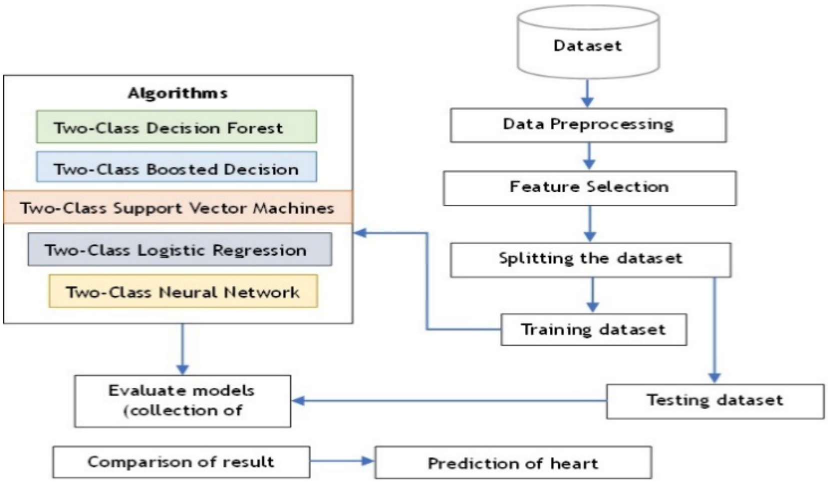

Figure 1: Process of Heart Disease System.

3.1 Collection of Data (Dataset)

The study utilized the Heart Disease Dataset, which was compiled into four distinct databases using the Kaggle platform [17]. The dataset has 76 attributes, however, for this experiment, only fourteen attributes were chosen based on the suggestions of several academics who believe they are the foremost important for anticipating heart illness in patients. The database file contains the records of (1026) patients. The number of values for each property is presented, along with a detailed explanation of each attribute. Heart disease has been studied using earlier published research, including the target attribute. The "target" field indicates whether the patient has cardiac disease [18]. It is a numeric value "0" means less heart attack or no disease and "1" means heart attack or disease. As shown in Table 1, each attribute is described in detail and its values are listed.

Table 1: Collection of data and attributes description.

S.	Attribute	Description	Values
1	age	Minimum 29, Maximum 77	Between 29 and 77
2	sex	Male=1, Female=0	0 and 1
3	cp	Types of chest pain: (0) normal angina (1) unnormal angina, (2) non-anginal pain, (3) symptomless	0, 1, 2 and 3
4	trestbps	Blood pressure at resting (in mm Hg)	Between 94 and 200
5	chol	cholesterol measured by BMI sensor in mg/dl	Between 126 and 564

6	fbs	Fasting blood sugar > 120	(1) have sugar, (0) have no sugar
7	restecg	Resting ECG results: (0) normal, (1) ST-T wave abnormalities (T wave inversion and/or ST elevation or ST depression >0.05 mV), (2) probable or obvious left ventricular hypertrophy by Estes' criteria.	0, 1 and 2
8	thalach	Reached maximum heart rate	Between 71 and 202
9	exang	Angina induced by exercise	(1) yes, (0) no
10	oldpeak	Exercise-induced ST depression in comparison to rest	Between 0 and 6.2
11	slope	Peak slope of ST segment during exercise	1, 2 and 3
12	ca	Number of major vessels	Between 0 and 3
13	thal	Thallium test	0, 1, 2 and 3

3.2 Preprocessing of Data

The initial phase of machine learning: actual data may contain many missing or noisy data [19], which can be solved by using preprocessing to prevent these problems and make accurate predictions either by removing values or computing the meaning of it. As a preprocessing, a data normalization strategy is used to make the data in the same range between 0 and 1 [20]. See figure (2) which is implemented by the correlation method of the Python Seaborn to elucidate the relation between normalized data via a heatmap.

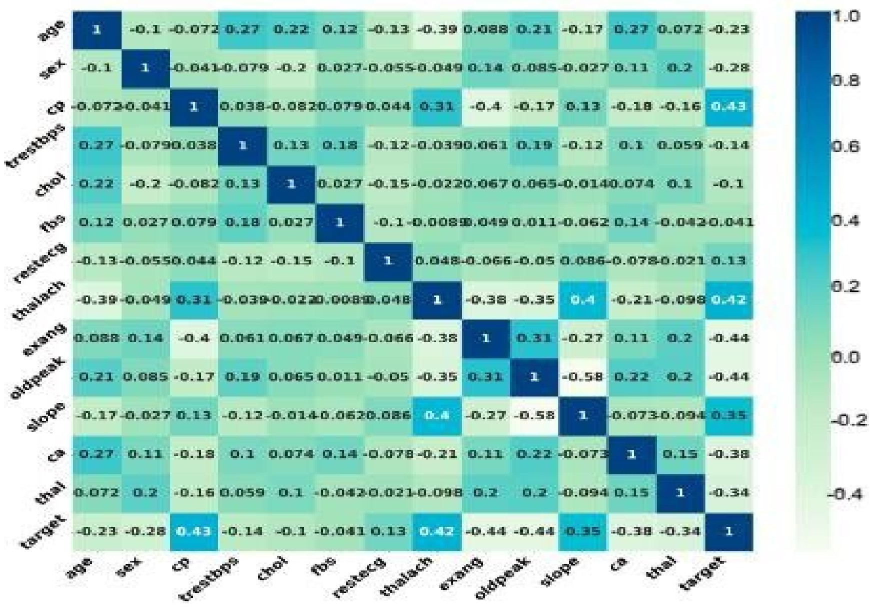

Figure 2: Heatmap correlation shows the leverage between features.

3.3 Feature Selection Algorithms

Choosing the most significant traits to input into the ML Models are called feature selections. It is also a fundamental component of feature engineering, eliminating the characteristics that are unnecessary or redundant and concentrating on the set of features that will benefit the machine learning model the most. As a result, the use of the most significant features increases the accuracy value and decreases the processing time [21]. Filter based feature selection is used here.

3.4. Dataset splitting

Dataset splitting is used to prevent the ML models from resulting in an overfitting type which could perform poorly on actual test data and reduce bias in training data. Azure Machine Learning experiments are used to partition the dataset into two logical groups, training sets which represent records that are utilized to train the model comprise 70% and testing sets which represent 30% of records that are used to test the model accuracy [22].

3.5. Model Selection and Training

For the purpose of choosing and training models, the Azure Machine Learning platform offers a multitude of features and techniques. In this research, five methods are used in the next subsections.

3.5.1. Boosted Decision Tree Algorithm

A boosted decision tree is a type of ensemble model that is mostly used to correct the flaws in earlier trees. The four important hyperparameters assess the performance of the two-class Boosted Decision Tree. In this instance, the maximum number of leaves indicates the greatest number of leaves that a tree may ever produce. The size of the tree can be extended by changing this value, but increasing the number of leaves leads to overfitting and lengthy training times. The minimum number of samples per leaf node describes how many examples are considered while forming a leaf node. The number 10 denotes that there are 10 examples in the training data that satisfy the rules as they were formulated. (0.2) was chosen as the starting learning rate value. It denotes the convergence rate. The ensemble produced 10 rate decision trees. Additionally, there is a provision to plant more than 100 trees, although doing so would require much more training time and is not advised [23].

3.5.2 Two-Class Decision Forest

The decision forest method, which functions by producing various decision trees, is one of the ensembles learning approaches used for categorization. Voting for the output category that you prefer. Voting is simply a version of aggregation since each unique tree is a classification decision forest output of a normalized frequency histogram of labels. In the final judgment, the trees with the highest forecast confidence are given precedence. Every class in every tree is subjected to several fundamental tests, with the level of the tree's structure increasing until a choice about its leaf node is reached [24].

3.5.3. Two-Class Locally-Deep Support Vector Machines (LDSVM)

A well-known and popular machine learning model for two-class classification is the LDSVM (Support Vector Machine). It functions by identifying an ideal hyperplane that can classify the provided data samples into different groups. Maximizing the margin, which encompasses both hard margin and soft margin, is the segmentation principle of SVM [25].

3.5.4. Two-Class Neural Network

For binary classification tasks, a well-liked machine learning approach is the Two-Class Neural Network algorithm. Artificial neural networks are employed in this procedure and are modelled after the structure and operation of the human brain [26].

3.5.5. Two-Class Logistic Regression

To learn about classification challenges, a supervised machine learning technique called logistic regression was developed. The presence of a categorical target variable indicates a learning difficulty in classification. Logistic regression transfers a function from the dataset's characteristics to the targets to anticipate the likelihood that a new example belongs to one of the target classes [27].

3.6. Experimental Tools

To implement this research, the models were run and compared across models using Microsoft Azure Machine Learning Studio (classic). In addition, the Kaggle website and Seaborn are used to proceed with code lines in Python.

4. Results

Accuracy, precision, and AUC scores were displayed for each algorithm both with and without feature selection and compare the effectiveness of the algorithms using statistical analysis or visuals.

Accuracy (ACC): The ratio of actual outcomes to all instances determines the accuracy of a classification model.

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

True negative (TN), false positive (FP), false negative (FN), and true positive (TP) were used to calculate the accuracy numerically. (TP) and (TN) stand for accurate predictions, while (FP) and (FN) stand for incorrect predictions.

Precision (Pr): split between the total number of false positives and real positives and the overall number of true positives. It evaluates the model's capacity to identify positive events.

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

Recall (Rc): the division of the sum of false negatives and true positives by the total number of true positives. It measures how well the model is able to recognize positive events.

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

F1 score (F1s): Recall and accuracy are fairly assessed by the harmonic means of the two measures.

$$\text{F1 score} = \frac{2*(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

Threshold: The binary classification threshold of the classification model is set at 0.5, which is commonly considered the industry standard.

Area Under the Receiver Operating Characteristic

Curve (AUC-ROC): assesses the trade-off between various categorization levels' true positive rate (TPR) and false positive rate (FPR).

Calculation: The ROC curve is typically computed using library functions.

Average Precision: The typical precision is determined at various recall thresholds.

Log Loss: a metric that evaluates a classification model's performance by penalizing inaccurate predictions.

5. Discussion

As a result, the experiment's primary goal was to compare the efficiency of several algorithms using a set of predetermined attributes. This study compares the performance of five two-class classification algorithms: two-class boosted decision trees, two-class decision forests, two-class Locally-Deep SVMs, two-class neural networks, and two-class logistic regression are all examples of two-class decision trees. The dataset was divided into two halves using the train-test-split approach, with 70% set aside for training and 30% put aside for testing. In predicting the target variable, Boosted Decision Tree achieved a perfect accuracy score of 100%. The Boosted Decision Tree outperformed the other algorithms, correctly predicting the target variable (100%) of the time. It also demonstrated exceptional recall and precision rates, leading to superior performance. The accuracy of the neural network approach, however, was (91.2%), which, while respectable, fell short of the performance of the top Boosted Decision Tree algorithm. The Two-Class Decision Forest outperformed the Boosted Decision Tree in terms of accuracy, with a rate of 99.4%. The Two-Class Locally-Deep Support Vector Machines demonstrated the competitiveness of this approach further by achieving an accuracy rate of 99%. After testing various methods, the Two-Class Logistic Regression showed the lowest accuracy of 83.1%. The Two-Class Boosted Decision Tree performed remarkably well in this experiment, despite having a small number of features. Intriguingly, the models' performance increased as the AUC range widened, highlighting the value of employing this metric for model assessment. This study offers insightful comparisons of various algorithms' performance that help choose the best method for two-class classification tasks.

Table 2: Results of classification using five of the two-class algorithms

Models (Two-class)	**TP, TN FP, FN**	**Acc (%)**	**Pr (%)**	**Rc (%)**	**F1s (%)**	**AUC (%)**
Boosted Decision Tree	158,150 0,0	100	100	100	100	100
Decision Forest	156,150 0, 2	99.4	100	98.7	99.4	99.9
locally-Deep Support Vector Machine	155,150 0,3	99	100	98.1	99	100
Neural Network	150,131 19,8	91.2	88.8	94.9	91.7	97.8
Logistic Regression	144,112 38,14	83.1	79.1	91.1	84.7	92

Figures 3,4, and 5 show the Evaluation Results False Position Rate, Evaluation Results Precision / Recall Rate and Evaluation Results Positive Rate respectively for the Two-Class Boosted Decision Tree algorithm.

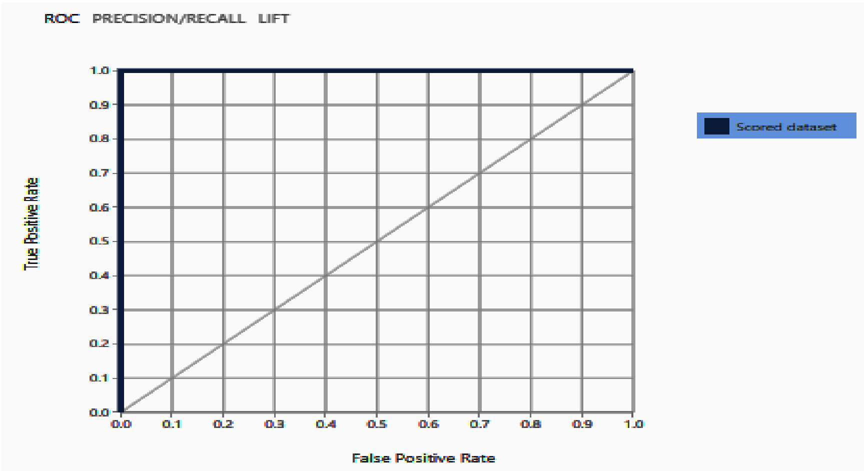

Figure 3: Evaluation Results False Position Rate.

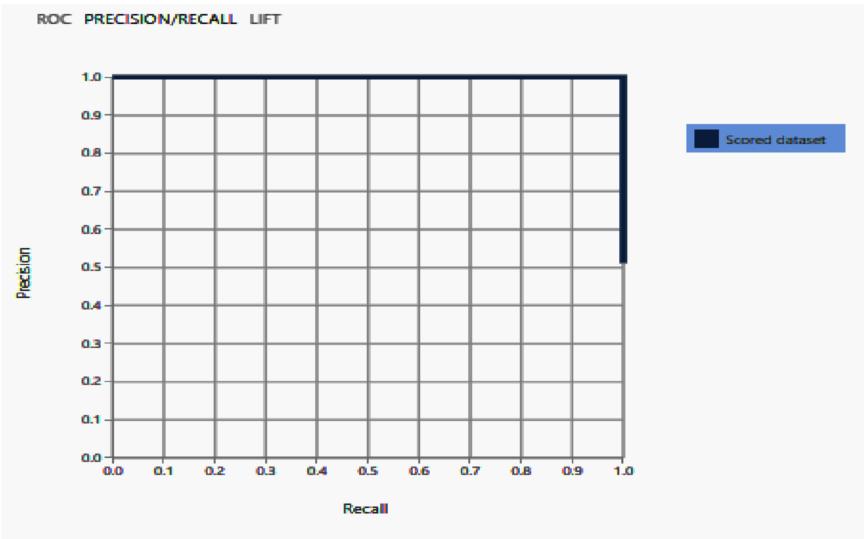

Figure 4: Evaluation Results Precision / Recall Rat

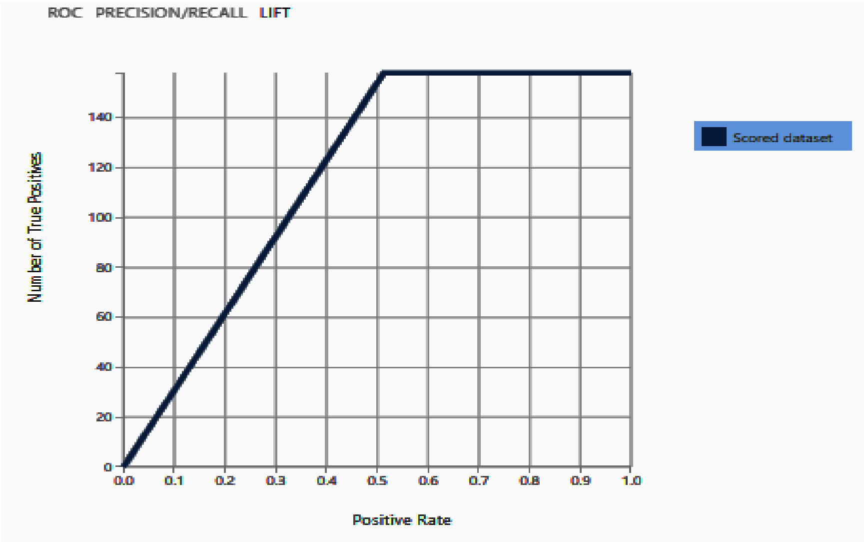

Figure 5: Evaluation Results Positive Rate.

Tables 3 and 4 have clearly explained all the relevant metrics and achievements of heart disease, based on the scores of Recall, F1 Score, Presentation of the Two-Class Boosted Decision Tree algorithms accuracy and precision.

Table 3: Final Evaluation Results.

True Position	158	**False Negative**	0	**True Negative**	150	**False Positive**	0
Accuracy	1.000	**Precision**	1.000	**AUC**	1.000	**Recall**	1.000
Threshold	0.5	**F1 Score**	1.000	**Positive Label**	1	**Negative Label**	0

Table 4: Final Evaluation Results in detail.

Score Bin	Pos. Ex-am-ple	Neg. Ex-am-ple	Fraction Above Thresh-old	Accu-racy	F1 Score	Preci-sion	Recall	Neg. Preci-sion	Neg. Re-call	Cumula-tive AUC
(0.900, 1.000]	158	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.800, 0.900]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.700, 0.800]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.600, 0.700]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.500, 0.600]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.400, 0.500]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.300, 0.400]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.200, 0.300]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.100, 0.200]	0	0	0.513	1.000	1.000	1.000	1.000	1.000	1.000	0.000
(0.000, 0.100]	0	150	1.000	0.513	0.678	0.513	1.000	1.000	1.000	1.000

6. Conclusions

The experimental findings conclusively show that, when using all available features, the Two-Class Boosted Decision Tree method outperforms all other algorithm approaches in predicting heart disease. The accuracy that resulted from the Neural Network algorithm (91.2%), the Two-Class Decision Forest algorithm (99.4%), the Two-Class Locally-Deep Support Vector Machines algorithm (99%), and the Two-Class Logistic Regression algorithm (83.1%) were all outperformed by the Boosted Decision Tree algorithm, which reached to 100% accuracy and precision rates with the chosen features. The models perform better as the AUC range widens, highlighting the value of the Boosted Decision Tree method for predicting heart disease. When all features are included, the most effective and dependable approach for forecasting heart disease is the Two-Class Boosted Decision Tree algorithm. These findings highlight the importance of machine learning algorithms in healthcare applications and have far-reaching consequences for medical diagnosis.

As a future work, a comparison study for various types of splitting ratio, execution time, and memory consumption vs input data size can make a difference to improve the results, in addition, review research between more than one framework can be designed.

Data availability: Data will be made available on request.

Conflicts of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] M. Chiarito, L. Luceri, A. Oliva, G. Stefanini, and G. Condorelli, “Artificial Intelligence and Cardiovascular Risk Prediction: All That Glitters is not Gold,” European Cardiology Review, Dec. 2022, doi: 10.15420/ecr.2022.11.

[2] C. Krittanawong, H. Zhang, Z. Wang, M. Aydar, and T. Kitai, “Artificial Intelligence in Precision Cardiovascular Medicine,” J Am Coll Cardiol, vol. 69, May 2017, doi: 10.1016/j.jacc.2017.03.571.

[3] P. J. Slomka, “Machine learning for predicting death and heart attacks from CCTA,” Journal of Cardiovascular Computed Tomography, vol. 12, no. 3. Elsevier Inc., pp. 210–211, May 01, 2018. doi: 10.1016/j.jcct.2018.05.008.

[4] Z. I. Attia et al., “An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction,” The Lancet, vol. 394, no. 10201, pp. 861–867, Sep. 2019, doi: 10.1016/S0140-6736(19)31721-0.

[5] K. W. Johnson et al., “Artificial Intelligence in Cardiology,” Journal of the American College of Cardiology, vol. 71, no. 23. Elsevier USA, pp. 2668–2679, Jun. 12, 2018. doi: 10.1016/j.jacc.2018.03.521.

[6] S. F. Weng, J. Reps, J. Kai, J. M. Garibaldi, and N. Qureshi, “Can Machine-learning improve cardiovascular risk prediction using routine clinical data?,” PLoS One, vol. 12, no. 4, Apr. 2017, doi: 10.1371/journal.pone.0174944.

[7] J. A. M. N. M. T. A. M. A. T. S. W. G. Azmi, “A systematic review on machine learning approaches for cardiovascular disease prediction using medical big data,” Med Eng Phys, vol. 105, p. 103825, Jul. 2022.

[8] A. Harsh, C. Janki, A. Sarvesh, and G. Yash, “Heart Failure Prediction using Machine Learning with Exploratory Data Analysis,” IEEE, Jun. 2021.

[9] R. Indrakumari, T. Poongodi, and S. R. Jena, “Heart Disease Prediction using Exploratory Data Analysis,” in Procedia Computer Science, Elsevier B.V., 2020, pp. 130–139. doi: 10.1016/j.procs.2020.06.017.

[10] N. Kagiyama, S. Shrestha, P. D. Farjo, and P. P. Sengupta, “Artificial intelligence: practical primer for clinical research in cardiovascular disease,” Journal of the American Heart Association, vol. 8, no. 17. American Heart Association Inc., Sep. 03, 2019. doi: 10.1161/JAHA.119.012788.

[11] C. Krittanawong et al., “Machine learning prediction in cardiovascular diseases: a meta-analysis,” Sci Rep, vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-72685-1.

[12] N. Komal Kumar, G.Sarika Sindhu, D.Krishna Prashanthi, and A.Shaeen Sulthana, Analysis and Prediction of Cardio Vascular Disease using Machine Learning Classifiers. 2020.

[13] T. R. Mahesh et al., “AdaBoost Ensemble Methods Using K-Fold Cross Validation for Survivability with the Early Detection of Heart Disease,” Comput Intell Neurosci, vol. 2022, 2022, doi: 10.1155/2022/9005278.

[14] A. Al Ahdal et al., “Monitoring Cardiovascular Problems in Heart Patients Using Machine Learning,” J Healthc Eng, vol. 2023, 2023, doi: 10.1155/2023/9738123.

[15] H. Jindal, S. Agrawal, R. Khera, R. Jain, and P. Nagrath, “Heart disease prediction using machine learning algorithms,” in IOP Conference Series: Materials Science and Engineering, IOP Publishing Ltd, Jan. 2021. doi: 10.1088/1757-899X/1022/1/012072.

[16] Bangladesh. F. of E. and E. E. Khulna University of Engineering & Technology, Institute of Electrical and Electronics Engineers. Bangladesh Section, and Institute of Electrical and Electronics Engineers, 2019 4th International Conference on Electrical Information and Communication Technology (EICT).

[17] “Heart Disease Dataset.” [Online]. Available: https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset

[18] F. Saleh Alotaibi, “Implementation of Machine Learning Model to Predict Heart Failure Disease,” 2019. [Online]. Available: www.ijacsa.thesai.org

[19] "Azure Machine Learning Documentation - Data preprocessing," https://learn.microsoft.com/en-us/azure/architecture/data-science-process/prepare-data.
[20] "Azure Machine Learning Documentation - Team Data Science Process," https://learn.microsoft.com/en-us/azure/architecture/data-science-process/overview.
[21] A. U. Haq, J. P. Li, M. H. Memon, S. Nazir, R. Sun, and I. Garciá-Magarinõ, "A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms," Mobile Information Systems, vol. 2018, 2018, doi: 10.1155/2018/3860146.
[22] J. Barnes, Azure Machine Learning Microsoft Azure Essentials. Microsoft Press, 2015.
[23] S. Rajagopal, K. S. Hareesha, and P. P. Kundapur, "Performance analysis of binary and multiclass models using azure machine learning," International Journal of Electrical and Computer Engineering, vol. 10, no. 1, pp. 978–986, 2020, doi: 10.11591/ijece.v10i1.pp978-986.
[24] N. I. M. Y. S. A. M. A. N. H. I. M. A. H. and A. S. B. A. A. Milad, "Using an azure machine learning approach for flexible pavement maintenance," 2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA), pp. 146–150, 2020.
[25] B. Gaye, D. Zhang, and A. Wulamu, "Improvement of Support Vector Machine Algorithm in Big Data Background," Math Probl Eng, vol. 2021, 2021, doi: 10.1155/2021/5594899.
[26] C. M. Bishop, Neural networks for pattern recognition. Oxford University Press, Inc.198 Madison Ave. New York, NYUnited States, 1996.
[27] B. Ekaba, Logistic regression. Building machine learning and deep learning models on google cloud platform," A comprehensive guide for beginners. 2019.