Heart Disease Detection Using ML

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***Abstract*— Hearth disease is one of the leading causes of death globally and a common disease in the middle and old ages. Among all heart diseases, heart attack and strokes are the most common cardiac illness that is the responsible majority of heart disease death. To identify heart diseases, for instance, Angiography is costly and has significant side effects. Therefore, machine learning can play an important role in identifying and predicting the potential risk factor of cardiac disease based on clinical and patient data, which is affordable and reliable. This study proposed and evaluated six machine learning models using survey data of 400k US residents to predict heart disease. This study also compared the evaluated six machine learning models, which are Xgboost, Bagging, Random Forest, Decision Tree, K-Nearest Neighbor, and Naïve Bayes. The accuracy, sensitivity, F1-score, and AUC of six machine learning algorithms are also evaluated and presented. In terms of performance results, the Xgboost model showed optimized results with an accuracy rate of 91.30%.**

Keywords—Hearth disease, Machine Learning Technique, heart disease prediction, classification algorithms, regression model formatting.

I. Introduction

Hearth disease is one of the crucial concerns that is responsible for the death of large-scale people globally. The World Health Organization reports that 32% of all deaths worldwide, equivalent to 17.9 million people per year, are attributed to heart disease [1]. Heart-related diseases are also categorized as cardiovascular diseases (CVDs). Around 85% CVDs death are due to strokes and heart attacks [2], [3]. Some of the potential risk factors that increase heart-related diseases include poor diets, insufficient exercise, alcoholism, and tobacco use. As a result, individuals are found to have intermediate-risk conditions such as high blood pressure, overweight, and obesity [4], [5]. However, the major challenges are that all these symptoms are similar to other diseases, and also these symptoms are seen in aging people. Therefore, it is essential to get an accurate diagnosis to reduce the casualty in the near future.

Machine learning (ML) is one of the new technologies which is capable of predicting or classifying diseases and diagnosis diseases like heart failure [6], [28], mental health analysis [23], cancer [27], [7] Parkinson's disease [8] [9], and so on [29], [25]. Not only in healthcare but also used in other sectors such as detection of website phishing [22], emotion detection [30], machine learning based VR video streaming [24], [26], cooling technology [9], Alzheimer's disease detection [31], renewable energy [32] and energy storage [33]. However, recent developments in machine learning (ML) applications show that it is possible to identify heart diseases in their early stages utilizing research data and clinical and patient records.

The healthcare industry is witnessing a rapidly growing trend in the use of machine learning, thanks to advancements in wearable technology and sensors that enable the collection and analysis of real-time health data of patients. A more affordable and accurate diagnosis of heart disease can be made by employing machine learning as opposed to the standard method. To assist clinicians, many studies have been done to develop the most accurate machine learning algorithms to identify the relation between patient symptoms and heart disease [10]. For instance, Pathak and his co-worker proposed a prediction model for the diagnosis of heart disease utilizing a decision tree and fuzzy rule-based methodology [11].

In this study, six machine learning algorithms were evaluated for their performance using four different datasets containing medical data of patients with heart disease. In this regard, our study's main contribution is finding the most important features in the raw dataset. The main goal of this study is to predict CVDs using machine learning. In this paper, we also compare our works with the previously published results. This study will assist the physician in promptly and accurately treating the potential risk factor of heart disease to prevent CVDs in the early stage.

This paper presents the literature review on ML in order to detect heart diseases in the following section. In the subsequent section, the methodology is also presented. Then, the datasets are discussed and presented in this study. In the following section, the results are discussed and presented. Finally, in the last section, we proposed our findings and offered recommendations for future research.

II. LITERATURE REVIEW

A study by Jian ping li et al. [12] developed an effective machine learning model for heart disease detection using various classification algorithms. In addition, feature selection algorithms such as minimum relevance maximum redundancy, Relief, as well as the Local learning least absolute shrinkage selection operator were used to eliminate irrelevant and redundant features. The system was evaluated using the Cleveland Heart Disease dataset and various evaluation metrics. The results showed that the accuracy of the Support Vector Machine algorithm with the proposed feature selection algorithm (FCMIM) was 92.37%. Furthermore, the performance of the machine learning-based method (FCMIMSVM) was found to be better than that of deep neural networks for heart disease detection.

K. Vembadasamy et al. [13] proposed a heart disease prediction system that uses data mining approaches and the Naive Bayes algorithm. The authors used the Naive Bayes algorithm to classify the dataset and found that it achieved an accuracy of 86.4198% with minimal computation time.

Ankur Gupta et al. [14] developed a farmwork MIFH which is a machine intelligence A framework for extracting and extracting features from the UCI Cleveland Heart Disease Data Set using Mixed Data Factor Analysis (FAMD) Cleveland dataset. This framework trains predictive machine learning models for heart disease diagnosis. Study validated the MIFH framework using a holdout validation scheme and found that it performed better than several recent baseline methods in terms of sensitivity, accuracy and specificity.

Mohamed Elhoseny et al. [15] proposed an automated heart disease diagnostics (AHDD) system that incorporates a binary convolutional neural network (CNN) and a state-of-the-art multi-agent shell model (MAFW). The system's effectiveness was assessed using the Cleveland HD database, and the hybrid model attained a maximum accuracy of 90.1%, a high accuracy of 88.9%, and a high recall of 98.4%. In contrast, other machine learning models and conventional CNN models typically achieved accuracy levels ranging from 72.3% to 83.8% on average.

Thankgod Obasi and M. Omair Shafiq [16] conducted a study in which they developed three machine learning models using the Logistic Regression, Random Forest, and Naive Bayes Classifier algorithms. The models were assessed using a dataset containing the medical records of existing patients, and the authors compared their accuracy and efficiency. The Random Forest model outperformed both the Logistic Regression and Naive Bayes Classifier models, achieving accuracy rates of 92.44%, 59.7%, and 61.96%, respectively.

Umarani Nagavelli et al. [17] evaluated four machine learning models for heart disease detection using An improved prediction-based SVM (ISVM) based on a duality optimization (DO) system, a weighted approach-based prediction, two XGBoost-based prediction SVMs, and a prediction based on XGBoost. The authors evaluated the models based on precision, accuracy, recall, and F1 measurement parameters. According to the findings, the detection of heart disease using the XGBoost algorithm resulted in high accuracy, precision, recall, and F1 scores. In comparison, the Naive Bayes model with a weighted approach had lower accuracy than the other models, and the dual-optimized (DO) SVM model had lower precision, recall, and F1 measurements.

In a study by Samir S Yadav and colleagues [18], various algorithms, including Naive Bayes, K Nearest Neighbors, and logistic regression, as well as hybrid algorithms, were compared for heart disease detection. The systems were implemented, trained, and evaluated using the UCI machine learning repository reference dataset on the Python platform. Based on the authors' findings, the Neural Network and Fuzzy KNN algorithms demonstrated superior performance compared to K Means Clustering, KNN, logistic regression, and other algorithms.

Ricardo Buettner and Marc Schuster [19] introduced a new method for classifying cardiac disease utilizing the Random Forest machine learning algorithm. The effectiveness of the approach was evaluated using a database containing clinical data and patient test results. The authors determined that the model achieved an overall accuracy of 84.448% when employing a 10-fold cross-validation procedure, surpassing the performance of other machine learning techniques tested on the same dataset. Additionally, without cross-validation, the model still demonstrated an overall accuracy of 82.895%.

Heart diseases detection using machine learning has been proposed in [21] where author proposed six machine learning methods-Xgboost, Adaboost, Random Forest, Decision Tree, Logistic Regression, and Naïve Bayes have been compared in detail. Through the prediction model for heart disease, they have achieved an impressive accuracy which is 91.57%

III. METHODOLOGY

In accordance with proposed method, data pre-processing commences following data collection. For the dataset pertaining to heart conditions, the chosen classification models - which include XGBoost, Bagging, Random Forest, Decision Tree, K-Nearest Neighbor, and Naive Bayes - are subsequently trained and assessed utilizing the conventional Hold-Out validation method. Then findings are computed and analyzed to determine the most effective method for anticipating cardiac problems. Figure 1 displays an outline of the whole procedure that we have used.

A. *Dataset collection*

In this research, we employed a dataset from the Kaggle online database titled "Key Indicators of Heart Disease" [20]. The dataset comprises of total 319795 cases and 18 characteristics, with only a single class characteristic and 17 predictive characteristics available. We should use only features that are highly related and accurately represent the symptoms when performing heart disease prediction. Our analysis of the dataset revealed that factors such as gender, age, race, obesity (high BMI), diabetes, insufficient physical activity, excessive alcohol consumption, smoking, stroke history, difficulty walking, asthma, kidney disease, and skin cancer are predictive attributes, with heart disease serving as the class attribute.

B. *Dataset pre-process*

"We narrowed down the original dataset, which consisted of over 300 variables, to a total of 18 variables that are significant for predicting cardiac illnesses or heart ailments, which include 9 boolean, 5 string, and 4 decimal variables. During the pre-processing stage, we applied various techniques to our dataset to ensure its suitability for analysis. One of the techniques we used was feature extraction, which involved identifying and selecting the most relevant features from the dataset. Other techniques we used included data cleaning, which involved removing any irrelevant or duplicate data, handling of missing values, and conversion of categorical variables, which involved converting variables with non-numeric values into a numerical format.

C. Validation Process

The data validation process is crucial as it ensures the accuracy and integrity of the data being used. Using the most appropriate methods during this stage is essential to ensure the reliability and usefulness of the final results. For example, we can use hold-out validation method as this method gives better results when we are using large dataset [21]. To sue hold-out validation technique we have to split out dataset into training and test dataset. Here we have used 80% the dataset as training dataset and 20% of it as test dataset. The validation process allowed us to evaluate the performance of various ML approaches by calculating various performance matrices such as accuracy, sensitivity, precision, F1-Score and area under the curve (AUC). The performance metrics of each approach offer valuable insights into their effectiveness and efficiency, and detailed explanations of these metrics, along with visualization output graphs, can be found in the result analysis section. Furthermore, we have provided an overview of the research work in a step-by-step flowchart.

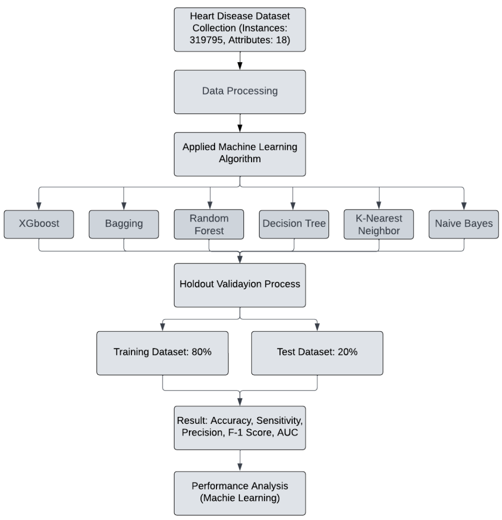


Fig. 1. An overview diagram of the ML study

IV. DATASET

The Behavioral Risk Factor Surveillance System (BRFSS) is a comprehensive survey system that aims to collect data on the health and well-being of Americans through annual telephone surveys. By gathering information on a wide range of health topics, the BRFSS aims to provide valuable insights into the health of the nation, and inform public health policy and interventions. The BRFSS acquires data from the CDC, and it comes from all 50 states, the District of Columbia, and three U.S. territories. This survey system is the world's largest continuously running health survey system, conducting over 400,000 adult interviews annually. The dataset includes 319795 cases and 18 characteristics, with only one class characteristic and 17 predictive characteristics available, all of which have a direct or indirect impact on heart disease. The dataset primarily consists of questions related to the health of the respondents. These include inquiries about mobility, such as difficulty walking or climbing stairs, as well as inquiries about smoking habits, such as lifetime cigarette consumption. The dataset underwent cleaning process to remove unnecessary variables and retain only those that have direct or indirect influence on heart disease. As a result, the dataset was reduced to around 20 variables from the original dataset's almost 300 variables. The presence or absence of heart disease was represented in the dataset as a binary variable, with "Yes" indicating the presence of heart illness and "No" indicating the absence of heart disease, allowing for an easy interpretation of results.

V. RESULTS

The accuracy, sensitivity, precision, F1-score and AUC findings were used to evaluate the performance of six ML models. Table 2 [comparison table] compares the presented six models.

As seen in Table 2, Xgboost performed better than other machine learning approaches in terms of performance output, achieving accuracy rates of 91.30 %, sensitivity rates of 92%, AUC rates of 83%, and F1-score rates of 95.40 %. Additionally, Random Forest also did reasonably well, and the output findings show that it is comparable to Xgboost. AUC was 78%, sensitivity was 92.50%, accuracy for Random Forest was 90.20%, and the F1-score was 94.78%.

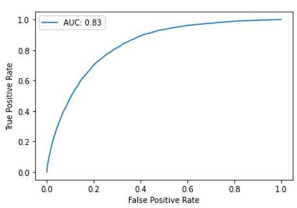
Table 2. Comparison of six machine learning models

Model	Accuracy	Sensitivity	Precision	F1-score	AUC
Xgboost	91.30%	92%	99%	95.40%	0.83
Bagging	90.10%	92%	97.30%	94.72%	0.73
Random Forest	90.20%	92.25%	97.44%	94.78%	0.78
Decision Tree	86.32%	93%	92.18%	92.50%	0.58
K-Nearest Neighbor	91%	91.75%	99%	95.26%	0.70
Naïve Bayes	91%	91.31%	99%	95%	0.64

However, accuracy solely cannot be used to evaluate the performance of a model. AUC value is also a significant matrix for analyzing model performance and assessing a model's ability to distinguish across classes. The probability curve compares the True Positive Rate and False Positive Rate at different thresholds, with the AUC serving as an indicator of a model's ability to differentiate between positive and negative classifications. The AUC value is an indicator of the performance of a model, where higher values are associated with better results. The scale for AUC values ranges from 0 to 1, where 0 indicates poor accuracy and 1 represents perfect accuracy. An AUC of 0.5 generally indicates that the model has no ability to distinguish between patients with and without the condition, while AUC values between 0.7 and 0.8 are considered an acceptable threshold for cancer or other disorders. An AUC score of 0.8 to 0.9 is regarded as excellent, while a score greater than 0.9 indicates exemplary performance [20].

The performance of six ML models was evaluated by providing AUC curves and average results using a hold-out validation approach, where 80% of the dataset was used for training and 20% for evaluation. Bagging, Random Forest, and K-Nearest Neighbor get comparable results. However, Xgboost outperformed other models in terms of accuracy, precision, and F1score, as demonstrated in Table 2.

XGBoost have the highest AUC scores, 0.83. In contrast, the Naive Bayes model has the lowest AUC value (0.64).



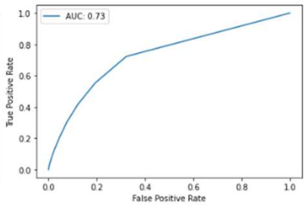
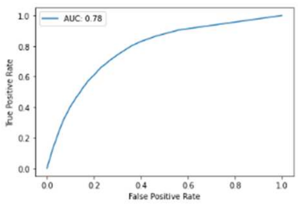


Fig.2. Xgboost AUC curve. Fig.3. Bagging AUC curve.



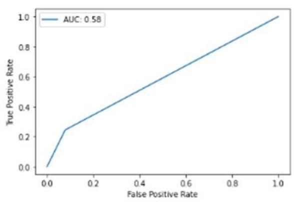
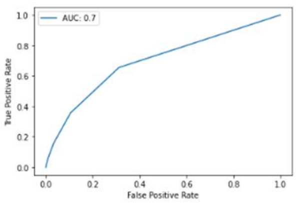


Fig. 4. Random Forest AUC curve. Fig.5. Decision Tree AUC curve.



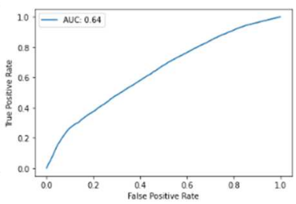


Fig. 6. K-Nearest Neighbor AUC curve. Fig.7. Naïve Bayes AUC curve.

VI. CONCLUSION

Heart disease prediction is one of the most challenging medical undertakings. The death rate can be substantially reduced utilizing ML approaches if the condition is identified. By using the patient medical history that results in a deadly heart illness from a dataset that includes patients' medical histories, present investigation predicts persons with cardiovascular disease. This study compared and evaluated six machine learning algorithms for predicting heart disease, with promising outcomes. In our investigation, the accuracy of the Xgboost technique was 91.30% higher for predicting heart disease. In future research projects, accuracy can be improved by utilizing a large data collection and effectively choosing more features. To improve the prediction, it also plans to use additional classification techniques, such as deep learning. The objective is to analyse and combine additional datasets to provide a more meaningful dataset that covers a variety of population kinds. For the prediction of heart disease, the feature selection can produce more useful characteristics and productive outcomes.

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