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Cardiovascular Risk Prediction Through Stacking Classifier †

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Abstract: Enormous amounts of patient data, including information on their liver, diabetes, heart, and maternal health, are being generated by medical sectors. Among them, cardiovascular diseases (CVD) are thought to be the deadliest, posing the greatest health risk to mortality by causing silent and not transmissible death. The preventive approach requires an examination of health records which is quite difficult; therefore, adopting machine learning (ML) technology that identifies early CVD is necessary. In this work, we used three different boosting techniques, namely, AdaBoost, gradient boosting, XgBoost, and stacked boosting algorithms, as well as a combination of these algorithms with and without hyperparameter tuning to predict CVD patients. Our analysis showed that, compared to a single boosting model, the recall score of the stacked boosting algorithm is much higher, demonstrating a 92.85% recall score after using hyperparameter tuning. Our predicted model will help hospital associates to take preventive measures in these cases as well as properly allocate the resources for hospital managers and, lastly, reduce the financial burdens of the patients.

Keywords: cardiovascular diseases; patient diseases prediction; machine learning; stacked boosting ensemble

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1. Introduction

Cardiovascular disease (CVD) is a medical disorder related to the heart and blood vessels connected to it. Any medical condition that might have a harmful effect on the heart can be considered as CVD. Based on statistics by the World Health Organization (WHO), more people die from CVD than from any other health condition throughout the world. It is one of the deadliest diseases that affects people of different age groups, gender, races, and tribes. In 2019 alone, about 17.9 million people died from CVD, which represents 32% of deaths globally according to WHO. The number of deaths from heart disease is expected to rise to 23 million by 2030 due to the aging population, urbanization, globalization, lifestyle, poverty, and stress [1]. There are various behavioral factors of risk of CVD, which include unhealthy eating, lack of physical exercise, consumption of alcohol and tobacco, high blood pressure, high glucose levels in blood, overweightness, DNA mutation, and obesity. Death from CVD can be prevented only when it can be detected as early as possible. Moreover, 75% of the deaths from CVD occur in middle- and low-income countries as CVD detection is expensive and requires advanced medical technologies. The tests for early detection of CVD require advanced medical equipment along with highly experienced doctors which is a time-consuming and costly process. Due to the scarcity of doctors and medical infrastructure, it is difficult to carry out tests on each of the CVD patients and analyze the health records.

Multiple factors related to health such as age, gender, blood pressure, cholesterol level, blood sugar, electrocardiography results, maximum heart rate, etc., affect CVD patients. The risk levels of CVD patients can be determined through regular tracking of these health factors. It is critical to monitor the severity level of CVD as it makes it easy to

take precautionary actions to save the life of a CVD patient. Machine learning (ML) [2] can be used to determine the risk level of CVD patients accurately and efficiently.

ML was first used in healthcare in 1970 to help with biomedical problems and blood infection treatment. The ML has a huge ability to strengthen the healthcare industry. Its application in healthcare has dramatically fastened data collection, helped in accurate and efficient surgeries, and improved the consistency of disease prediction. The recent COVID-19 pandemic has shown the potential of ML in healthcare by speeding up disease detection along with identifying the sequence of the genetics of SARS-CoV-2 [3]. ML has helped minimize the number of medical tests to diagnose patients, which has led to a considerable decrease in duration, complications, cost, and threats to patients' lives [4] (pp. 71–92). Therefore, the ML model must forecast the probability of CVD in a person. ML model can investigate and analyze large volumes of data to anticipate a pattern and determine a trend that will help to predict CVD without any involvement of human efforts. Recently, ML technologies have been applied broadly by researchers in medical-related fields like maternal health [5], surgical training [6], CVD, and a few more as they help in the rapid diagnosis of CVD; moreover, they can identify abnormalities or irregularities in data with a high rate of precision.

Ref. [7] (pp. 33–45) utilized ensemble techniques to create a smart CVD model by applying classification algorithms. They combined five classifier models such as the Artificial Neural Network, Random Forest, Support Vector Machine, Regression Analysis, and Naive Bayesian to carry out the diagnosis of CVD. Similarly, ref. [8] used ML algorithms to identify the major risk for CVD. The top 2 and top 4 attributes from CVD data are identified by evaluating the functioning based on accuracy measures. Ref. [9] (pp. 1100–1113) proposed ML classifiers for risk forecasting of CVD. They implemented K-Nearest Neighbour (k-NN) and Multi-Layer Perceptron (MLP) for the detection of CVD. Ref. [10] postulated ML methodology for CVD risk prediction in ethnically diverse populations. They trained Logistic Regression with L2 penalty, Random Forest, Extreme Gradient Boosting, Grading Boosting Machine, and Lasso Penalty either with or without the inclusion of EHR Variables. Ref. [11] applied ML to predict CVD. Models developed by applying Neural Network, Bayesian Network, QUEST, Random Forest, and C5.0 were compared for this study. Ref. [12] (pp. 106575–106588) presented an integrated ML framework for the efficient detection of CVD. They proposed K-Nearest classifiers and ensembles of Logistic Regression for CVD prediction with a greater level of precision. Ref. [13] (pp. 81542–81554) anticipated effective CVD prognostication by applying hybrid ML technologies. They introduced an enhanced prediction model with several combinations of ML techniques to achieve 88.7% precision using a hybrid random forest with a linear model (HRFLM). However, no one has applied the Stacked Boosting Ensembles Algorithm to predict CVD. In this paper, we have applied the Stacked Boosting Ensembles technique with a combination of three individual boosting algorithms such as AdaBoost, gradient boosting, and XgBoost to boost comprehensive functioning by eliminating deficiencies. It brings exceptional ability to the ML model and can boost weak learners by learning from previous mistakes and managing complex datasets with speed and precision. The other advantages of ensembled models are that they can learn complex patterns, generate detailed and robust predictions, have a lower chance of overfitting, and show effective handling of outliers and noise in the data. The objectives of this paper are:

- To use machine learning algorithms such as Gradient Boost, AdaBoost, Extreme Gradient Boost, and Stacked Ensembles Boosting classifiers for model valuation on forecasting the CVD by applying four various base metrics.
- Perform hyperparameter tuning by applying grid search techniques on these four classifiers to boost the consistency of predictableness.
- Applying the Brier score and Youden index for model performance improvement.
- Using a SHAP algorithm to measure the feature impact to detect CVD.

The rest of this paper progresses as follows: Section 2 consists of a data description followed by a machine learning algorithm in Section 3. Section 4 elaborates on the result analysis and, finally, it concludes with a conclusion and implications in Section 5.

2. Data Description

The cardiovascular diseases dataset from Table 1 is compiled from the test report from 303 individuals from Cleveland Clinic. From 1981 to 1983, they underwent an angiographic test. The reason behind using the old dataset is because of its reliability and clinical utility in the test group, which has not been seen in any other coronary disease datasets. This study utilizes three different ensemble machine learning algorithms and combines all of the ensemble classifiers to create a stacked ensemble algorithm. To increase the score further, we use hyperparameter tuning on all of the algorithms.

Table 1. Predictor variables.

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
57	1	0	150	276	0	0	112	1	0.6	1	1	1	0
59	1	3	170	288	0	0	159	0	0.2	1	0	3	0
57	1	2	150	126	1	1	173	0	0.2	2	1	3	1
56	0	0	134	409	0	0	150	1	1.9	1	2	3	0
71	0	2	110	265	1	0	130	0	0	2	1	2	1

The dataset is collected from [14] (pp. 304–310). The table contains 303 observations with 13 predictor variables. The initial dataset had 352 observations, and the observations with missing values have been removed from the dataset because we are predicting from an individual's health report; if we use mean or median imputation, the data might lose its credibility. Each record represents the medical history of the patient. The predictor variables are independent, and the target variables are dependent on the predictors. The predictor variable demonstrates the symptoms of the patients, and the target variables illustrate if the cardiovascular diseases are present or not in that patient. It is coded as 1 if present and 0 for absent. The descriptions of the predictor variables are as follows:

Age indicates an individual's age; sex, where 1 refers to male and 0 to female; cp refers to an individual's chest pain type as there are various types of chest pain; trestps means an individual's blood pressure at rest, which is measured in mm Hg; chol refers to the amount of cholesterol in the blood serum measured in mg per dl; fbs describes if the fasting blood sugar (1 if >120 mg/dL and 0 if <=120 mg/dL); restecg provides the electrocardiogram results at rest; thalach indicates the highest heart rate observed during exercise; exang describes whether angina is present (1 for yes if angina was induced by exercise and 0 if no); oldpeak quantifies the difference in ST segment depression among exercise and rest; slope indicates the ST segments at the time of extreme physical activity; ca depicts the quantity and clarity of the main blood arteries that are exhibiting blood flow; thal refers to the thalassemia type, which is categorized as 3 for normal, 6 for fixed defect, and 7 for reversible.

3. Machine Learning Algorithms

3.1. AdaBoost Classifier

AdaBoost is a meta-algorithm that combines with other classifiers to boost the performance of classification. It follows the method of iteration, in which the dataset splits into outcome variables and predictor variables. The Adaboost classifiers learn from their mistakes and work together to make better decisions. It becomes a powerful tool by improving on the areas where they struggled making predictions and detecting patterns that are highly accurate. Equation (1) shows AdaBoost classifiers. After applying Ada Boost-

ing, the error function is calculated based on Equation (2). $X_{s-1}(y)$ = boosted classifier; β_s = co-efficient of weak classifier

$$W_s = \sum_p W\left[X_{s-1}(y_p) + \beta_s c(y_p)\right] \quad (1)$$

3.2. Gradient Boost Classifier

The gradient boost (GB) classifier is one of the ensemble learning techniques that utilizes the residuals from prior weak models to boost the precision of the final prediction. In gradient boosting, the models learn from the strengths and weaknesses of each other. Each model focuses on the particular part of the problem, where they struggled before, and combine the outcomes to generate the final result, which is highly robust and accurate. The equation below shows the gradient boost algorithm.

$$x(p) = x_0(p) + \sum_{t=\frac{1}{B}} x_t(p) \quad (2)$$

where $x(p)$ = final prediction of the gradient boost algorithm for a given input x; $x_0(p)$ = Initial prediction; B = total number of boosting iterations; $x_t(p)$ = t-th weak learner prediction

3.3. Extreme Gradient Boost Classifier

The extreme gradient boosting is also known as XGBoost. It is the upgraded application of gradient boosting with comparatively higher speed of computation, improved performance, and expandability. Extreme gradient boosting is the collection of models in which each model is specialized in solving a particular part of the problem. They combine to form a powerful tool that can make predictions and identify trends that are precise [15]. The equation below presents the formula to calculate the reducing objective function at the time of iterations.

$$M^s = \sum_{p=1}^{q} m\left(a_p, \hat{a}_p^{(s-1)} + (x_s y_p)\right) + \Omega(x_s) \quad (3)$$

where x_s = the phrase which inclusion reduces the objective function; $\hat{a}_p^s$ = p-th instance prediction at iteration level s-th; Ω = model complexity is penalized by this function; m = loss function which is differentiable

3.4. Stacked Boosting Ensemble Model

A stacking classifier combines several base or individual models. However, if we use boosting models like AdaBoost, GradBoost, and XgBoost instead of individual models, it is called a stacked boosting ensemble model from Figure 1, which takes advantage of boosting algorithms combining all the models. Additionally, the boosting model can catch patterns more efficiently than other models; therefore, this stacking model can use the benefits of their complementing strength.

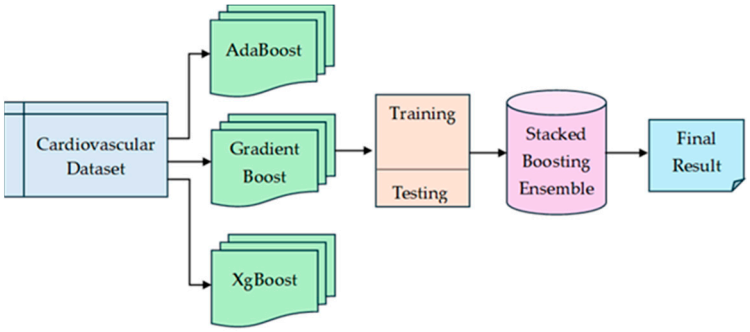


Figure 1. Stacked boosting ensemble.

3.5. Hyperparameter Tuning

Hyperparameter tuning is like determining a set of hyperparameter values to optimize the model's performance. This is one of the major aspects of managing a machine learning model's behavior. In our study, we have used hyperparameter tuning to improve our recall score with Gridsearch inputs in Table 2. It is summarized as follows:

Table 2. GridSearch input.

Classifier	Hyperparameters	Classifier	Hyperparameters
AdaBoost	adab__n_estimators: [50, 100, 150], adab__learning_rate: [0.01, 0.1, 1.0], adab__algorithm: [SAMME, SAMME.R]	XgBoost	xgb__n_estimators: [50, 100, 150], xgb__learning_rate: [0.01, 0.1, 1.0], xgb__max_depth: [3, 5, 7], xgb__min_child_weight: [1, 3, 5], xgb__gamma: [0, 0.1, 0.2], xgb__subsample: [0.8, 1.0], xgb__colsample_bytree: [0.8, 1.0], xgb__objective: [binary: logistic]
Gradient Boost	n_estimators: [100, 150, 200, 250], subsample:[0.8, 0.9, 1], max_features:[0.7, 0.8, 0.9, 1]		

4. Performance Metrics

We have evaluated the quality of our model with six different metrics. The details are given below.

Accuracy—The number of accurate predictions divided by the number of predictions made in all classes; Recall—The number of positive cases has been identified by the model among all the positively leveled models; Precision—The number of genuine positive cases among all the positive cases it predicted; F1 Score—F1 score blends the precision and recall together as both of them work differently, F1 score works as a balance between those two; Brier Score—This assessment tool is used to determine how well is the prediction probability score; Youden Index—This evaluates the performance by fusing sensitivity and specificity into one metric.

5. Result Analysis

Table 3 depicts the findings of each method employed in this work, both tuned and untuned models. It provides an overview of the four performance scores, namely, accuracy, precision, recall, and F1 score.

Table 3. Performance metrics.

Data	Performance Metrics	AdaBoost	Gradient Boost	Extreme Gradient Boost	Stacked Ensemble
Original	Accuracy	79.12%	78.02%	74.72%	78.68%
Tuned		80.33%	80.21%	85.25%	86.88%
Original	Precision	78.18%	77.77%	74.54%	75.86%
Tuned		75%	79.62%	80.65%	81.25%
Original	Recall	86%	84%	82%	78.57%
Tuned		85.71%	86%	89.29%	92.85%
Original	F1	81.90%	80.76%	78.09%	77.19%
Tuned		80%	82.69%	84.75%	86.66%

Table 3 provides the probability of having cardiovascular diseases in an individual patient in four different key metrics. Our work consists of three popular ensemble models such as Adaboost, GradientBoost, and XgBoost, and a stacked boosting ensemble model combining those three ensemble models. However, since it is crucial to identify each cardiovascular-positive patient among all the positive patients in our dataset, we have concentrated on recall scores within the model.

In terms of predicting cardiovascular diseases, the stacked boosting ensemble tuned model exceeded all other models in terms of recall score. It achieved an impressive 92.85% score, which is the highest score among all. This score indicates that this is the most efficient model to use when predicting any kind of cardiovascular disease if it happens to apply an unseen dataset with the same predictor variables. Almost all of the ensemble models performed within the range of 80–90% range. Surprisingly, the lowest performance observed on the stacked boosting ensemble original model was 78.57%; therefore, this model had a big leap on its tuned model with over 14% recall score gain. The only decrease has been observed on AdaBoost where the score unexpectedly dropped by 0.3%. Its initial model had 86% accuracy but sadly enough the score was reduced to 85.71%. For gradient boosting, a 2% score improvement has been noticed on its recall score. After hyperparameter tuning the recall score raised from 84% to 86%. Therefore, there is a chance of 86 patients with cardiovascular diseases if there are 100 patients available. Lastly, XgBoost also demonstrated a satisfactory result compared to other models after its tune. Though it was below the stacked boosting ensemble tuned model, it achieved 89.29%, a big raise from its original model of 82%. So far, it is critical that our algorithm identifies each and every cardiovascular patient. Most of the original models were ineffective for detecting those patients. However, the stacked ensemble-tuned model, which is the combination of three different ensemble-tuned models, has surpassed all the models, making it an ideal model to use in the future.

The average Brier score from Figure 2 indicates the squared difference between the predictions and true results. The lower the score, the more accurate the model is. Gradient boosting had the lowest score making it the most accurate and well-calibrated model with a 0.1638 score in terms of probabilistic predictions. Whereas the stacked boosting ensemble model achieved 0.1692, which makes it a moderately accurate model. AdaBoost and XgBoost had the lowest scores (0.1830 and 0.1762, respectively). Even though XgBoost was better at differentiating CVD patients, it performed poorly on the Brier score.

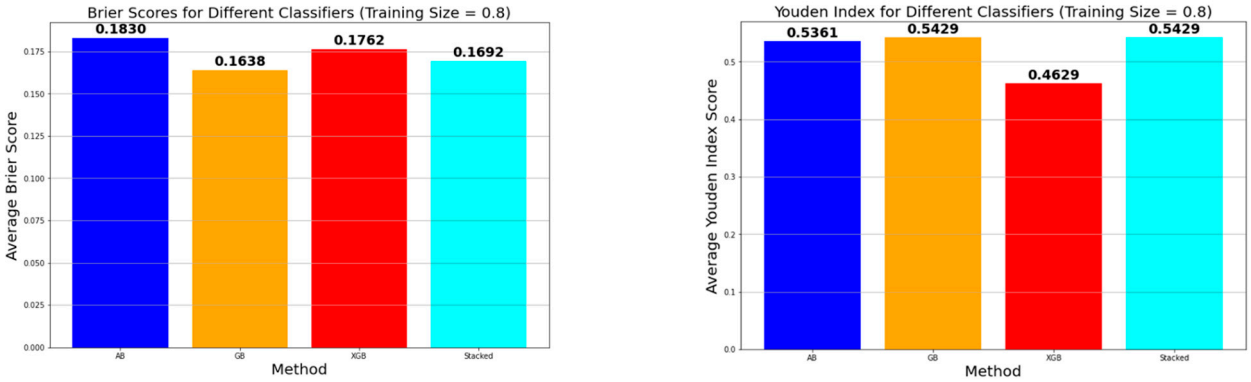


Figure 2. Brier Score and Youden Index.

The Youden index shows the balance between sensitivity and specificity and in terms of that, the stacked ensemble and gradient boost model had the highest score though compared to standards it was rather a poor result with 0.5429. However, XgBoost had the lowest score with 0.4629.

We also figured out the most influential factors in predicting CVD patients using the SHapley Additive explanation (SHAP) algorithms in Figure 3. This algorithm helps identify the feature that had the highest contribution to the identification. From the 13 different predictors thal (thalassemia), ca (number of major blood vessels), and cp (chest pain type) topped the list. Among them, thalassemia was the highest. Therefore, it is evident that thalassemia is the most effective predictor in detecting cardiovascular patients. However, "ca" and "cp" had, comparatively, an almost similar influence. The lowest influence was observed on fasting blood sugar (fbs), and the rest of the predictors had a somewhat medium influence.

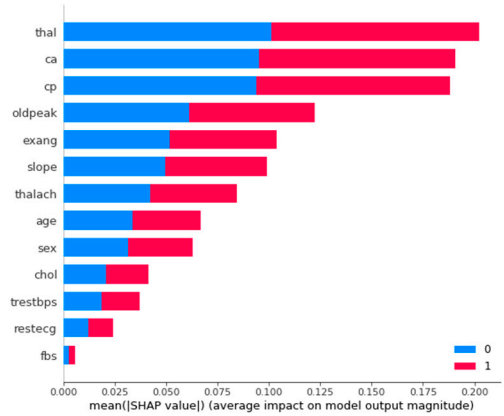


Figure 3. SHAP algorithms.

6. Conclusions and Implication

It is important to identify the diseases before they become worse. In this study, we set out to predict cardiovascular patients via four state-of-the-art machine learning algorithms. We mainly concentrated on improving the recall score as it is important to identify all the CVD-positive patients among the patients present in the dataset. AdaBoost, GradBoost, and XgBoost are among the best ensemble machine-learning models available. We developed a stacked boosting ensemble model, which is a combination of Ada, GB, and XGB models. On top of that, we have used hyperparameter tuning on every individual model, as well as the stacked boosting ensembles. According to the analysis, the tuned stacked boosting ensemble model showed a remarkable recall score, demonstrating that it performs effectively while detective genuine positive cases as we all know in that case false negative results can create serious repercussions. Our research can aid doctors and individuals in various aspects. The most important implications are as follows:

- Our model may have a better chance to find people who are at risk for cardiovascular diseases, particularly those who tend to go unnoticed. This prompt detection system is extremely helpful in providing preventive measures for CVD patients such as having a healthy lifestyle, proper treatments, balanced diets, and a few more.
- The hospital and healthcare practitioner can optimize their budgets and the use of medical equipment to focus on the patients who are at risk of CVD diseases.
- The algorithms can help in the creation of individualized medication regimens, as the treatments are different for individuals. By knowing which factor most influences these diseases, they can provide proper intervention.
- A higher recall score helps reduce the cost by providing proper knowledge regarding the diseases. It helps an individual to lower their financial burden by shortening their expensive medical care.

To sum up, our model concludes by highlighting the stacked ensemble tuned model and its recall score. The ramifications go above the treatment of a person. They have an additional impact on resource allocation, healthcare strategies, as well as cost-cutting approaches. The current limitations of this study include the lack of availability of data. Cardiovascular diseases might have an influence geographically; therefore, if we only consider the data from North America, our model might produce biased results when it comes to using a report from Asia. Therefore, in future works, we are planning to include CVD patient reports from across different continents so that our machine can learn them to provide accurate results.

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