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A New Efficiency Improvement of Ensemble Learning for Heart Failure Classification by Least Error Boosting

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Abstract

Heart failure is a very common disease, often a silent threat. It's also costly to treat and detect. There is also a steadily higher incidence rate of the disease at present. Although researchers have developed classification algorithms. Cardiovascular disease data were used by various ensemble learning methods, but the classification efficiency was not high enough due to the cumulative error that can occur from any weak learner effect and the accuracy of the vote-predicted class label. The objective of this research is the development of a new algorithm that improves the efficiency of the classification of patients with heart failure. This paper proposes Least Error Boosting (LEBoosting), a new algorithm that improves adaboost.m1's performance for higher classification accuracy. The learning algorithm finds the lowest error among various weak learners to be used to identify the lowest possible errors to update distribution to create the best final hypothesis in classification. Our trial will use the heart failure clinical records dataset, which contains 13 features of cardiac patients. Performance metrics are measured through precision, recall, f-measure, accuracy, and the ROC curve. Results from the experiment found that the proposed method had high performance compared to naïve bayes, *k*-NN, and decision tree, and outperformed other ensembles including bagging, logitBoost, LPBoost, and adaboost.m1, with an accuracy of 98.89%, and classified the capabilities of patients who died accurately as well compared to decision tree and bagging, which were completely indistinguishable. The findings of this study found that LEBoosting was able to maximize error reductions in the weak learner's training process from any weak learner to maximize the effectiveness of cardiology classifiers and to provide theoretical guidance to develop a model for analysis and prediction of heart disease. The novelty of this research is to improve original ensemble learning by finding the weak learner with the lowest error in order to update the best distribution to the final hypothesis, which will give LEBoosting the highest classification efficiency.

Keywords:

Adaboost.m1;

Ensemble;

k-NN;

Learning Algorithm;

Heart Failure;

LEBoosting.

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1- Introduction

Heart failure is a clinical syndrome characterized by shortness of breath, fatigue, and frequent clinical manifestations that lead to hospitalization, causing the population to have a poor quality of life and a shortened lifespan [1], especially if the case (acute heart failure) is often a silent threat and occurs in an emergency condition that requires immediate treatment. The patient may not notice any abnormalities in the body and often cannot go to the hospital in time, eventually causing death. According to statistics, the incidence of congestive heart failure continued for 28 years from 1990-2016, and the prognosis to 2030 shows that the incidence rate will continue to increase [2].

There is also an incidence rate with younger people. In Sweden, the incidence of heart failure increased from the first to the last five years by 50% and 43% among people aged 18-34 years old and 35-44 years old, respectively [3]. There is also a high cost of treatment. From the past to the present, many heart failure analyses and predictions have been made.

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Machine learning was one of the tools that was used to analyze a large number of heart failures, using a variety of methods, but popular methods used in predicting include supervised learning, deep learning, and ensemble. In this case, supervised learning is a method for creating a model for predicting the results of the analysis or the heart failure prognosis by learning the existing patient data to make decisions on new data to analyze [4-7]. Supervised learning was used to increase the efficiency of the prediction of heart failure; for example, Chicco & Jurman [8] applied several machine learning classifiers with feature ranking tested on heart failure datasets of 299 patients. It was found that serum creatinine and ejection fraction were the two most relevant features, and an important feature can lead to more accurate predictions than using the original dataset features in a variety of machine learning test methods. This is similar to the research by Myint & Khaung [7], which uses supervised learning in the decision tree method to classify comparisons of heart disease analysis, including C4.5, C5.0, and Cart. The results showed that the C5.0 decision tree was perfected with the greatest accuracy.

However, the use of supervised learning in forecasting, although the experimental results were found to have a high forecasting efficiency, but actually hidden among other factors that caused the prediction discrepancy, such as height, weight, body mass index, etc. And their occupational history can cause heart disease, so research should increase the efficiency of prediction to be higher than this. Subsequently, a deep learning method, or the simulation of the processing patterns of the human brain, was introduced by using a neuron-like network to process information when it receives information, and use it to make predictions. Mehmood et al. [5] presented the *CardioHelp* application to predict the probability of cardiovascular disease, which is the first step before heart failure, using the convolutional neural networks (CNN) algorithm, which is a type of deep learning with high efficiency. Results showed that the proposed method was highly effective, with an accuracy of 97% considered supportive. The doctor's decision to diagnose the disease was very well. Although deep learning is a very effective method of prediction, deep learning requires very large amount of data in order to perform better than other techniques and is extremely expensive to train due to its complex data models. Moreover, deep learning requires expensive GPUs and hundreds of machines, which increases the cost of development and for the user.

Another type of machine learning that is highly predictive of a wide range of data, including heart failure data, and does not require very high model processing resources, is ensemble learning. Ensemble learning is a machine learning technique that combines several machine learning models, also called weak learners, in order to produce improved results. Ensemble learning has many sub-methods, including Bagging, Boosting, and Stacking, among others. These sub-methods are commonly used for precision classifications. Some studies using ensemble learning in predicting heart failure include, Angraal et al. [9] developed a model for classification from 5 methods: logistic regression with a forward selection of variables; logistic regression with a lasso regularization for variable selection, random forest, gradient descent boosting, and support vector machines. When tested with patients with heart failure with preserved ejection fraction, the results of the 5 methods found that random forest performed with the best efficiency, in which the random forest uses the bagging technique. Many ensemble learning methods are also used in comparison for the effectiveness of heart failure predictions for the most effective methods, such as synthetic minority oversampling technique (SMOTE) [4] and deep ensemble methods [10, 11]. However, the boosting technique is one of the highly effective ensemble learning subsets for predicting heart failure data, as can be seen from the research of Ali et al. [12] research has developed a smart healthcare system that can predict heart disease progression using ensemble deep learning, using LogitBoost, which is a boosting method, as a meta-learning classifier, and feature fusion to increase efficiency in classification. The experiment will conduct pre-processing on the dataset and then select important features using information-gathering techniques and classification. The result shows that the proposed method has the highest efficiency compared to other machine learning methods, with an accuracy of 98.5% in the general feature weighting method. It can be seen that machine learning is being applied to predict heart failure, where researchers are trying to develop algorithms that are more accurate. Which can predict or group the severity of the disease in patients up to the case of death if there is an accurate prediction. It can help you recognize the severity and prepare for treatment in a timely manner. Although these previous methods are effective in the classification of heart failure, but it is still not enough if the training stage for weak learners in each iteration produces a large error value, even less than 0.5. Then the sum of the final hypothesis has a potentially high error value, which our proposed method will solve this problem.

In order to have an algorithm that can accurately predict. In this paper, we therefore present an improved efficiency of boosting techniques, LEBoosting, by this method will find optimizing hypothesis selection procedures from various weak learner training procedures to achieve optimal hypothesis based on the least error values in each iteration, then lead to the vote process to achieve the best efficiency for the final hypothesis. It also compares the effectiveness of the proposed methods with the existing learning models, which are supervised learning and ensemble learning to predict heart failure, including being tested with LEBoosting with standard datasets that relate to other heart failures and consist of various types of data that differ in each dataset, such as personal data, blood test results, risky lifestyle habits, electrocardiograms, illness, etc. In order to confirm that LEBoosting is the most effective method for classification that can be used.

This paper is organized as follows: Section 2 explains the materials and method. Section 3 the simulation results are shown, whereas Section 4 discusses the LEBoosting for heart failure classification. Section 5 described the conclusion. Finally, the declaration is given in section 6.

2- Materials and Method

In this section, we describe the process of heart failure prediction detection applied according to the data mining technique. The method consists 5 stages: Data collection and pre-processing, Training weak learner, Build strong classifier, Final Hypothesis and Evaluate performance and compare the results with the overall structure as shown in Figure 1.

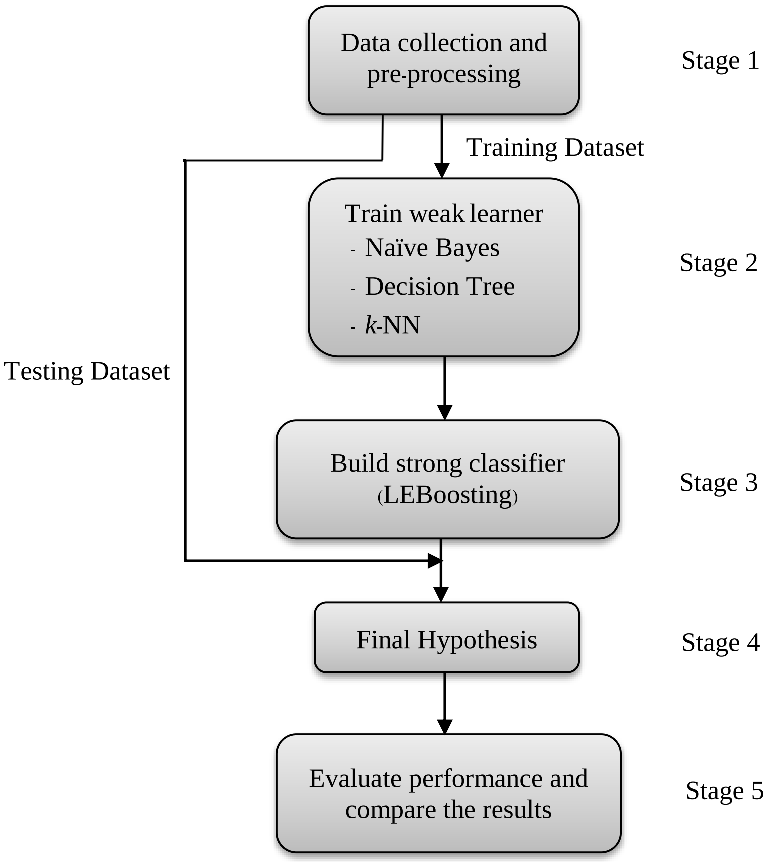


Figure 1. This proposed model

From Figure 1, our proposed model is explained in the following stages:

2-1- Data Collection and Pre-Processing

The research used the heart failure dataset from the UCI repository [13]. The dataset comprised of heart failure patient records from the Faisalabad Institute of Cardiology and at the Allied Hospital in Faisalabad which consisted of 194 male and 105 female patients aged between 40-95 years old, there are a total of 299 records who had heart failure, which were collected during their follow-up period, and consisting of 13 features as follows (Table 1):

Table 1. The details of heart failure dataset [8]

Feature	Explanation
Age	Age of the patient
Anaemia	Decrease of red blood cells or hemoglobin
High blood pressure	If a patient has hypertension
Creatinine phosphokinase (CPK)	Level of the CPK enzyme in the blood
Diabetes	If the patient has diabetes
Ejection fraction	Percentage of blood leaving the heart at each contraction
Sex	Male or female
Platelets	Platelets in the blood
Serum creatinine	Level of creatinine in the blood
Serum sodium	Level of sodium in the blood
Smoking	If the patient smokes
Time	Follow-up period
(target) death event	If the patient died during the follow-up period

There are a number of data classified by class as in Table 2.

Table 2. Number of data by class

Class	Number of data
Died	96
Survived	203

In the experiment, datasets are split into 70% training and 30% testing, so the number of training datasets is 209 records and the number of testing datasets is 90 records where validation sets are separate 10% from the training set to validate the model during the training process.

2-2- Train Weak Learner

2-2-1- Classification Technique

This research modified adaboost.m1, is one of the ensemble methods. Ensemble is one of the machine learning techniques in which several weak learner models are modeled in order to predict the best outcomes by vote from every model [14]. Weak learner can be any machine learning algorithm such as naive bayes, decision tree, *k*-NN, Support vector machine, etc. Adaboost.m1 is an algorithm developed from the original AdaBoost method. Classification can be multiclass. The distinguishing feature is that adaboost.m1 is to update the distribution weight of the current hypothesis sample. Each hypothesis must have an error value of less than 0.5 [15]. The LEBoosting method we propose will modify adaboost.m1 to be more efficient in classification by selecting the best model from any weak learner to represent the hypothesis in that iteration. This study defines the weak learner as naive bayes, *k*-NN and decision tree. LEBoosting architecture is shown in Figure 2.

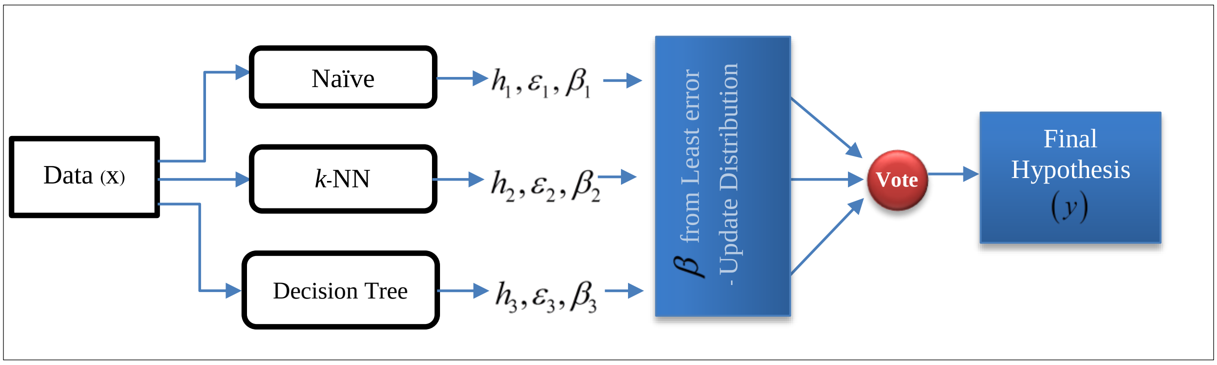


Figure 2. LEBoosting architecture

2-2-2- Weak Learner

In the experiment, machine learning is used as a weak learner of 3 algorithms: naïve bays, *k*-NN and decision tree classification [6, 8, 16]. The researchers envisioned that with the use of an effective weak learner, the vote process would provide highly accurate predictions for the final hypothesis.

2-2-3- Naive Bayes

Naïve Bayes is a statistical method used to determine the probability for finding the appropriate class based on Bayes's theorem [17] To classify the data, Naïve Bayes calculates the probability of each class C_i as follows:

$$p(C_i \mid X) = \frac{p(C_i)\prod_{k=1}^{n} p(X_k \mid C_i)}{P(X)} \tag{1}$$

That C_i is the class label and X is an instance which is classified.

2-2-4- k-Nearest Neighbour Methods (k-NN)

k-NN is to identify *k* records in the training dataset that are similar (neighbouring) records to classify a new record to predominant classes among the neighbour. The algorithm measures the distance between the center and any data of the case or condition that gives any class the same as the closest class [18] ,the most popular measure is the Euclidean distance between two records $(x_1, x_2, \dots, x_p)$ and $(u_1, u_2, \dots, u_p)$.

$$Dist = \sqrt{(x_1 - \mu_1)^2 + (x_2 - \mu_2)^2 + \cdots + (x_p - \mu_p)^2} \tag{2}$$

k-NN looks for samples in the training data that are similar or near the record to be classified in the predictor.

2-2-5- Decision Tree

A decision tree is a classifier model that uses a tree-like structure to perform decisions. Decision trees are commonly used in many research fields which have better performance compared with other algorithms [19, 20]. The decision tree learning algorithm can be described as follows.

- Select the Attribute with the highest information gain value.
- Let P_i be the probability of an arbitrary tuple in D belonging to class D_i estimated by $|C_i\ , D|/\ |D|$
- Expected information *(*entropy*)* needed to classify a tuple can be calculated as:

$$Info(D) = \sum_{i=1}^{m} P_i\, log_2(P_i) \tag{3}$$

- Information needed to classify D can be computed as:

$$Info_A(D) = \sum_{i=1}^{v} \frac{D_j}{D} * ID_j \tag{4}$$

- Information gained by branching on attribute A can be computed as:

$$Gain_A = Info_D - Info_A D \tag{5}$$

2-3- Build Strong Classifier and Final Hypothesis

For each iteration, the errors obtained from the weak learner are compared, in each learning cycle, to get the best model, number from T iteration, there will be 3 training weak learners namely naïve bays, k-NN and decision tree. For example, T_1 will start training weak learners and measure errors, if found any weak learner with an error value greater than 0.5 must iterate to training again until the error value is less than 0.5, if all values are less than 0.5 then the error value from all weak learners is compared to whichever is the smallest, then calculate the β value and then update the distribution. It then iterates to compute T_2 until any number of T_n iteration are desired, updating the same distribution, as if to find the best weak learner in order to update the best distribution to the final hypothesis. LEBoosting algorithm is shown in Algorithm 1.

Algorithm 1. **LEBoosting**

Input: Sequence of m example $\left((x_1, y_1),...,(x_m, y_m)\right)$ with labels $y_1 \in Y = \{1,...,k\}$
Weak learning algorithm ***Weaklearn***
Integer T specifying number of iterations
Integer J specifying number of weak learner
Initialize $D_1(i) = \frac{1}{m}$ for all i
Do for $t = 1, 2, ..., T$
Do for $j = 1, 2, ..., J$
1. Call ***Weaklearn*** providing it with the distribution D_t
2. Get back hypothesis $h_{tj} = X \rightarrow Y$
3. Calculate the error of $h_{tj} : \varepsilon_{tj} = \sum_{i=h_{t(x_i)\neq y_i}} D_t(i)\ if\ \varepsilon_{tj} > \frac{1}{2}$
   Then set $T = T - 1$ and abort loop
   $\varepsilon_t = \min \varepsilon_{tj}$
4. Set $\beta_t = \frac{\varepsilon_t}{(1-\varepsilon_t)}$
5. Update distribution $D_t : D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} \beta_t & h_t(x_i)=y_i \\ 1 & otherwise \end{cases}$
Where Z_t is a normalization constant (Chosen so that D_{t+1} will be a distribution)
Output the final hypothesis: $h_{fin} = \underset{y \in Y}{\arg\max} \sum_{t: h_t(x)=y} \log \frac{1}{\beta_t}$

2-4- Evaluate Performance and Compare the Results

Using the confusion matrix, this research can analyse the efficiency of doing classification, and in Table 3 the four Values' performance was measured.

Table 3. Confusion matrix

Predicted Classes	Actual Class	
	Positive	**Negative**
Positive	TP = True Positive	FP = False Positive
Negative	FN = False Negative	TN = True Negative

The performance analyses include accuracy, precision, recall and f-measure. The calculations are as follows:

Precision is the ratio of correctly predicted positive sample to the total predicted positive observations.

$$Precison = \frac{TP}{TP + FP} \tag{6}$$

Recall is the ratio of correctly predicted positive sample to the total predicted in actual class

$$recall = \frac{TP}{TP + FN} \tag{7}$$

f-Measure is the weighted average of Precision and Recall.

$$f - Measure = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \tag{8}$$

Accuracy is ratio of the correctly predicted label to the total sample label.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

3- Results

The classification experiment in this paper was implemented with a MATLAB 2016, in the process of pre-processing, we used 70% of the total dataset for the training step and the remaining 30% for the testing step. Therefore, the classification results are shown in the confusion matrix as shown in Figure 3.

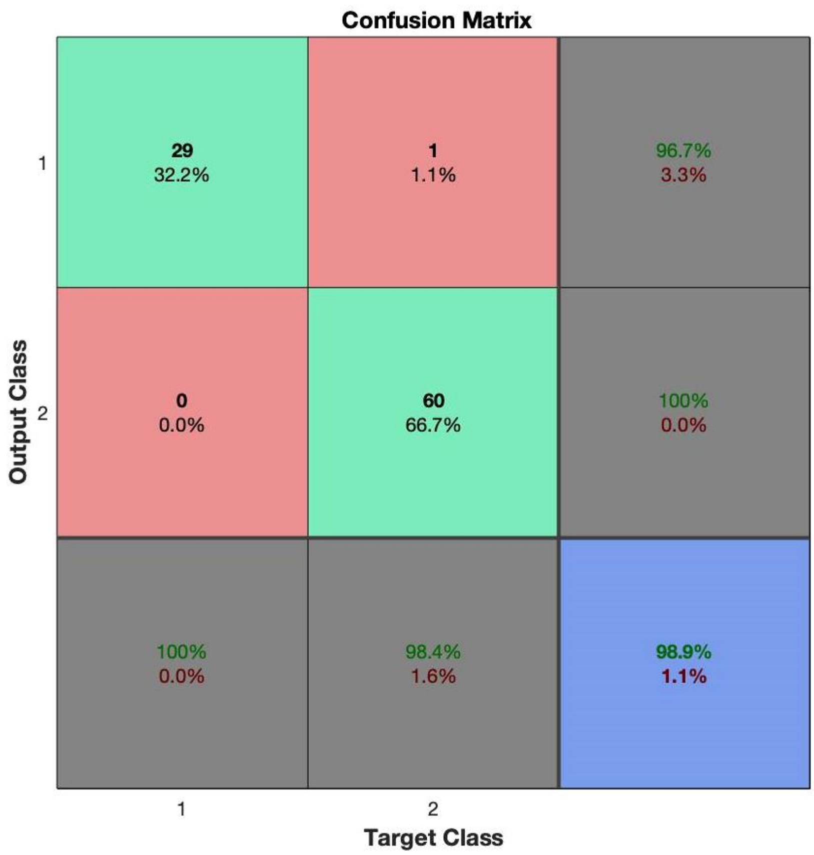


Figure 3. LEBoosting classification confusion matrix

Figure 3 shows that LEBoosting has a very high classification accuracy. Accuracy is 98.89% compared to classified efficiency using traditional adaboost.m1 and machine learning and the results of the weaklearn test have the following performance comparisons:

When looking at the results of Table 4 LEBoosting has the highest overall efficiency, with the highest Accuracy, which, when compared to the f-Measure, is the highest when considering classifying by class, and when compared to the effect of machine learning. It will be likely to classify efficiency value without voting with the method we offer. Therefore, it can be clearly seen that the vote method that the experiment will offer can increase the efficiency of doing classification clearly with a machine learning approach.

Table 4. **Comparison of the efficiency of classification**

Method	**Efficiency**				
	Class	**Precision**	**Recall**	**f-Measure**	**Accuracy**
k-NN	Died	27.59	38.1	32	62.22
	Survived	78.69	69.57	73.85	
NB	Died	3.45	100	6.67	68.89
	Survived	100	68.54	81.33	
Tree	Died	0	0	0	67.78
	Survived	100	68.78	81.5	
Adaboost.m1	Died	88.16	100	93.71	95.69
	Survived	100	93.66	96.73	
LEBoosting	Died	96.67	100	98.31	98.89
	Survived	100	98.36	99.17	

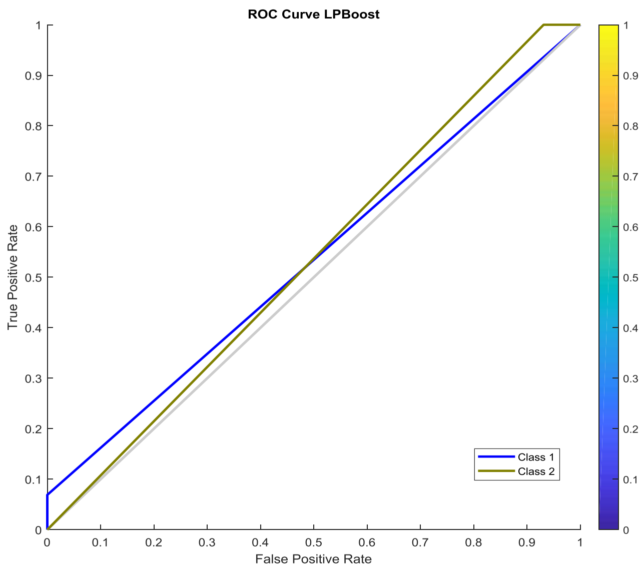
Compared to ensemble methods, it showed higher accuracy than other methods. But all machine learning methods have similar performance values. It has an accuracy of less than 70%, but when compared to the adaboost.m1 method, which is 95.69% effective, it can improve performance to 98.89%, meaning LEBoosting is able to learn traditional machine learning methods. A weak learner with low classification efficiency, by using our improved LEBoosting adaboost.m1, can increase efficiency up to 98.89%.

It is worth noting that some methods have very low precision of the class died and some methods cannot classify the class died at all, as shown in Table 5.

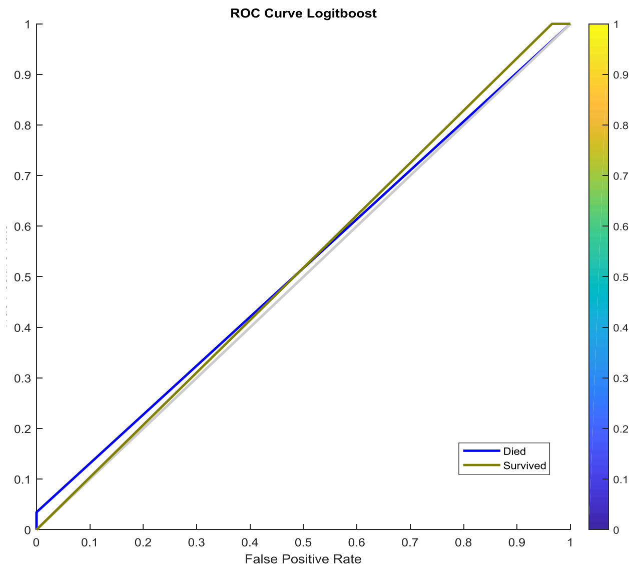
Table 5. **Performance Comparison with other Ensemble Methods**

Method	**Efficiency**				
	Class	**Precision**	**Recall**	**f-Measure**	**Accuracy**
Bagging	Died	0	0	0	67.78
	Survived	100	68.78	81.5	
LogitBoost	Died	3.45	100	6.67	68.89
	Survived	100	68.54	81.33	
LPBoost	Died	6	100	11.32	70
	Survived	100	69.32	81.88	
LEBoosting	Died	96.67	100	98.31	98.89
	Survived	100	98.36	99.17	

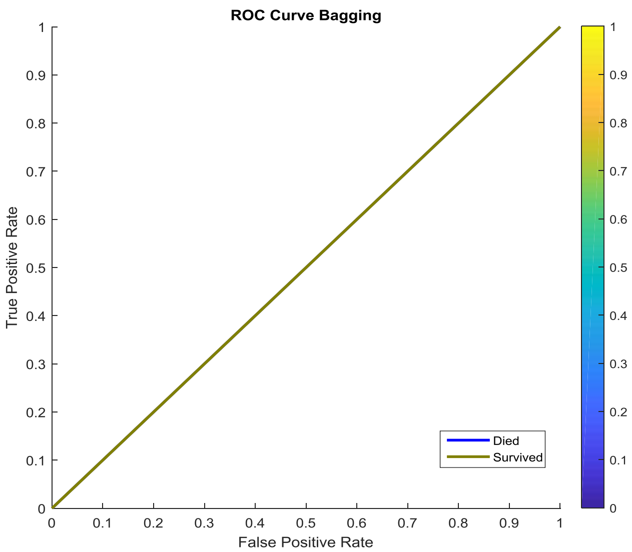
From the results of the performance analysis, it was found that compared to other ensemble methods, Bagging, LogitBoost and LPBoost methods are more effective in classification which is not more than 70% or the classification error which is almost 1/3. The interesting point is almost all methods of the died class were difficult to classify, had low f-Measure values and some methods had values of 0 such as decision tree and bagging, but LEBoosting was the highest among all methods. The value is as high as 98.31%, which means that the patient will be able to accurately classify who will die. This Displays a 2-class ROC curve analysis of all methods tested. Shown as in Figure 4.



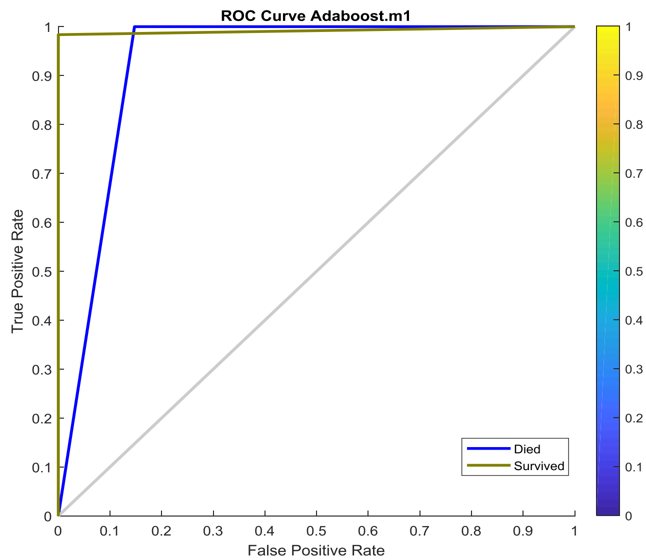
(a) LPboost



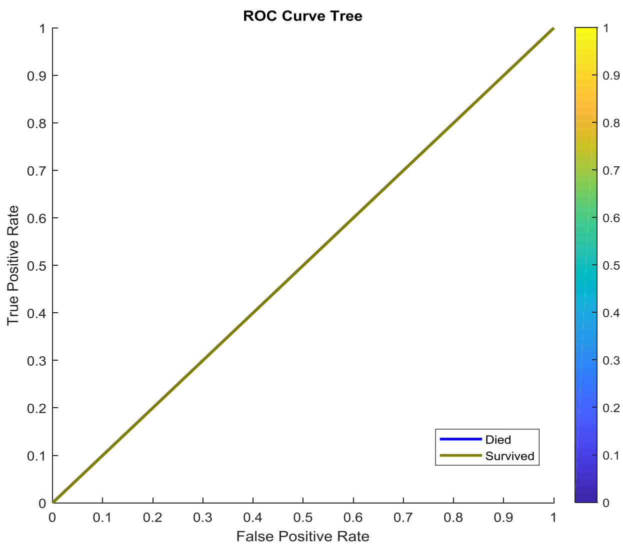
(b) Logitboost



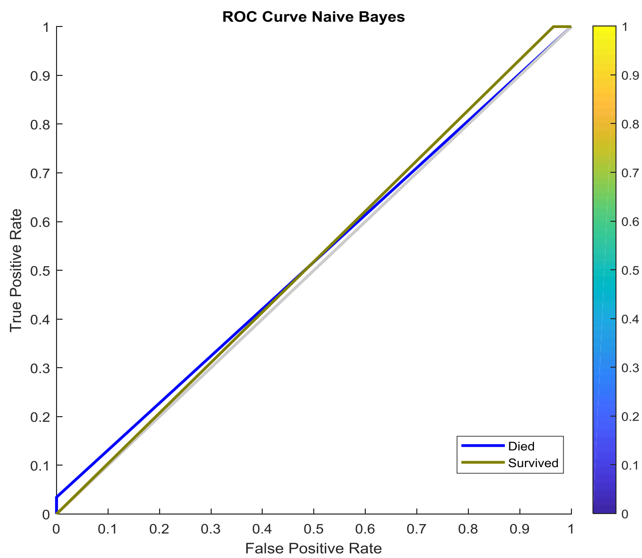
(c) Bagging



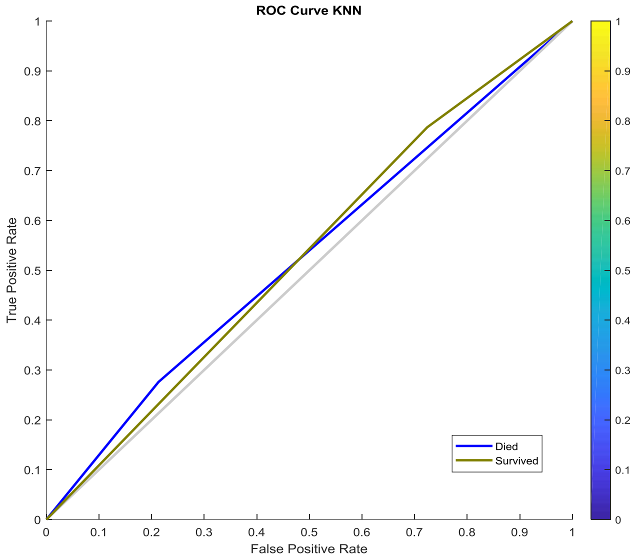
(d) Adaboost.m1



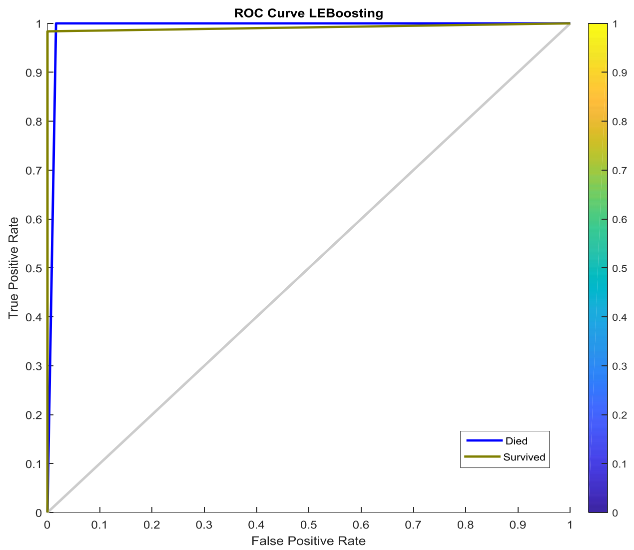
(e) Decision Tree



(f) Naïve Bayes



(g) *k*-NN



(h) LEBoosting

Figure 4. Comparison of the ROC curve of the various methods that have been tested

It is a curve plotted between sensitivity and 1-specificity. It was found that the LEBoosting graph shows the most accurate performance in the classification test between heart failure and the died class and the least error compared to other ensemble methods.

In addition, the trial was compared with other datasets related to heart disease, including cardiovascular disease [21]. It is the patient's personal information. Blood results and smoking behavior, etc., Heart Statlog [22] is the patient's personal data, blood results, electrocardiogram results and results from other physical examinations related to the heart, Heart disease dataset was the patient's personal data, blood results, blood pressure, chest pain, electrocardiogram results and ECG values, etc. [23] to test the effectiveness of the method, it was found that the proposed method had the efficacy of the procedure classification which is also shown in Table 6.

Table 6. Tests with other cardiac datasets

Dataset	Accuracy				
	***k*-NN**	**Naïve Bays**	**Decision Tree**	**AdaBoost.m1**	**Proposed Method**
Cardiovascular	50.18	59.15	55.94	60.17	63.34
Heart Statlog	60.49	82.72	81.48	88.89	92.59
Heart Disease Data Set	65.93	75.82	68.13	83.52	91.51
Heart Failure Clinical Records Dataset (This Research Dataset)	62.22	68.89	67.78	95.69	98.89

From Table 6 it is found that the proposed method has the highest accuracy value compared to other methods. Which indicates that the proposed method can be improved from the traditional boosting technique, and it performs better than the machine learning used as a weak learner, it is capable of predicting a wide variety of heart disease data. This research compared the efficacy of LEBoosting to other studies using the same dataset and comparison results which are shown in Table 7.

Table 7. Comparison of efficacy with other studies

Source / Year	Method	Accuracy (%)
Louridi et al. (2019) [24]	SVM with Linear Kernel	86.8
Khennou et al. (2019) [25]	*k*-NN and Naïve Bayes	87
Ali et al. (2019) [26]	Linear SVM + LDA	90.0
Escamilla et al. (2019) [27]	ChiSq + PCA	90.9
Satyanandam & Satyanarayana (2021) [28]	Ensemble Learning based analysis	92.0
Ishaq et al. (2021) [4]	SMOTE	92.62
Ali et al. (2019) [31]	χ^2 Statistical Model and Gaussian Naive Bayes	93.33
Javeed et al. (2019) [29]	RSA based random forest	93.33
Katarya & Meena (2021) [30]	Random Forest	95.60
Mehmood et al. (2021) [5]	Convolutional neural networks (CNN)	97
Proposed Method (2022)	LEBoosting	98.89

When testing a heart failure dataset, it was found that LEBoosting method was highly effective at classifying compared to other methods such as hybrid machine learning, ensemble learning and deep learning. When testing a heart failure dataset, it was found that LEBoosting method was highly effective at classifying compared to other methods such as hybrid machine learning, ensemble learning and deep learning by comparison, it was found that LEBoosting had a higher efficiency than hybrid machine learning, i.e., research [24-27] because LEBoosting is a combination model from various machine learning. This is like combining the outstanding capabilities of each algorithm together. Including research [4, 28-30] in which each algorithm does not have the process of applying the best model or the lowest error to use in voting results. Therefore, this issue is a weak point that LEBoosting developed to solve the problem directly, which was found to be able to solve very well for the efficiency of classification which was the highest among all the studies compared. Finally, when compared to deep learning in the research [5] it was found that the efficiency was similar. Although deep learning is an algorithm with outstanding accuracy, but not all of them are suitable for the data they bring to the classification and deep learning which also has disadvantages in terms of the need for high computing resources and takes more time to process than other common methods. This makes it a barrier for researchers to analyze large data with developed algorithms and can be highly complex or take many forms.

4- Discussion

This paper has shed light on LEBoosting, a new approach that streamlines computational accuracy by focusing on maximizing error reductions in the weak learner's training process so that it can generate the most efficient final hypothesis. LEBoosting is proven to be highly effective for classification. It is appropriate to use it to classify heart failure patients by groups at risk of death. When comparing the results of the experiment as shown in Tables 4 and 5, it was found that LEBoosting has the highest classification efficiency, whereas some algorithms could not classify or there was very low classification. While LEBoosting can be highly classified in all groups, even in comparison with other ensemble methods, it also has the highest accuracy compared to past studies, as shown in Table 7, where the findings of this study found that the accuracy is due to the fact that the algorithm only selected the lowest error in the weak learner's training process for each iteration to calculate. This resulted in the best error values, best beta values, and best distribution values for boosting. There is also a wide variety of weak learner combinations of selected machine learning capabilities to create the most accurate method of prediction. Unlike the traditional adaboost.m1 approach, the model is created from the weak learner and then voted, so if the weak learner is used appropriately for the dataset, there is a high potential for voting. However, if a weak learner is used that is not suitable for the dataset and causes overfitting, it can lead to poor predictive performance.

The strength of this research is that, if the weak learner is to be replaced by other methods in the future, LEBoosting will still have good performance. Because the error-correcting computational process is not specific to any weak learner but rather to finding the lowest possible error value based on the weak learner's model created that LEBoosting is quite flexible. The limitation of this research is that this trial uses clinical record datasets for classification; therefore, the data of ECG patients cannot be analyzed. The LEBoosting developed in this research can improve the efficiency of classification datasets for patients with heart disease with a higher degree of efficiency than other comparative methods or research in the past. The recommendations for this research are that it should be developed to be able to classify with ECG patient datasets.

Future research will develop LEBoosting with the ability to classify image datasets of Covid-19 patients from the past to the present as a guideline for the prevention and treatment of emerging infectious diseases that are still developing subspecies continuously.

5- Conclusion

Heart disease is a chronic, non-communicable disease that requires patients to seek ongoing medical care. It has a high cost and can also be a silent disaster. This would be especially acute where heart failures could lead to increased death rates, thus making the population worse off and shorter-lived. Knowing about the disease early will help the patient seek treatment in a timely manner through more modern medical devices that have been developed to predict heart disease, but the efficiency of forecasting needs to be improved to be more accurate. This will be a good aid for the doctor in diagnosing the disease. This research presents a method for categorizing patients suffering from heart failure in cases of life and death. The researchers proposed LEBoosting, a new algorithm that improves the performance of AdaBoost.m1 with higher classification accuracy our trial uses the UCI Repository, which contains 13 features of the patient's clinical records. In the training step, the least error is obtained by comparing the weak learner output from different weak learners: naive bayes, *k*-NN and decision tree. LEBoosting can use maximizing error reductions in the weak learner's training process to maximize classification efficiency. The results showed that the proposed method can increase the efficiency of classification, which is very high, and is more efficient than other ensemble methods, especially doing well with the class-died category, which is usually difficult to predict. Also, testing on other heart disease datasets was not highly effective, including higher figures than other studies that have been compared as well. For future research, it is expected that this algorithm will be applied to other disease databases in which the population is still active, such as cancer, diabetes, or COVID-19.

6- Declarations

6-1- Author Contributions

Conceptualization, P.S. and S.P.; methodology, P.S.; software, P.S.; validation, P.S., P.J. and S.P.; formal analysis, P.S.; investigation, P.S.; resources, P.J.; data curation, P.S.; writing—original draft preparation, P.S.; writing—review and editing, S.P.; visualization, P.S.; supervision, P.S.; project administration, P.J. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

Publicly available datasets were analyzed in this study. This data can be found here: *https://archive.ics.uci.edu/ml/machine-learning-databases/00519*.

6-3- Funding

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6-5- Institutional Review Board Statement

Not Applicable.

6-6- Informed Consent Statement

Not Applicable.

6-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Bazoukis, G., Stavrakis, S., Zhou, J., Bollepalli, S. C., Tse, G., Zhang, Q., Singh, J. P., & Armoundas, A. A. (2021). Machine learning versus conventional clinical methods in guiding management of heart failure patients—a systematic review. Heart Failure Reviews, 26(1), 23–34. doi:10.1007/s10741-020-10007-3.

[2] Lippi, G., & Sanchis-Gomar, F. (2020). Global epidemiology and future trends of heart failure. AME Medical Journal, 5(15), 1-6. doi:10.21037/amj.2020.03.03.

[3] Groenewegen, A., Rutten, F. H., Mosterd, A., & Hoes, A. W. (2020). Epidemiology of heart failure. European Journal of Heart Failure, 22(8), 1342–1356. doi:10.1002/ejhf.1858.

[4] Ishaq, A., Sadiq, S., Umer, M., Ullah, S., Mirjalili, S., Rupapara, V., & Nappi, M. (2021). Improving the Prediction of Heart Failure Patients' Survival Using SMOTE and Effective Data Mining Techniques. IEEE Access, 9, 39707–39716. doi:10.1109/access.2021.3064084.

[5] Mehmood, A., Iqbal, M., Mehmood, Z., Irtaza, A., Nawaz, M., Nazir, T., & Masood, M. (2021). Prediction of Heart Disease Using Deep Convolutional Neural Networks. Arabian Journal for Science and Engineering, 46(4), 3409–3422. doi:10.1007/s13369-020-05105-1.

[6] Sohrabi, B., Vanani, I. R., Gooyavar, A., & Naderi, N. (2019). Predicting the Readmission of Heart Failure Patients through Data Analytics. Journal of Information and Knowledge Management, 18(1), 1950012. doi:10.1142/S0219649219500126.

[7] Myint, K., & Khaung Tin, H. H. (2020). Analyzing the Comparison of C4.5, CART and C5.0 Algorithms on Heart Disease Dataset using Decision Tree Method. Proceedings of the 2nd International Conference on ICT for Digital, Smart, and Sustainable Development, ICIDSSD 2020, 27-28 February 2020, Jamia Hamdard, New Delhi, India. doi:10.4108/eai.27-2-2020.2303221.

[8] Chicco, D., & Jurman, G. (2020). Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. BMC Medical Informatics and Decision Making, 20(1), 1–16. doi:10.1186/s12911-020-1023-5.

[9] Angraal, S., Mortazavi, B. J., Gupta, A., Khera, R., Ahmad, T., Desai, N. R., Jacoby, D. L., Masoudi, F. A., Spertus, J. A., & Krumholz, H. M. (2020). Machine Learning Prediction of Mortality and Hospitalization in Heart Failure with Preserved Ejection Fraction. JACC: Heart Failure, 8(1), 12–21. doi:10.1016/j.jchf.2019.06.013.

[10] Lorenzoni, G., Sabato, S. S., Lanera, C., Bottigliengo, D., Minto, C., Ocagli, H., De Paolis, P., Gregori, D., Iliceto, S., & Pisanò, F. (2019). Comparison of machine learning techniques for prediction of hospitalization in heart failure patients. Journal of Clinical Medicine, 8(9), 1298. doi:10.3390/jcm8091298.

[11] Wang, L., Zhou, W., Chang, Q., Chen, J., & Zhou, X. (2019). Deep ensemble detection of congestive heart failure using short-term RR intervals. IEEE Access, 7, 69559–69574. doi:10.1109/ACCESS.2019.2912226.

[12] Ali, F., El-Sappagh, S., Islam, S. M. R., Kwak, D., Ali, A., Imran, M., & Kwak, K. S. (2020). A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Information Fusion, 63, 208–222. doi:10.1016/j.inffus.2020.06.008.

[13] UCI Repository (2017). Heart failure clinical records Data Set. UC Irvine Machine Learning Repository, California, United States. Available online: https://archive.ics.uci.edu/ml/machine-learning-databases/00519/ (access 21 June 2021).

[14] Zhou, Z. H. (2012). Ensemble methods: foundations and algorithms. CRC Press, Boca Raton, United States. doi:10.1201/b12207.

[15] Freund, Y., & Schapire, R. E. (1996). Schapire R: Experiments with a new boosting algorithm. 13th International Conference on Machine Learning, 3-6 July, 1996, Bari, Italy.

[16] Jones, Y., Hillen, N., Friday, J., Pellicori, P., Kean, S., Murphy, C., & Cleland, J. (2020). A comparison of machine learning models for predicting rehospitalisation and death after a first hospitalisation with heart failure. European Heart Journal, 41(Supplement_2), 946–0984. doi:10.1093/ehjci/ehaa946.0984.

[17] Holmes, D.E., Jain, L.C. (2008). Introduction to Bayesian Networks. Innovations in Bayesian Networks. Studies in Computational Intelligence, 156, Springer, Berlin, Germany. doi:10.1007/978-3-540-85066-3_1.

[18] Kramer, O. (2011). Dimensionality Reduction by Unsupervised K-Nearest Neighbor Regression. 2011 10th International Conference on Machine Learning and Applications and Workshops. doi:10.1109/icmla.2011.55.

[19] Salzberg, S. L. (1994). Book Review: C4.5: Programs for Machine Learning by J. Ross Quinlan. Morgan Kaufmann Publishers, Inc., 1993. Machine Learning, 16, 235-240. doi:10.1023/A:1022645310020.

[20] Shmueli, G., Patel, N. R., & Bruce, P. C. (2011). Data mining for business intelligence: Concepts, techniques, and applications in Microsoft Office Excel with XLMiner. John Wiley and Sons, Hoboken, United States.

[21] Kaggle. (2019). Cardiovascular Disease dataset. Kaggle Inc. San Francisco, United States. Available online: https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-dataset (accessed on August 2022).

[22] UCI Repository. (2017). Statlog (Heart) Data Set. UC Irvine Machine Learning Repository, California, United States. Available online: https://archive.ics.uci.edu/ml/datasets/statlog+(heart) (accessed on August 2022).

[23] UCI Repository (2022). Heart Disease Data Set (Issue value 0). UC Irvine Machine Learning Repository, California, United States. Available online: https://archive.ics.uci.edu/ml/datasets/Heart+Disease

[24] Louridi, N., Amar, M., & Ouahidi, B. E. (2019). Identification of Cardiovascular Diseases Using Machine Learning. 2019 7th Mediterranean Congress of Telecommunications (CMT). doi:10.1109/cmt.2019.8931411.

[25] Khennou, F., Fahim, C., Chaoui, H., & Chaoui, N. E. H. (2019). A machine learning approach: Using predictive analytics to identify and analyze high risks patients with heart disease. International Journal of Machine Learning and Computing, 9(6), 762–767. doi:10.18178/ijmlc.2019.9.6.870.

[26] Ali, L., Khan, S. U., Anwar, M., & Asif, M. (2019). Early Detection of Heart Failure by Reducing the Time Complexity of the Machine Learning based Predictive Model. 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE). doi:10.1109/icecce47252.2019.8940737.

[27] Escamilla, A., El Hassani, A., & Andres, E. (2019). Dimensionality Reduction in Supervised Models-based for Heart Failure Prediction. Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods. doi:10.5220/000731370388039.

[28] Satyanandam, N., & Satyanarayana, C. (2021). An Effective Analytics using Machine Learning Integrated Approaches for Diagnosis, Severity Estimation and Prediction of Heart Disease. IOP Conference Series: Materials Science and Engineering, 1074(1), 012006. doi:10.1088/1757-899x/1074/1/012006.

[29] Javeed, A., Zhou, S., Yongjian, L., Qasim, I., Noor, A., & Nour, R. (2019). An Intelligent Learning System Based on Random Search Algorithm and Optimized Random Forest Model for Improved Heart Disease Detection. IEEE Access, 7, 180235–180243. doi:10.1109/ACCESS.2019.2952107.

[30] Katarya, R., & Meena, S. K. (2021). Machine Learning Techniques for Heart Disease Prediction: A Comparative Study and Analysis. Health and Technology, 11(1), 87–97. doi:10.1007/s12553-020-00505-7.

[31] Ali, L., Khan, S. U., Golilarz, N. A., Yakubu, I., Qasim, I., Noor, A., & Nour, R. (2019). A Feature-Driven Decision Support System for Heart Failure Prediction Based on $\chi 2$ Statistical Model and Gaussian Naive Bayes. Computational and Mathematical Methods in Medicine, 2019, 1–8. doi:10.1155/2019/6314328.