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ORIGINAL ARTICLE

A comparative study on prediction of survival event of heart failure patients using machine learning algorithms

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Abstract

Cardiovascular diseases cause approximately 17 million deaths each year and 31% of deaths worldwide. These diseases generally occur as myocardial infarction and heart failure. The survival status, which we used as a target in our classification study, indicates that the patient died or survived before the end of the follow-up period, which is a mean of 130 days. Various machine learning classifiers have been preferred to both predict survival of patients and rank the characteristics corresponding to the most important risk factors. For this purpose, the data set that is occurred totally 299 samples is traditionally divided into 70% for training and 30% for test cluster to be used in machine learning algorithms, with have been analyzed with many methods such as Artificial Neural Networks, Fine Gaussian SVM, Fine KNN, Weighted KNN, Subspace KNN, Boosted Trees, and Bagged Trees. As a result, according to the data obtained, it has been seen that there are algorithms that can predict heart failure diagnosis with full accuracy (100%). Thus, it was concluded that it is appropriate to use machine learning algorithms to predict whether a heart failure patient will survive. This study has the potential to be used as a new supportive tool for doctors when predicting whether a heart failure patient will survive.

Keywords Machine learning · Heart failure · Survival prediction · Support vector machine · Artificial neural networks

1 Introduction

The continuity of human life depends on the smooth functioning of all organs. The heart, which presents in the human body and is the most important vital organ after the brain, is responsible for pumping and circulating the blood that carries the oxygen and nutrition needed by the body, to the body [1, 2].

Various medical diseases such as coronary heart attack, stroke, paralysis, heart failure, and hypertensive and rheumatic heart diseases can be mentioned as cardiovascular diseases (CD), which is defined as heart or vein diseases [4–6]. 31% of deaths occurring worldwide are due to the cardiovascular diseases. For the reason of cardiovascular diseases every year approximately 17.9 million people worldwide lose their lives, as shown in Fig. 1 [7, 8]. People who have high cardiovascular risks, such as hyperlipidemia, diabetes, and hypertensive, need a right, effective, permanent treatment and monitoring program [5].

One of the CD which is heart failure (HF) is a clinical symptom that characterized with deterioration occurred in body functions as a result of decrease in blood pumping or filling with blood ability of heart [9, 10]. The increase of filling pressure of the left ventricular often indicates HF and the risk factors, such as diabetes, obesity, high cholesterol level, hypertension, and smoking, generally accelerate the occurrence of HF [6, 11, 12].

In its every beat, heart pumps the blood, which comes to heart, to the body. Ejection Fraction (EF) shows how much of the blood, which comes to heart is pumped by the heart. EF with normal level is between 50 and 75%. HF is observed clinically in two ways pursuant to the percentage

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Fig. 1 An example of cardiovascular disease [3]

value of blood that pumped out of the heart in a single convulsion, in other words, the EF value [6]. The first is the heart failure due to reduced EF, which is known as systolic HF and is characterized by the degree of EF that less than 40% [4]. The second is "diastolic HF" and in this anomaly that occurs in the left ventricle, although it contracts normally during systole, while passing to diastole, the ventricle cannot relax normally and remains stiff, thus disrupting filling [7, 13–16]. Patients with diastolic HF may have normal EF level. Therefore, its detection can be made by looking at different parameters.

Although chronic HF is a complex clinical condition that affects the quality of patients' life globally, the morbidity and mortality rates gradually increase [17–19]. HF leads an excessive burden on family and society by increased infection in patients, high utilization in healthcare sources, rising cost of treatment, prolonged stay at hospital, and consequently decrease in the life quality of HF patients [17]. In this context, HF is not only wearing but also economically destructive factor that results death in ages, limb manipulation, reduced mobility, decay in quality of life, and the need for intensive drug therapy [20]. HF not only worsens the life quality of patients and increases the morbidity and mortality risks, but also leads a significant responsibility on the general health system, especially in countries having limited economical resources [21, 22].

In physical examination, there may be some mistakes due to symptoms evoking other diseases and these mistakes can cause death in the future when it comes to heart diseases [23]. When the importance heart for life of body is thought, prediction of HF becomes a precedence for doctors. However, predicting situations regarding HF in the clinically applications has generally fall through to achieve high accuracy to date [6, 24]. In this context, recorded electronic medical data can be considered as a beneficial knowledge source not only for investigation but also for clinically applications in uncovering hidden and unclear correlations and relationships among the patient data [25, 27, 28]. For this purpose, many scanning studies have been conducted with various data sources involving different conditions and demographic characteristics to deepen the knowledge regarding risk factors in recent years. Especially, machine learning can be an effective instrument by performed to the recorded medical data, both to predict the mortality risk of patient owing to HF [27, 28] and to determine clinical risk factors which cause to this [29, 30]. Scientists who works around the clinical data can benefit from machine learning both for prediction [31, 32], and feature ranking [33]. Computational intelligence indicates its estimation power, especially when implemented to the recorded medical data [34, 35] or when combined with medical imaging [36–38]. Moreover, in this working area, meta-analysis and deep learning applications have taken place in the literature [39–42] recently and have improved the performance of experts (0.75–0.59), although they show relatively lower accuracy [43].

Various techniques have been improved to estimate the death risk of HF patients. ADHERE model [44] and Seattle HF Model [45] are among well-known models. Despite these methods are righteous, they are not intuitive and based on comprehensively recorded medical data. This situation makes the methods difficult to perform in the clinical area [10].

Machine learning algorithms are frequently used in academic studies in recent years due to the successful prediction and classification results they show in ready data sets. Machine learning takes place in different study fields such as health [46, 47], cryptology [48], and time series [49, 50]. There are many studies in the literature about the diagnosis and classification of heart diseases. Due to the growing number of recorded medical data, it has been an obligation to run machine learning algorithms to relief healthcare workers in resolving data and doing correct and definite diagnosis. Expert systems which are based on Machine learning algorithms successfully diagnose cardiovascular disease and ultimately the mortality rate decreases [51]. A lot of different classification methods and algorithms are used for data mining in medical and they are aimed to estimate deaths due to the cardiovascular disease and the heart attack [52].

For people who have cardiovascular disease or cardiovascular disease risk, to detect the disease earlier with an artificial intelligence model is promising. There are many methods used in prediction algorithms for this purpose.

Being capable of determining risk in advance using objective criteria related to death (mortality) from heart failure is important both for informing patients and their relatives, and for process planning of medical team [53]. In this study, it was mainly aimed to address the problem of "Determining the life-threatening risk developed at the patient due to heart failure using classification-based machine learning techniques". For this purpose, 27 different machine learning methods were trained by performing feature engineering operations on the same data set and their performances were compared.

2 Related works

Some studies in the literature have compared the performance of different artificial intelligence methods to detect heart failure [10, 54–74] using different dataset. Since these studies are not done on the same dataset, it would not be correct to directly compare the performances with our study. Therefore, similar studies in the literature were focused on.

Some studies about the use of machine learning methods on heart failure in the literature can be summarized as follows:

The death ratio of HF patients is high and doctors need dependable prognostic estimation to produce aware decisions for implementing of palliative care, medication, appliance, and graft appropriately [10]. Therefore, predicting HF is a priority for physicians when the importance of a vital organ like heart is thought. For this purpose, many scanning studies on risk factors have been conducted with different data sources in recent years. Smith et al. [75] aimed to develop a prognostic risk model that could differentiate vitally high-risk and low-risk patients among HF patients and investigates the effect of EF and left-ventricular wall's thickness on related risk estimation. In their studies, Voors et al. [54] worked on developing risk models to predict hospitalization due to HF and on external verification. Lassus et al. [55] studied on the differences in prognosis of long-term survival—acute decompensated chronic and onset acute HF after hospitalization due to acute HF.

The prediction of mortality-survival based on HF can be defined as controlled classification problem in terms of machine learning. Accordingly, all the features in the data set for the classification problem were classified by machine learning methods. Nowadays, modeling survival for HF is a problem yet in terms of both in obtaining superior predictive accuracy and in defining the risk factors [6]. For this aim, a lot of the methods are developed, but most of them could achieve an accuracy in only a medium level [75]. Although researchers have defined a wide range of predictive models, there is no concurrence about the relative effects on survival estimation of these models have been [56]. To reduce the mortality rate in HF or to extend the duration of patient's survival, HF should be known in advance and predicted to be treated as soon as possible.

In 2017, Ahmad et al. [57] reported a study regarding 299 heart failure patients, who went to the Pakistan's Faisalabad Institute of Cardiology and Faisalabad Allied Hospital. They used time-dependent Cox regression [58], which a traditional biostatistics model is using far less associated variable than the "Seattle Heart Failure Model", and "Kaplan Meier" survival graphics [59] to estimate the ratio of the mortality of patients. Ahmad et al. made the data sets, analysis descriptions, and results publicly available online, and this provided the scientific community to freely access them [60]. Then, in 2019, Zahid et al. [61] analyzed the same data set for men and for women to detail a mortality estimation method based on gender.

Then, Wilstup et al. [10] defended that the combined version of Cox proportional hazards model with symbolic regression improved the ability to estimate survival due to HF. They used a new symbolic regression technique "QLattice" named to analyze the same dataset involving the recorded medical data of 299 patients that diagnosed with HF, and QLattice method was used with a Cox method to estimate death or survive.

Although these studies [57, 61] presented promising results, the problem was solved using standard bio statistical methods [76]. Such methods were insufficient for large-scale data sets [23]. Most researchers conducted their studies on HF patients using linear mixed method. However, Seid et al. [77] suggested that this linear mixed impact method applications and separate Weibull or semi-parametric (Cox) proportional hazard model analysis for such data are not appropriate when associating the changeable patient health status [19].

This situation motivated Chicco and Jurman [6] to develop machine learning models to estimate the death of patients with HF and to attempt to assist healthcare professionals. They defended that with the same data set of 299 patients, to estimate the survival of HF patients in advance using several data mining techniques with the machine learning methods which has best predictive performance can be achieved only based on two features. One of them was EF and the other was serum creatinine, which is known as an important biomarker in renal dysfunction related to HF in the literature [78–86]. With the Random Forest algorithm, which uses these two characteristics to estimate the survival of HF patients, the highest accuracy was achieved as 74% [6].

Ishak et al. [23] made analysis on the same data set using nine machine learning models, which are Logistic Regression (LR) [62], Gaussian Naive Bayes (G-NB) [63], Decision Tree (DT) [64], Random Forest (RF) [65], Extra Tree Classifier (ETC) [66], Adaptive Augmentation model (AdaBoost) [67], Gradient Boosting classifier (GBM) [68], Stochastic Gradient Descent (SGD) [69], and Support Vector Machine (SVM) [70]. They applied the SMOTE technique to solve the class imbalance problem. It was stated that the SMOTE method expressively developed the performance of tree-based classifiers in estimating the death or survive situation of cardiac patients, and an accuracy performance of 93% was concluded with this method.

Gürfidan [71] used 67% of the 299 data as training and 33% as test data and obtained the highest accuracy value as 83% with the Support Vector Machine among different algorithms. Rahayu [2] applied Artificial Neural Networks (ANN), DT, KNN, SVM, Naive Bayes (NB), and RF algorithms for again the same data set with the SMOTE and resample technique. As a result, he achieved the best accuracy of 94.31% with the RF algorithm using the resample technique.

When these studies were examined, although the machine learning methods were used on an anonymous dataset taken from international database, not so many algorithms as we suggest were tried. In addition, when the performance parameters of these studies in the literature are examined, it is seen that there is an improvement in terms of our study's results. It is understood that it makes contribution to the literature with this regard.

The rest of this research is designed as follows. Section 2 gives details about the components and of the presented approach and the framework of the network. The experimental settings are introduced in Sect. 3 too. The experimental outcomes are offered in Sect. 4 to verify the effectiveness and superiority of the machine learning algorithms. In Sect. 5, this paper is summarized and concluded.

3 Materials and methods

In this section, it will be presented details of the background on the basic components of the used dataset, the description and an overview of the various machine learning algorithms, and proposed approach.

3.1 Data description

Various factors have an effect on the life quality of HF patients. These include alterable and inalterable factors. The lifestyle habits such as smoking, physical inactivity, and alcohol consumption or health problems as drug use for lipid lowering or hypertensive, diabetes, systolic blood pressure, cardiomyopathy, and hormone treatment which are among alterable factors, were determined as critical factors for HF development [87]. However, genetic, age and gender were defined as inalterable agents [88]. These uncontrollable factors cause the development of symptoms such as pneumonia, pulmonary emboli, stroke, organ failure, death and disabilities [17].

In this study, the data set shared by Ahmad et al. [57] to be used at experimental studies regarding classification of death situations due to HF using machine learning algorithms according to measurement values and life information obtained from individuals, and consisting of recorded medical data of 299 HF patients, who presented to the Faisalabad Cardiology Institute and Allied Hospital in Faisalabad (Punjab, Pakistan) from April 2015 to December 2015, and was shared anonymously at international database UCI-Irvine Machine Learning Repository, was used [89].

105 of the patients constituting the data set were women and 194 of the patients constituting the data set were men, and the ages of the patients change between 40 and 95. The left-ventricular systolic dysfunction was existed in all of patients and they were presented in the class III or IV by means of the New York Heart Association (NYHA) in terms of HF stage [90]. This data set [57, 89] involves 12 features and target, which can be used to predict deaths due to HF; in other words, the status information of mortality realization. The 13 features aforementioned and their definitions are as follows:

1. Age; patient age, in years
2. Anemia; decrease in red blood cells or hemoglobin,
3. Creatinine; CPK enzyme levels in the blood (mcg/L),
4. Diabetes; whether the patient is diabetic,
5. Ejection fraction (EF); the percentage of blood that leaves the heart with each contraction
6. High blood pressure; whether the patient has hypertension
7. Platelets; platelets in the blood (kilo platelets/mL)
8. Serum creatinine; serum creatinine level in the blood (mg/dL)
9. Serum sodium; serum sodium level in the blood (mEq/L)
10. Sex (gender); male or female
11. Smoking; whether the patient smokes or not
12. Time; Patient follow-up time in days
13. Death event; death of the patient during the follow-up period

The features of age, serum creatinine, left-ventricular dysfunction, and pulmonary hypertension in the data set are numerical. In binary categorical (binary) features, "0" indicates that there is no risk factor and "1" indicates that there is a risk factor. Six of the features, including anemia, hypertension, diabetes, sex, smoking, and death event, were transformed as binary to make the data set usable for the classification task. The enrolling physician hypothesized that the patients whose hematocrit levels were less than 36% had anemia. Creatine phosphokinase (CPK) is an enzyme and refers to the level of CPK in the blood. When a muscle texture is harmed, CPK mixes in blood. Therefore, if the level of CPK is in high values in the patient's blood, it may indicate HF or traumatization. EF indicates the blood ratio that the left ventricle pumps as percent with each contraction. Serum creatinine is an organic residual that constituted by muscle metabolism [5]. Sodium is a mineral which provides muscles and nerves to function properly. The serum sodium test shows whether sodium presents at normal levels in patient's blood. In the blood, very low sodium level may stem from HF [5, 91, 92]. In this study, the status of death or survival used as classification target which indicates that a patient died or not in follow-up period that ranging from 4 to 285 days. This period is accepted as mean 130 days in this study. The survival (mortality = 0) and death (mortality = 1) status of the patient were expressed as binary.

When the data set was examined, it was seen that it was quite imbalanced [76, 93]. Regarding the data set imbalance, the data set has an imbalance of approximately 2:1 [93], since the number of patients surviving was 203 (% 67.89) and the number of patients who died was 96 (% 32.11) [5].

In the proposed model, in which the first 12 features were considered as independent variables and the last feature as dependent variable among these clinical features, the dependent variable part is anticipated by training the independent variables. The realized transaction is classification of anticipated value as 0 or 1.

3.2 Machine learning algorithms

Machine learning gives computers the ability of "learning from experiences", which is naturally found in humans. Machine learning algorithms use computation methods to "learn" information directly from data, without relying on a predetermined equation as a model. Algorithms adaptively improve their performances as the number of existing samples for learning increases [94]. Machine learning is basically to predict the future from past experiences [95]. The algorithms, which are used for plenty of aims such as classification, estimation, and forecasting forming [96], and can make effective and errorless estimation, consist of software design, which can learn rule from data, adapt to changes, and improve its performance with experience. The field of machine learning is computer programming by engaging with how to form computer programs that develop automatically with experience and using sample data or past experience to optimize performance [97]. When a machine improves its performance through experiences, it is considered that the machine has learned; the learning mentioned here requires computer models that keep the data and reveal beneficial samples [98].

The situations aiming to assign each input vector to discrete categories which have a finite number are handled as classification problem. In classification problems, the class specifies each element in the output space and the classifier specifies the algorithm which solves the problem of classification. In the literature, there are many algorithms used for classification in machine learning, such as DT, NB Classifier, ANNs, SVM, and KNN algorithms. Classification in other words, a classification model, is a mapping toward estimated classes from examples. Classification, which is also called as pattern recognition, is one of the most known and fundamental mission of machine learning and is used to combine an unknown part of data set with a known group. The purpose of classification, also known as inference from samples, is to develop a classifier that will obtain samples that have not been introduced to the algorithm before, with the highest accuracy, after the concept definition is obtained [99].

The idea that human intelligence can be transferred to the computers forms the basis of artificial intelligence studies. In this way, it is possible to benefit from many advantages such as fast processing capacity, portability, and easy copying offered by artificial intelligence compared to human intelligence. Moreover, these studies address problems that cannot be solved with classical mathematical equations and algorithms, such as determining whether a patient has cancer or not and detecting the risk status of a customer who comes to a bank. Machine learning is used in solving many different problems such as medical diagnosis, optical character detection, face recognition, spam e-mail filtering, understanding of speech language, partition of the customer, detection of swindle, and weather prediction [99]. When the studies in the literature are examined, it is seen that machine learning studies for classification are used in a wide diversity of fields such as customer risk analysis for bank loans, earthquake prediction, stock prediction, text classification, disease diagnosis, and genetic studies. In these areas, health is an important sector where machine learning studies are carried out and it is thought to benefit both doctors and patients if successful results are achieved. Rana et al. [100] support this idea by stating that machine learning algorithms and data mining method are increasingly applied in medicine and healthcare. Since the heart is the most vital organ on which human life depends, it is thought that the research on cardiovascular have a more special place in health.

In this study, classifier models with different structures were developed using the MATLAB programming language's machine learning toolbox to estimate the probability of death due to HF by looking at the characteristics of HF people such as age, sex, smoking, diabetes, and blood pressure. These models are the methods of multi-layered neural network, NB classifier, KNN algorithm, DT algorithms, and SVM, whose details are given below. All numerical results are obtained using MATLAB R2020 on an Intel processor under Windows 10 operating system.

3.2.1 Artificial neural networks (ANN)

The ANN structure, designed for artificial neural networks classification processes, was formed with 1, 2 and 3 hidden layers and modeled as a single output and feedback structure. It was tested in the range of hidden layers in the network with 12 input vectors and it was seen that the best result was obtained with 20 hidden layers. A classical neural network structure is given in Fig. 2.

3.2.2 Support vector machine (SVM)

The SVM classification method is a process which has two steps. In first step, the input of the classifier which is high dimensional is matched nonlinearly to another attribute space. In the second step, a new linear hyperplane is formed from this attribute space with the maximum portion to decorate the parts of the samples [5]. According to the mathematical model given in Eq. (1), "h" represents the hypothesis function, and the X and y parameters represent the classification dimensions. The point on or above the hyperplane is classified as + 1, and the point below the hyperplane is classified as − 1 [71]

$$h(x_i) = \begin{cases} -1, & \text{if } w \cdot x + b < 0 \\ +1, & \text{if } w \cdot x + bx \geq 0 \end{cases}. \quad (1)$$

In Eq. (2), n is the number of features, and w is a point in the hyperplane. Choosing a sufficiently small value for lambda is used in the soft-margin classifier, since it gives the precise boundary classifier for input data that can be classified linearly [71]

$$\left[\frac{1}{n}\sum_{i=1}^{n} \max(0, 1 - y_i(w \cdot x_i - b))\right] + \gamma\|w\|^2. \quad (2)$$

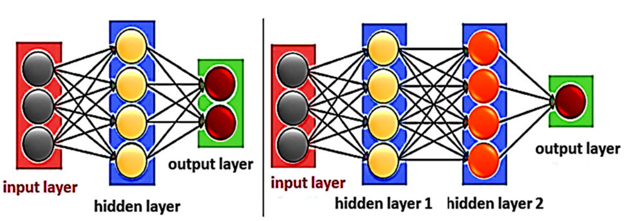

Fig. 2 Artificial neural network model with one (in left) and two (in right) hidden layers

3.2.3 Decision tree classifier algorithm

Tree-based learning algorithms which is one of the most used inspected algorithms are one of the data mining classification algorithms. In this method, a series of multiple decision trees are created for training a model. The DT structure resembles a flowchart that indicates a test on an attribute which is indicating the sample corresponding to each internal node. Each branch indicates the test result, and each node indicates a class. Each DT is formed with values that are choose from input data randomly. First, the entropy for the data set is calculated with H method shown in Eq. (3). Entropy, which is symbolized as $H(S)$, is the measure of the amount of uncertainty in the set of data. S is the existing set which is used to calculate the entropy. In S, C = {True, False}, is the classes set. The P function is the ratio of the number of elements in class "c" to the number of elements in the set S [71]

$$H(S) = \sum_{c \in C} -p(c) \log_2 p(c). \quad (3)$$

3.2.4 k-Nearest neighbor algorithm (KNN)

The basic principle of k-nearest neighbor algorithm in classification problems is that a selected K algorithm can detect the closest neighbor of the hidden data point. Then, it is assigned to the most obviously classified hidden data point. The data numbers refer to all K neighbor classes. The Euclidean equation shown in Eq. (4) is used to measure distances [71]

$$d(x, x') = \sqrt{(x - x_1)^2 + \cdots + (x - x_n)^2}. \quad (4)$$

At the end, x that is the input is appointed to the class with the highest probability. In Eq. (5), the variable x is defined to specify a feature, and y to specify the target. "K" in KNN is a hyperparameter and is effective in obtaining the optimal fit for the data set [71]

$$P(y = j | X = x) = \frac{1}{K}\sum_{i \in A} I\left(y^{(i)} = j\right). \quad (5)$$

3.2.5 Naive Bayes

NB is a classification model which is a statistical method, and is based on Bayes' theorem. As seen in Fig. 3, the NB classifier supposes that the effect of a specific attribute in the class is independent from the other attributes. Even if these attributes are interconnected, they are evaluated as independent. This supposition facilitates the calculation and is called naive for this reason. This assumption is also called class conditional independence [101].

3.3 Feature engineering

Machine learning algorithms learn from input data representing the problem. It is very important to feed the algorithm with the correct data for the solution of a specified problem. Even if the data are necessary and collected carefully, significant features should be included in the system in a specified format and sensitivity. To get this significant data format:

1. Data selection.
2. Data preprocessing.
3. Data transformation.

Transactions are applied. Data conversion steps are also called feature engineering.

By selecting a specific subset from the entire existing data set, “Data Selection” transaction is done. In general, there is a desire to select the entire data set that exists with the philosophy of ”much better“. This may not be true. It is necessary to know which data actually have an impact on the problem that needs to be solved. Data selection for important data can be done on assumptions and in the manner of confirming the assumption later. In this study, 70% of data were randomly selected for training and 30% of data for test set traditionally.

There are three widely used ”data preprocessing“ steps in the literature: cleaning, formatting, and sampling. These transactions are carried out, respectively, as follows: first, the unnecessary and missing data are cleaned from data. Then, a formatting process known as numerical values and normalization is performed on the cleaned data. Machine learning methods cannot work on text data. Inputs given to the network are converted into numerical values. Gender can be given as an example for this transformation (digitized as male = 1, female = 2). Subsequently, the normalization process is carried out to prevent the features applied to the inputs of the network from having a biased effect on the network. After ensuring that all inputs have a homogeneous effect on the network, the sampling transaction is carried out. Two common methods used here: traditional data segmentation and k-fold cross validation.

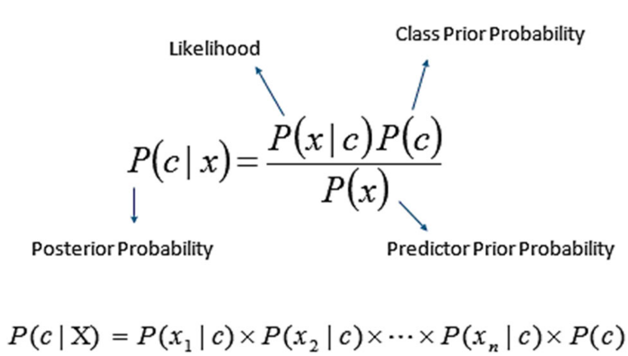

Fig. 3 Naive Bayes algorithms [101]

The last step is the ”data conversion” transaction which directly affects the problem area of the algorithm used. Multiple data transformation transactions may be needed in many studies. There are three general data transformation methods: scaling, feature decomposing, and combining. When the literature is examined, it is seen that the transactions of combining, decomposing, or scaling are done together in the preprocessing step of many problems.

It is the transaction of investigating the effects of features on the network after beginning with scaling transaction at the point of classifying the features within themselves and determining their characteristics. The principal component analysis (PCA) method is the primary of the most widely used methods here. PCA method is also a dimension reduction and feature extraction method that gives extensive results under the assumption that the data has a normally distribution. The combining transaction is based on the process of combining the entries involving similar characteristics during the feature. The algorithms such as deep learning perform these data conversion transactions as a closed box within themselves, but this transaction has to be done by an expert in machine learning algorithms.

In this study, we used the basic operations in feature engineering. No additional processing was done after a sample reduction process made by the database owner. In addition, we focused only on improving the performance of feature engineering on this dataset. The data operations were performed on the entire data set. Afterward, the data set was divided with different strategies for training and testing. In this way, possible statistical errors are prevented.

In the data selection step, the data selection transaction was carried out using the traditional validation method determined randomly and k-fold (threefold, fivefold) cross validation method, respectively. In this study, 203 samples for the traditional value method, 200 samples for the threefold-cross-validation method, and 239 samples for the fivefold-cross-validation method were used for the training process of the network. Then, for the testing process of the network, 96 samples for the traditional value method, 99 for the three-fold-cross-validation method, and 60 samples for the five-fold-cross-validation method were used, respectively. In the second step, all data preprocessing steps were performed automatically on the data set used. In addition, the scaling transaction, as a data transformation transaction, has been performed on the existing data set by the originator, and no operation has been performed at this step. However, in the third step, the PCA method was used in feature determination. For this purpose, 1, 2, and 3 feature dimension reduction combinations were tried during principal component analysis for 12 input data in the dataset and as a result of PCA processes the best size reduction performances are given in results. During these processes, general information in the literature was used to find the most accurate network parameters. For example, the number of hidden layer neurons is determined around 2 times the input layers number and the mean-square-error method was used to find the local minimums of the total-error. Since too many networks are used in the study, the parameters of each method and confusion matrix are not given. However, the performance of all networks was examined in parallel by applying the same feature engineering methods for all different methods of machine learning algorithms. The effect of applied feature engineering steps on performance is given in Table 1.

4 Experimental result

This section shows the survival estimation performance of the proposed machine learning algorithms. The assessment of the prognostic prediction performance is performed on the HF patients' dataset.

In this section, we predict whether the HF patient will survive or not by evaluating the artificial neural network results based on classification accuracy. For this purpose, a data set involving 13 features (12 Inputs–1 Output) and 299 samples was used. Traditional validation and k-fold cross validation approach have been used to evaluate the performance of the proposed algorithms. HF diagnostic data were tested with many different machine learning techniques to demonstrate the success of the study. For this purpose, Logistic Regression, NB, Linear SVM, Cubic SVM, Quadratic SVM, Fine Gauss SVM, Medium Gaussian SVM, Coarse Gaussian SVM, Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN, Subspace KNN, Boosted Trees, Bagged Trees, Fine Tree, Medium Tree, Coarse Tree, RUSBoosted Trees, Subspace Discriminant, and Multilayer Neural Network (with 1–2–3 hidden layer) methods have been tested, and the classification performance results obtained with different classifiers using all features (with PCA or not) are shown in Table 1.

For the same data set, the accuracy performance of the methods proposed in this study was more successful than other machine learning methods in the literature and an influential decision support system was designed which could successfully determine the survival of HF patients. Despite the imbalance in the data set, the Multilayer NN (with 2 hidden layer), Fine Gaussian SWM, Fine KNN, Weighted KNN, Subspace KNN, Boosted Trees, and Bagged Trees algorithms that showed the best performance in risk estimation has achieved a successful prediction score (100%).

When the performance analysis of different feature engineering methods on the data set is examined, the structure of used dataset is decisive. As seen in Table 1, it is understood that data segmentation reduces performance in all methods similarly. In addition, different parameter variations were tried in the PCA method and the best results are given in the table. When these results were examined, it was seen that it did not affect the performance much.

In machine learning method, the confusion matrix is used to interpret the performance of the used classification models. For comparing the predictions and actual values of the target attribute, the Confusion Matrices belonging to the most successful algorithm and the most unsuccessful algorithms among the applied algorithms are given in Figs. 4 and 5.

As seen in the Fig. 4, Fine Gaussian SVM algorithm confusion matrix, 299 of 299 samples were determined as a heart failure patient will survive truly and 0 as will not survive.

As seen in the Fig. 5, Coarse KNN algorithm confusion matrix, 286 of 299 samples were determined as a heart failure patient will survive truly and 13 as will not survive.

The receiver-operating characteristic (ROC) curve is a graphical plot which indicates the ability of a binary classifier system to classify as the discrimination threshold changes. The ROC curve obtained as a result of determining the algorithm performances. The ROC curves for the best-performing Fine Gaussian SVM algorithm and the worst-performing Coarse KNN algorithm are shown in Figs. 6 and 7, respectively.

The highest accuracy value achieved with this data set is 94.31% so far in the literature [71]. In this regard, the study becomes prominent among others. This difference between errors may be seen as insignificant for another practice field; however, it is thought that the same attitude is not possible for a significant subject such as determining life threat of patient.

As stated in the literature, SWM has worked efficiently on feature ordering with medical informatics data [6, 102, 103]. When the obtained results are examined, it is understood that the artificial neural network methods mentioned above have an extraordinary success in predicting whether an HF patient will survive or not. Thus, it was concluded that the study conducted with this current situation was successful and it was appropriate to use machine learning algorithms to estimate the survival of patients. In addition, this study has the potential to be used as a new support tool for doctors when estimating whether an HF patient will survive or not.

As a result, 27 different machine learning techniques were applied to heart failure problems and it was seen that 5 different methods achieved 100% accuracy performance.

Table 1 Machine learning techniques for comparison (%)

Machine learning models	TV		Threefold CV		Fivefold CV	
	PCA Disable	PCA Enable	PCA Disable	PCA Enable	PCA Disable	PCA Enable
Logistic Regression	85.6	84.9	81.6	81.6	82.3	82.6
Naïve Bayes (Kernel)	84.9	87.0	78.6	78.6	76.9	75.9
Naïve Bayes (Gaussian)	76.9	76.6	75.6	75.6	74.9	74.6
Linear SVM	84.6	83.3	82.3	82.3	81.3	80.9
Cubic SVM	98.0	99.0	72.9	72.6	71.9	75.9
Quadratic SVM	90.3	88.6	77.3	76.9	76.9	76.9
Fine Gaussian SVM	**100**	**100**	67.6	67.6	67.9	67.9
Medium Gaussian SVM	90.0	88.6	78.6	78.6	78.6	80.3
Coarse Gaussian SVM	78.6	77.9	74.2	74.2	75.3	73.9
Fine KNN	**100**	**100**	66.6	66.6	68.6	67.9
Medium KNN	78.6	78.6	74.6	74.6	74.9	75.6
Coarse KNN	69.2	68.2	67.9	67.9	68.9	68.2
Cosine KNN	77.6	77.9	74.9	74.9	74.2	75.3
Cubic KNN	79.6	78.3	71.9	71.9	73.2	73.9
Weighted KNN	**100**	**100**	73.9	73.9	74.2	73.2
Subspace KNN	**100**	**100**	58.5	59.9	62.5	60.5
Boosted Trees	**100**	**100**	79.3	79.3	82.3	81.3
Bagged Trees	**100**	**100**	84.3	84.6	82.9	83.9
Fine Tree	93.0	94.3	80.6	80.6	77.3	77.9
Medium Tree	92.6	94.0	80.6	80.6	77.3	78.3
Coarse Tree	86.3	86.0	82.3	82.3	82.9	80.6
RUSBoosted Trees	97.3	98.7	79.3	81.9	79.9	79.3
Subspace Discriminant	81.9	80.9	79.3	77.9	78.3	79.6
Multilayer NN (with 1 hidden layer)	92.6	91.7	80.6	80.6	82.3	81.7
Multilayer NN (with 2 hidden layer)	**100**	**100**	83.9	83.9	84.3	83.9
Multilayer NN (with 3 hidden layer)	96.3	97.4	82.3	80.6	83.9	82.3

TV, traditional validation; CV, cross validation

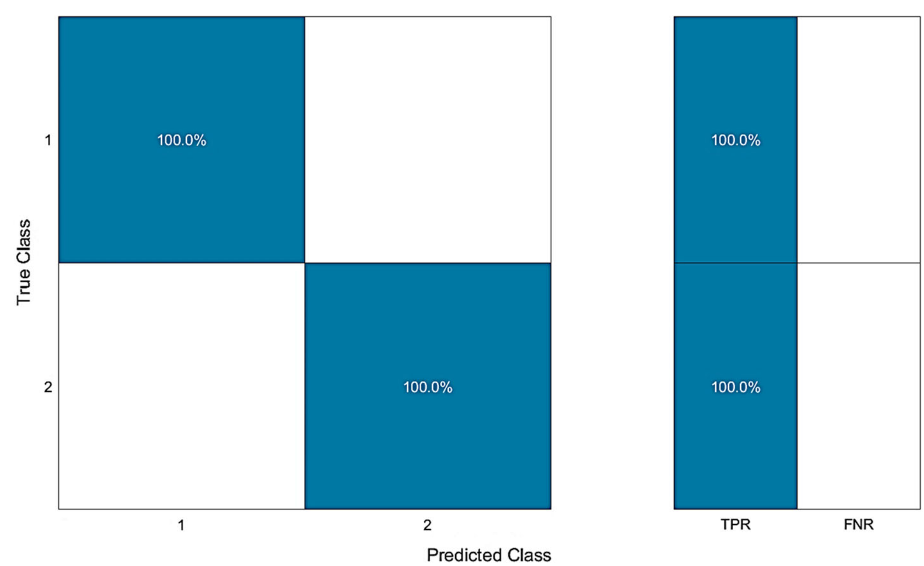

Fig. 4 Confusion matrix for the most successful Fine Gaussian SVM algorithm

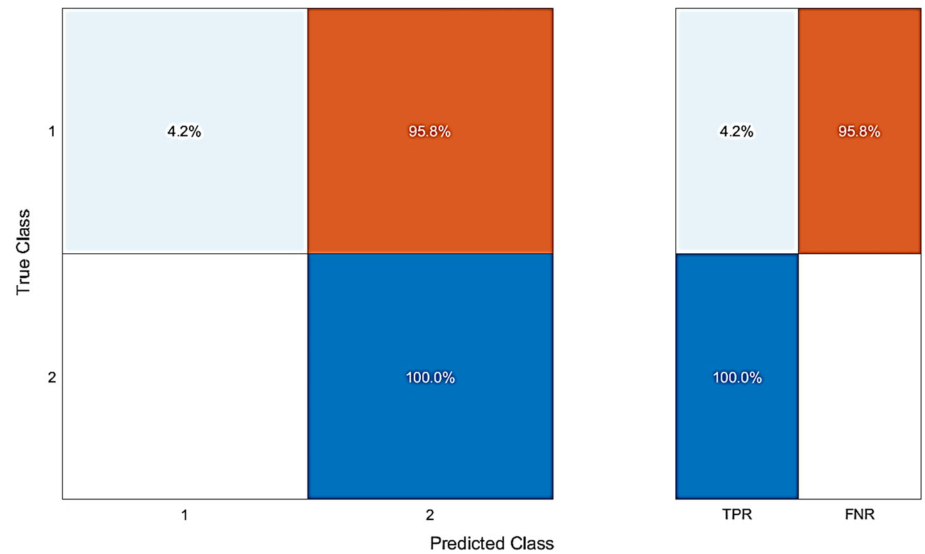

Fig. 5 Confusion matrix for the worst successful Coarse KNN algorithm

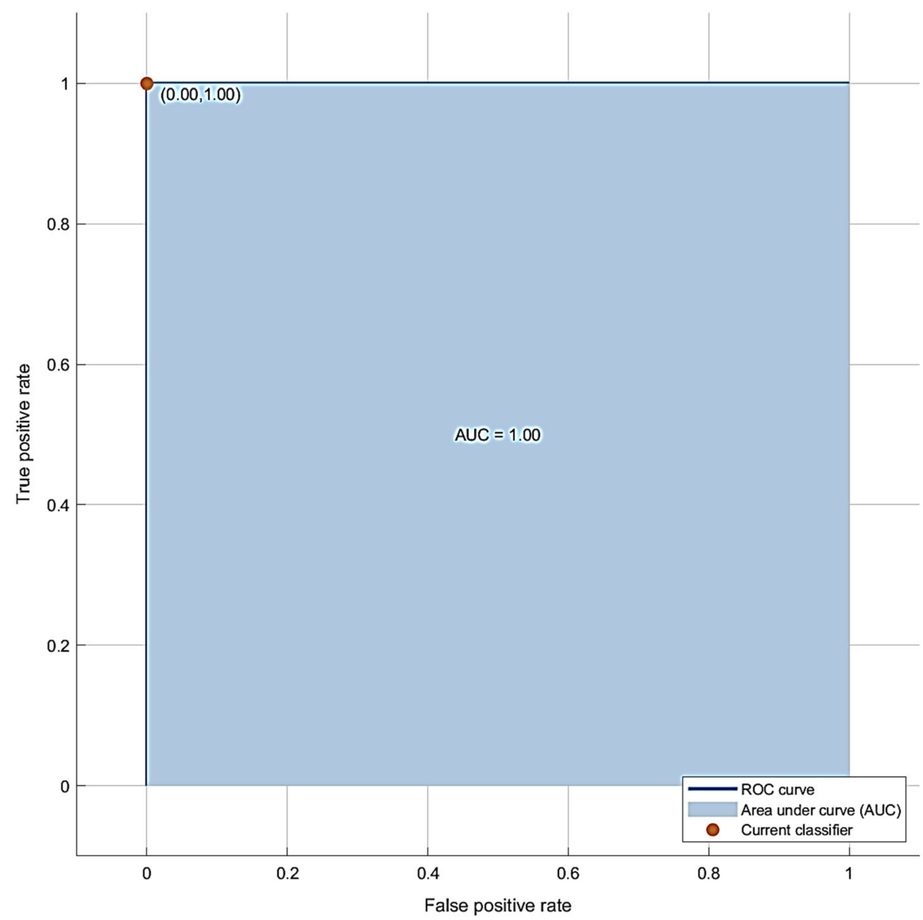

Fig. 6 ROC curve for the best-performing Fine Gaussian SVM algorithm

The success rates of other methods varies between 69.2% and 98.0%, and they cannot be underestimated. When these performances were examined, it was seen that machine learning algorithms could be integrated into applications as decision support systems for heart failure. It is recommended to use SVM methods for predicting mortality- survival status linked to heart failure due to its high accuracy prediction capability.

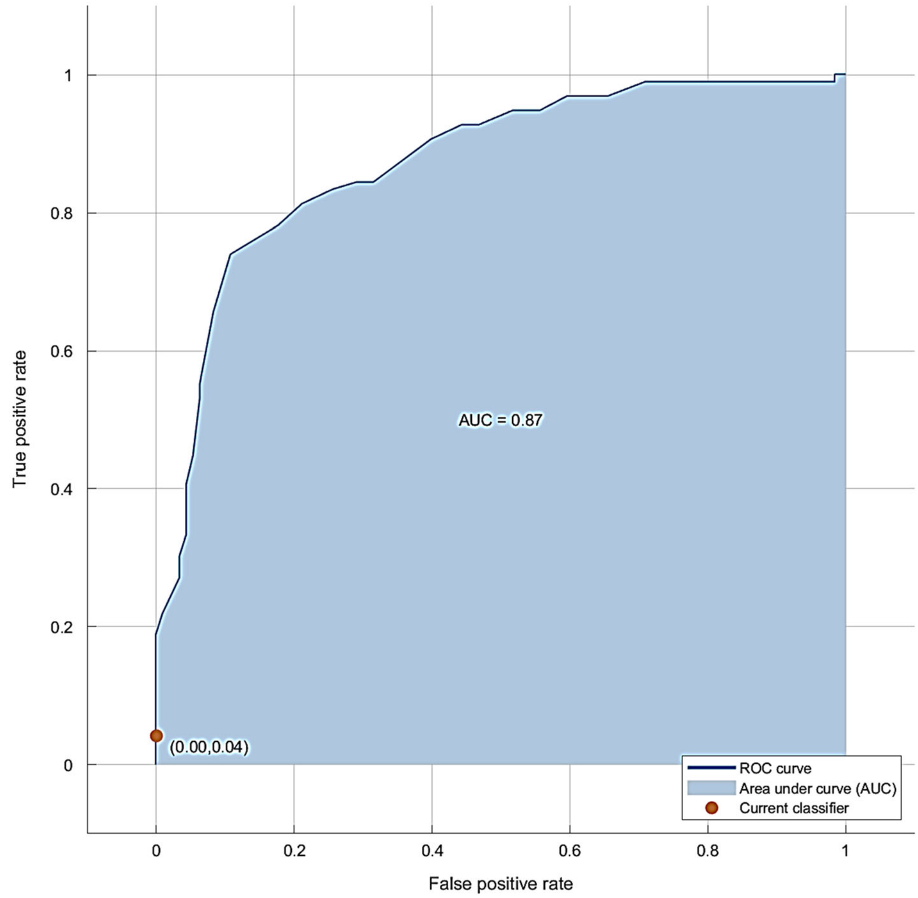

Fig. 7 ROC curve for the worst-performing Coarse KNN algorithm

5 Conclusion

HF patients have a penetrating death rate and doctors require confident prognostic estimations to make aware decisions for implementing of devices, transplantation, medications, and palliative care properly. In our unique research, which is considered as the application of Informatics Science in the health sector, prediction-based learning models and decision support systems learning from data were produced on cardio logical data set. It is aimed to contribute to the science by evaluating the risk of losing human life through these models.

In this study, all the features in the data set for a controlled classification problem in terms of mortality-survival prediction due to heart failure were classified by machine learning methods and predicted with 100% accuracy. In this respect, our study has shown that machine learning can be used effectual in the dual classification of health records of HF patients.

For comparison, different types of machine learning methods with different variants have been tried, and classification accuracy was achieved between 69 and 100%. It has been observed that the performances of Fine Gaussian SVM and KNN methods, which are among the machine learning methods, are maximum.

As a limitation of the current study, the small size of the data set (299 patients) and being imbalanced for classification should not be ignored. In addition, extra information about patients' physical characteristics such as body mass index, physical environment, blood type, and genotype which were not in the data set, could be useful for identifying supplementary risk factors for cardiovascular diseases. Therefore, it will be interesting to include a new data set, which will be formed with additional information obtained, to a prospective study. It is seen that the bias of the data set is not at a level that will affect the performance, and this problem can be solved by increasing the sample size of the data set; thus, feature engineering instead was carried out in this study. Feature engineering is suggested to solve such problems in similar studies.

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Declarations

Conflict of interest The authors of the article have no relationship (either financial or personal) with any people or organizations that can affect or bias the paper's contents.

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