Enhancing the Precision of Heart Disease Risk Prediction Using Mining & Classification Techniques

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ABSTRACT

Machine learning, is used to address a variety of data science issues. Predicting a result based on data that already exists is a popular use of machine learning. In order to anticipate the result, the machine applies patterns it has learned from the existing dataset to an unknown dataset. One effective machine learning method that is frequently used for prediction is classification. While some categorization systems show limited accuracy, others make predictions with satisfactory accuracy.

This work examines a technique called ensemble classification, which combines different classifiers, such as Random Forest Classifier and MLP Classifier to increase the accuracy of weak methods. A dataset on cardiac diseases was used to do experiments with this tool. In “addition to improving the accuracy of weak classification algorithms, this research demonstrates the algorithm's usefulness in disease prediction at an early stage by implementing it on a medical dataset.Results from this research show that ensemble methods, such as the bagging technique, perform satisfactorily in determining heart disease risk and are useful in increasing the prediction accuracy of weak classifiers.

A feature selection implementation significantly improved the process's performance, and the outcomes demonstrated a notable increase in prediction accuracy. Bagging is one of the ensemble strategies that improve prediction accuracy for Deep Neural Network (DNN) and long short-term memory” (LSTM), respectively. Ensemble classification helped weak classifiers achieve an accuracy gain of up to 10%.

Keywords: Cardiac disease, Machine learning, Ensemble classifier, Random Forest Classifier, MLP Classifier.

INTRODUCTION

Heart disease is the world's leading cause of death. [1] It is very difficult to identify and diagnose heart problems. [2] Machine learning has made medical data analysis easy and convenient. [3] In the early detection of cardiac disease, the ensemble learning approach offers a solution that enhances performance and produces better and more accurate results.

A machine learning method called ensemble learning makes use of several classifiers to improve the performance of our system. The ensemble learning framework includes the Random Forest classifier, MLP classifier, and bagging algorithm.Using ensemble learning increases prediction accuracy for heart disease detection since performance of the model is much higher than that of individual classification models when many classifiers are merged.

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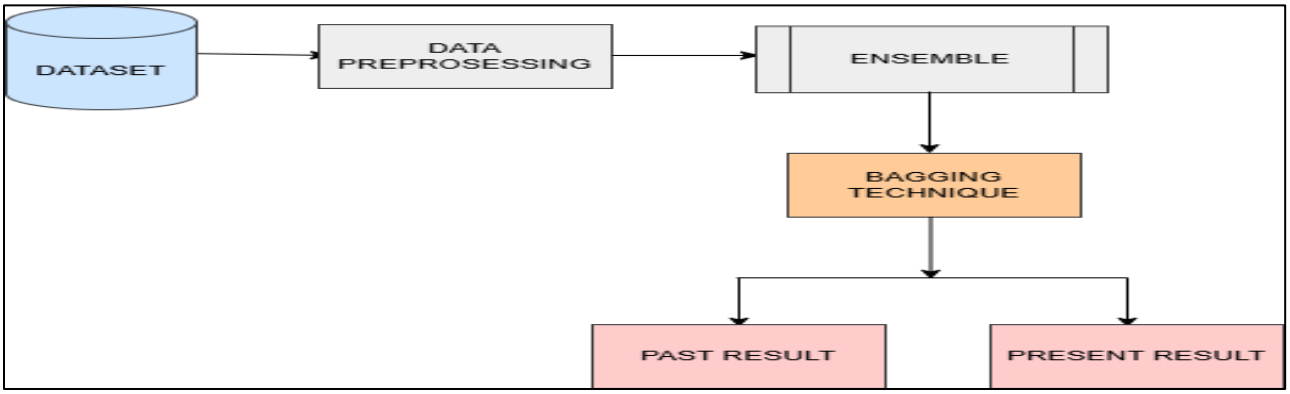


Fig. 1. A methodical flowchart illustrating the hybrid LSTM-DNN model-based heart attack prediction system.

In this "work, we use various machine learning(ML) and data mining classification techniques to increase accuracy of the classifier. In order to compensate for the drawbacks of each individual model, the ensemble machine learning technique has been used, which combines multiple models into a single predictive model that utilizes the benefits of multiple simple models, also known as weak learners. We intend to use an iterative ensemble technique to merge several low-performance classifiers to produce a powerful classifier" with high accuracy.

Factors other than accuracy should be considered when evaluating heart attack risk prediction systems. A thorough assessment should include a range of statistical measures to determine how well the model predicts heart attacks. By applying cutting-edge machine learning algorithms and reliable data preparation methods, this study closes the gaps in heart attack risk prediction methods. The hybrid technique shows that heart attack risk can be accurately calculated by combining complex algorithms with multiple data sources.

The following describes how the following sections are organized: The pertinent literature is reviewed in Section 2. This paper's methods and suggested model structure are explained "in Section 3. The empirical results are analyzed in Section 4. Section 5 concludes the work and addresses possible directions for further" investigation.

Related Work

Data mining and ML are practical methods for resolving a range of issues. These techniques are commonly used to predict a dependent variable based on the values of independent variables. The healthcare sector benefits greatly from data mining due to the vast amount of available data, which can be difficult to manage manually.

Mio et al. present their comparative study in [2] by applying their "ensemble technique for coronary heart disease prediction on four distinct datasets: the Hungarian Institute of Cardiology (HIC), Long Beach Medical Centre (LBMC), Switzerland University Hospital (SUH), and the Cleveland Clinic Foundation (CCF). According to the testing findings, model's accuracies—which are greater than those of previously published studies—are 80.14% for CCF, 89.12% for HIC, 77.78% for LBMC, and 96.72% for" SUH.

The optimal subset of clustering in the study indicates that the best ensemble approach, L-SVM-KNN-WMA, is utilized to overcome the bottleneck of weak learners and is typically much more accurate than base learners. [3] by Li H. et al., Yekkala et al., compared a number of ensemble methods in [4], such as "bagging, boosting (AdaBoost), and random forest. Particle swarm optimization (PSO) was utilized to choose features. The bagging tree yielded the best results for SVM (0.9652%). With an 88.7% prediction rate, Mohan et al.,'s hybrid model for heart disease prediction in [5] incorporates the random forest with the linear model (HRFLM).The hybrid" model has been used by the author to compare different algorithms. When compared to other individual classifiers, the suggested model has demonstrated the highest accuracy. In [6], it was shown that using neural networks and fuzzy logic-based evolutionary algorithms for feature extraction increased accuracy by 99.97%.

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In [7], a trained recurrent fuzzy neural network based on genetic algorithms achieved 97.78% accuracy for the diagnosis of cardiac illness. In [8], Rahma Atallah et al., [9] used an identical set-based "classification method with a varied dataset and achieved up to 93% classification accuracy in the forecast of heart disease risk. They combine multiple machine learning techniques using an ensemble approach to predict cardiac disease, predicting a person's likelihood of having heart disease and determining the majority vote using an ensemble method.[10] Xiao et al. proposed a deep residual neural network (DRNN) has been proposed. Compared to other ML techniques such as decision trees (68%), logistic regression (87%), naive bayes 80%, knearest neighbours (KNN) 60%, and random" forests (83%), the accuracy was almost 95%. In a similar vein, Chowdhary and Singh et al., utilized the decision tree (DT) algorithm in [11]. The Ada-Boost technique has been used to maximize DT output. When max_depth = (6), the model's accuracy was at its peak. The precision of the AdaBoost algorithm was 0.89.S.

Mohan and associates [12] created an efficient "hybrid random forest with a linear model (HRFLM) was created utilizing Cleveland dataset, which contains 297 records and 13 characteristics, in order to enhance the prediction precision of heart disease. According to their findings, the LM and RF techniques produced the best error rates. Kodatietal., S. Using the 280-item UCI dataset, V. Pavithra et al., [13] presented a brand-new hybrid feature selection method for the prediction of heart disease that combines random forest, AdaBoost, and linear correlation (HRFLC). Filter, wrapper, and" embedding procedures were used to pick eleven (11) features, resulting in a 2% rise in precision for hybrid model. An ensemble model for forecast of cardiac disease has been suggested by C. Gazelogluetal Lakshmanrao et al., [14]. Three sampling methods have been used to balance the uneven dataset. To select characteristics, two methods were employed: ANOVA and mutual information approaches. The two different datasets used in the experiments are the UCI and Kaggle datasets. M. Alshraideh et al., [15] investigate how the precision of heart disease risk forecasts is increased by ensemble classification techniques, which offer a customized framework integrating several elements such as medical history and demographic data. They experiment with a number of ensemble approaches, including bagging and boosting, as well as machine learning approach in order to determine the optimal strategy. Latha et al., concentrated on using ensemble techniques including majority voting, bagging, boosting, and stacking to rise prediction precision of weak classifiers in [16].

A weighted ageing ensemble (WAE) classifier-based ensemble model for heart disease forecasts was presented by Mieyne et al., in [17]. This model was created using a variety of CART models. The datasets from Framingham and Cleveland were used. The dataset was divided at random using the mean splitting-based approach. An ensemble classifier utilizing the CART decision tree approach, support vector machines (SVM), modified k nearest neighbor (M-KNN), and k nearest neighbor (KNN) was proposed by Kumar et al. in [18] for the forecast of cardiac disease. In terms of precision, the ensemble approach outperformed the individual classifiers. A cardiac disease prediction monitoring system for smart healthcare was proposed by Ali et al. in [19]. The ensemble technique effect than the individual classifiers in terms of accuracy.

Accuracy was raised to 98.38% by Priyanka Gupta et al. in [20] utilizing the bagging methods of feature selection and hyperparameter tweaking.

Mustafa Jan et al. proposed utilizing a model with many classifiers to improve prediction accuracy in their ensemble method to create a smart heart disease forecast system utilizing classification algorithms in [21]. The recurrence of cardiovascular disease was predicted and identified in this research using ensemble learning, which includes five classifier "model approaches: support vector machines, artificial neural networks, Naïve Bayesian, regression analysis, and random" forests. The results that Beulah Christalin Lath et al., and colleagues reported in [22]. To find out how the ensemble strategy could improve accuracy with weak classifiers by up to 7%, a comparative analytical approach was conducted. According to [23] Abdullah Alqahtan et al., the suggested ML ensemble model predicts cardiovascular sickness with the maximum disease forecast precision of 88.70% using (ML) and deep learning (DL) models with six classification algorithms.
Originally put forth by Narendra Kumar Sharma et al. in [24], the ensemble machine learning approach integrates several models "into a single predictive model that makes use of the benefits of several basic models—often referred to as weak learners—to offset the defects of each" individual model.

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Karna Vishnu Vardhana Redd et al., suggest in [25While the maximum accuracy number utilizing the ideal attribute set generated by "the chi-squared attribute evaluator was 86.468%, sequential minimum optimization (SMO) obtained an accuracy of 85.148% utilizing the entire set of attributes. By setting the hyperparameter "k" to 9 with the chi-squared attribute set, the meta classifier bagging with logistic regression (LR) achieved the greatest ROC area of 0.91 utilizing both the entire and optimal attribute sets acquired by the Relief attribute evaluator. Accuracy" increased by 8.25% as a result. Our research concentrated on merging weak classification algorithms with other classification methods in order to mitigate their shortcomings. This enhances both the effectiveness of such categorization algorithms and the forecast accuracy for heart disease. Utilizing ensemble processes like bagging, boosting, majority voting, and stacking, research is carried out and findings analyzed. Findings have significantly better when feature selection is used. The results provide an indication of how successfully these classifiers might be used in a certain domain.

METHOD AND METHODOLOGY

The supervised learning method for forecasting the result from available data is classification. In order to increase the classification precision, this research suggests a method for diagnosing heart disease combining classification algorithms and an ensemble of classifiers[4]. Every stage of the hybrid LSTM-DNN model's heart attack risk prediction process is covered by the suggested "system flow diagram, which is displayed in fig. 1. These steps include data preparation, feature extraction and selection, model training, assessment, and forecast. After the dataset was separated into a training set and a test set, individual classifiers were trained using the training dataset. Efficacy of the classifiers is assessed using test" dataset.

Fig. 1 illustrates a flow diagram of hybrid LSTM-DNN model with attention mechanism utilized in the heart attack prediction system.

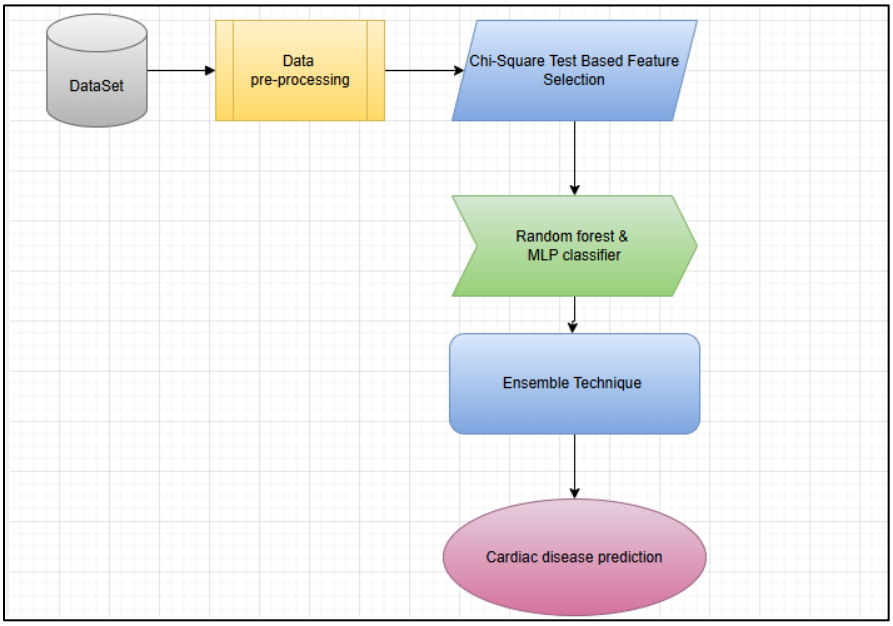


Figure 1:A proposed approach for cardiovascular disease detection

Dataset

The Heart Failure Prediction dataset from Kaggle, the Kaggle dataset is used here for undergo a number of crucial pre-processing processes in order to be suitable for analysis and modeling. The first phase is dealing with missing values, where a method for interpolation, imputation, or elimination is selected according to the kind and volume of missing data in each column. To make sure that every attribute conforms to the designated data type, as stated in the attribute table, data type conversion is then applied. For each category, nominal variables like "PCP" are converted into binary columns by one-hot encoding, whilst categorical

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variables like "PSex" and "PExang" are encoded using numerical representations. The given ordinal scale is followed when mapping ordinal variables, such as "PSlope of ST," to numerical values.

To obtain a consistent scale, numerical features like "PAge," "Test BPS," "PChol," "Thalach," "Old peak," and "pca" are normalized or standardized. This is important for several machine learning methods. During modelling, binary features such as "FBPS" can be scaled to avoid dominance. To prevent multi-colinearity, dummy variables included during one-hot encoding are carefully controlled. Numerical feature outliers are found and dealt with, either by transformation or removal. The alignment of categorical values with designated ranges and categories is ensured by a comprehensive data consistency evaluation. To evaluate distribution and correct for imbalances, target variable analysis is carried out. In order to improve predictive skills, feature engineering—the creation or modification of features based on domain knowledge—is also taken into consideration. Lastly, To assess the model, the dataset is separated into training and testing sets., if applicable. Together, these processes create a well-prepared dataset that serves as the foundation for accurate and dependable modelling outcomes. The following table compiles the feature types for each dataset.

Table 1:Heart Disease Prediction set using from Kaggle

S.No.	Attribute	Parameter
1.	**Pt_Age**	Patient_Age.
2.	**Pt_Sex**	Patient_Gender.
3.	**Pt_CP**	The patient's chest pain experience
4.	**Test Pt B_P_S**	The patient's blood pressure level
5.	**Pt_Chol**	Patient cholesterol-level
6.	**Pt_F_BP_S**	The patient's fasting blood sugar level is higher than 120 mg/dL.
7.	**Pt_Rest_ECG**	The patient's electrocardiogram results
8.	**Pt_Thala_ch**	The maximum heart rate that a patient could obtain during exercise testing.
9.	**Pt_Exang**	The patient experienced angina throughout the exercise testing. (Categorial) A patient's ST depression during an ECG.
10.	**Pt_Old-peak**	The ST-segment slope of the patient's ECG readings
11.	**Pt_Slope of S_T**	The number of patient vessels seen in fluoroscopy images.
12.	**Pt_c_a**	The outcome of the patient's stress test for Thallium.
13.	**Thal_Pt**	If the patient has received a diagnosis of cardiac illness.
14.	**Pt_Target**	The patient's status regarding a heart disease diagnosis is unknown.

Data Pre-Processing

The initial step was pre-processing, which included cleaning the data and handling null and missing values. The data was cleansed of any discrepancies.Framingham dataset used in this study has missing values that must be addressed. Duplicate values in the dataset were examined.

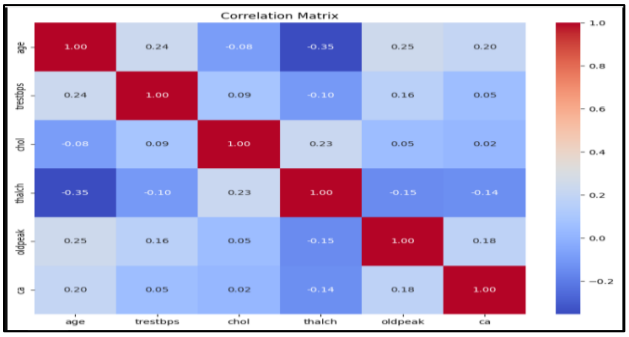


Figure 2:Correlation Matrix

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As shown in Fig. 2, the correlation matrix is utilized to determine link between the elements in order to reduce redundant, duplicate features from the data. The range of the correlation coefficient is -1 to 1. The features are tightly connected and have a considerable impact on performance “if the value is close to 1, and adversely correlated if it is close to -1 [5]. To determine the correlation, we set the threshold values at 0.85%; if the correlation value is higher than the threshold, the feature is disregarded; if it is lower, the feature is kept. After the" feature correlation analysis, every characteristic is the same.

Outlier Detection and Elimination

Finding observations in a dataset that deviate from the norm and are significantly distinct from the other values is known as outlier detection. We refer to them as outliers. Precision of the model is increased by removing the outliers. Box plots were utilized in this investigation to identify the outliers. The total cholesterol and systolic blood pressure columns have been found to contain outliers[6,7]. From these columns, the outliers were eliminated.

Data Balancing

Dataset has now examined to determine its balance. Negative cases were found to be significantly more prevalent than positive cases. The dataset was therefore extremely unbalanced and must be balanced to avoid issues during model fitting. The dataset was balanced in this instance by using the Random forest approach. To make them equal to the majority class, the minority class's number of instances was raised.

Chi-Square Test Based Feature Selection

Feature selection is essential since it improves the model's prediction accuracy. Because there are fewer features, the model is lighter. Both training time and memory usage are also reduced. The features in this research were chosen from the dataset using the chi-square test approach. The dataset has fourteen attributes. For the six best characteristics in the dataset, chi-square test results were determined. The better qualities were chosen using these scores, which are shown in downward order. Six of the top chracteristics out of 14 were taken into consideration. The features are arranged in descending order in Fig. 2 based on their chi-square test results[22].

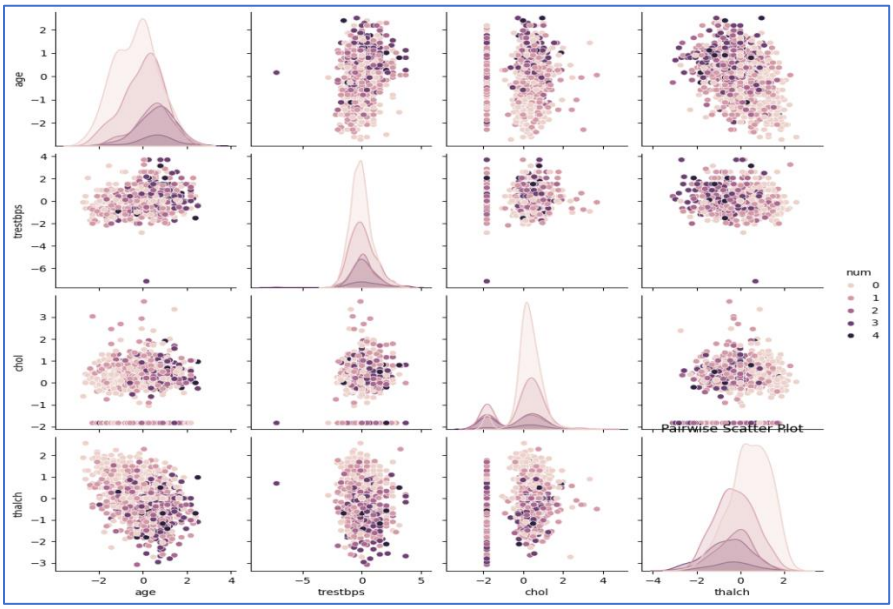


Figure 3: Association Analysis of CDV dataset

Classification and ensemble algorithms

A supervised learning method called classification uses the data at hand to generate predictions. This paper suggests a strategy for diagnosing heart disease that uses an ensemble of classifiers and classification

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algorithms to increase classification accuracy. Individual classifiers are trained on the training dataset and subsequently separated into a training set and a test set. Test dataset is utilized to examine classifiers' performance.

DNN

Deep neural networks are made up of multiple layers, each with numerous neurons. Each node obtains a higher input value by combining its weights and capacities, and an activation function processes the total[10]. The signal is then divided by this function to permit more propagation. The output of one layer in a deep neural network becomes input for a following forward-oriented layer, and layers in the network can be turned on or off. Typically, an artificial neural network has one input, one output, and at most one hidden layer. However, deep neural networks require a number of hidden layers in order to function properly.

1.Initialize the input layer using the input data.

2. Calculate each hidden layer's weighted input total.

a)Include a bias term in the weighted sum.

b) Examine the result using an activation function.

3.Calculate the weighted sum of the inputs for the output layer.

4.Include a bias term in the weighted sum.

5. Use an activation function to run the result and obtain the network's output.

LSTM

Long Short-Term “Memory networks (LSTMs) are made up of input, output, and forget gates that control the information flow within the network, as well as memory cells that have the capacity to store data for extended periods of time[11]. By enabling selective update and retention of information across several time steps, these gates allow LSTMs to effectively capture temporal patterns and dependencies in sequences. LSTMs are consequently well suited for tasks like speech recognition, natural language processing, and time series prediction since successful modelling relies on an understanding of context and long-term relationships. The LSTM architecture was developed to effectively capture long-range dependencies in sequential data” and address the vanishing gradient problem.

The steps of the LSTM algorithm are as follows:

Step 1: Using appropriate vectors for every input, compile data from the LSTM sequence length.

Step 2: Set both the hidden and cell states to zeros or extremely tiny random values. The LSTM requires initialization of a set of weights and biases.

Step 3: Determine how much of the prior cell state to forget by calculating the forget gate. The weight matrix, bias, and sigmoid function of the forget gate are calculated using sigma.

Step 4: Determine the input gate's value, which establishes the amount of newly acquired data that must be maintained in the cell state. to discover the input gate's weight matrix and bias.

Step 5: Determine which new cell state—also referred to as the candidate cell state—is being proposed. the bias weight matrix and the condition of the candidate cell.

Step 6: Use the input and output gates to combine the desired cell state with the prior cell state in order to update the cell state. Where it indicates element-wise multiplication, it is calculated.

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Step 7: Determine how much of "the cell state should be output as the concealed state by calculating the output gate. Sigma is computed along with the weight matrix and bias of the output gate.

Step 8: Output: Apply the output gate to the cell state in order to ascertain the concealed state.

Step 9: To generate the final hidden states, repeat steps 3 through 8 for each time step in the input sequence. The" final hidden states of the neural network can be transferred to other layers or utilized for prediction.

Ensemble Techniques

Precision of a classifier can be enhanced by using the ensemble technique. An effective meta categorization technique that boosts the effectiveness of the weak learner is to combine strong and weak learners. Precision of several algorithms for forecasting heart disease is increased in this study by utilizing the ensemble method. The purpose of combining multiple classifiers is to enhance effectiveness as opposed to using each classifier alone. Combining several machine learning models to enhance overall prediction performance is known as ensemble modeling. The fundamental premise is that one strong student might emerge from a group of weak learners. There are usually two steps in an ensemble model: Several machine learning models are trained separately. Some method, like voting, averaging, or weighting, is used to combine their forecasts. The overall prediction is then made using this ensemble.

Ensembles tend to produce better results since the many models compliment one another and overcome their particular flaws. Additionally, they avoid overfitting and lower variance. To improve accuracy and robustness, ensemble learning is widely employed in machine learning applications such as clustering, regression, and classification.

Bagging

Bootstrap aggregation is another name for bagging. Bagging uses replacement to choose a limited number of patterns at random from training set. New training set has some repetitions and omissions, but it has the same amount of structures as previous training set. We refer to the new training set as Bootstrap replicate. The classifier is trained using bootstrap samples extracted from the data in the in-bagging process. Either average or majority voting is used to decide the classification outcome after adding the votes from each classifier. Bagging has been shown to be an effective technique for improving a weak classifier's performance.

Bagging lowers prediction variance by generating multiple sets of data from random samples of the original dataset with replacement. In Fig. 4, the bagging method is shown.

```
Let D={d1,d2,d3, ...  dn} be the given dataset
E = {}, the set of ensemble classifiers
C = {c1, c2, c3, ...cn}, the set of classifiers
X = the training set, X €D
Y = the test set, Y€ D
L = n(D)
for i =1 to L do
S(i) = {Bootstrap sample I with replacement}  I€ X
M(i) = Model trained using C(i) on S(i)
E = E U C(i)
next i
for i = 1 to L
R(i) = Y classified by E(i)
next i
Result = max(R(i): i=1,2, ..., n)
```

Figure 4: Bagging algorithm

Random Forest

A machine-learning method called RF builds several decision trees with training data sets to produce a classification model. By choosing a tree based on the majority of selections, this method offers exceptional accuracy when working with big data sets. This method combines two feature selection strategies—random selection and bagging—to produce an ensemble model that is more effective. By employing several trees,

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the RF approach minimizes training time and the possibility of overfitting. It also offers estimates for significant classification variables and missing data, all of which improve accuracy.

Random Forest Algorithm

Step 1: From "a data set with k records, n random records are selected for Random Forest.

Step 2: For every sample, a separate decision tree is built.

Step 3: An output will be produced by each decision tree.

Step 4: For classification and regression, the final output is examined utilizing either majority voting or" averaging.

Multi-Layer Perceptron(MLP)

Both the hidden and other layers of the multilayer perceptron technique make use of artificial neurons. In situations involving binary classification, several techniques are employed. There is an activation function for every perceptron neuron. Algorithms modeled after real neurons are called multilayer perceptrons. They make use of perceptrons, which are artificial neurons. There are only two layers because the activation function maps each neuron's weighted inputs. By altering the weights that are allocated to it, a perceptron can learn. In Fig. 5, the MLP algorithm is shown.

Initialize weights and biases in N, where N is the Network
while *condition is true {*
for *each training tuple* $\boldsymbol{X}$ *in D {*
for *each input layer unit j {*
$O_j = I_j$
for *each hidden or output layer unit j {*
$I_j = \sum_i W_{ij} O_i + \theta_j$
$O_j = \frac{1}{1 + e^{-I_j}}$
for *each unit j in the output layer*
$Err_j = O_j(1 - O_j)(T_j - O_j)$
for *each unit j in the hidden layers, from the last to the first hidden layer*
$Err_j = O_j(1 - O_j) \sum_k Err_k w_{jk}$
for *each weight* w_{ij} *in N {*
$\Delta w_{ij} = (l) Err_i O_i$
$w_{ij} = w_{ij} + \Delta w_{ij}\}$
for *each bias* θ_j *in N {*
$\Delta \theta_j = (l) Err_j$
$\theta_j = \theta_j + \Delta \theta_j$
}}

Figure 5:MLP algorithm

Metrics Used

The matrix can be used in research to examined the efficiency of the suggested technique performs. It contingent on test data's real values. The size of the matrix varies with the classes. The matrix structure uses rows to shows forecast values and columns to show actual values. Table 1 below displays sample confusion matrix, where TP stands for True Positive and indicates total no. of disease data that were categorized as CVD positive. Total quantity of illness data that are now categorized as CVD negative but are actually CVD positive is known as False Negative, or FN.

The overall number of illness data that are currently categorized as CVD negative is produced by the True Negative (TN) algorithm. The term False Positive (FP) describes the total number of disease records that are currently categorized as CVD negative but are in fact classified as positive. The confusion matrix provides support for accuracy, precision, recall, F1-score, and other model effectiveness indicators.

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Accuracy: The ratio of all correctly identified samples to all samples is known as accuracy.

$$\text{ACCURACY} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} * 100$$

Precision: Determines the proportion of correctly predicted positive classes.

$$\text{PRECISION} = \frac{\text{TP}}{\text{TP+FP}} * 100$$

Recall: Determines a single score that takes precision and recall problems into consideration.

$$\text{RECALL} = \frac{\text{TP}}{\text{TP+FN}} * 100$$

The F1-score determines how many accurate class predictions there are based on the database's positive instances.

$$\text{F1 SCORE} = \frac{(2 * \text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

The "ratio of correctly predicted to total evaluation is used to calculate accuracy. It represents the overall preciseness of the model. This work assesses the efficacy of DNN and MNN for cardiovascular disease using the previously described measures. Accuracy is defined as the ratio of correctly predicted observations to total observations. It represents the overall preciseness of the model. This study assesses the" efficacy of DNN and LSTM for cardiovascular disease using the aforementioned metrics.

RESULTS AND DISCUSSIONS

In this section, Findings are briefly described, and the baseline approaches are compared. The primary aim "of this work is to analyze the classification efficiency of proposed ML classifiers for detecting cardiovascular diseases. The Cardiovascular Disease dataset is utilized for conducting the experiments in this" investigation. There are two steps used to conduct the experiments. The first step in reaching enhanced results is adoption of ML models. We developed an ensemble model based on machine learning that did well on the provided dataset. This is done to produce more dependable outcomes. In order to improve ML outcomes, we experimented with stacked ensemble models in the second stage. Accuracy, precision, recall, F1 score, and confusion matrix had been among efficiency metrics employed in this work. Dataset is separated into two sections: 30% is used for model testing, and 70% is used for model training.

LSTM CONFUSION MATRIX

TARGET / OUTPUT	Class0	Class1	Class2	Class3	Class4	SUM
Class0	57 30.98%	18 9.78%	0 0.00%	0 0.00%	0 0.00%	75 76.00% 24.00%
Class1	21 11.41%	33 17.93%	0 0.00%	0 0.00%	0 0.00%	54 61.11% 38.89%
Class2	6 3.26%	19 10.33%	0 0.00%	0 0.00%	0 0.00%	25 0.00% 100.00%
Class3	5 2.72%	21 11.41%	0 0.00%	0 0.00%	0 0.00%	26 0.00% 100.00%
Class4	1 0.54%	3 1.63%	0 0.00%	0 0.00%	0 0.00%	4 0.00% 100.00%
SUM	90 63.33% 36.67%	94 35.11% 64.89%	0 0.00% 0.00%	0 0.00% 0.00%	0 0.00% 0.00%	90 / 184 48.91% 51.09%

Figure 6:Confusion matrix of LSTM

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Experimental Results: Findings of ML classifiers used to determine whether cardiovascular disease exists are illustrates in Table 2. Performance of several classification methods on the CDV dataset was examined and contrasted. The association analysis of the CDV dataset is displayed in Figure 3. While some classifiers have performed well, some have not.

DNN CONFUSION MATRIX

TARGET / OUTPUT	Class0	Class1	Class2	Class3	Class4	SUM
Class0	89 43.20%	3 1.46%	0 0.00%	0 0.00%	0 0.00%	92 96.74% 3.26%
Class1	4 1.94%	87 42.23%	0 0.00%	0 0.00%	0 0.00%	91 95.60% 4.40%
Class2	5 2.43%	3 1.46%	0 0.00%	0 0.00%	0 0.00%	8 0.00% 100.00%
Class3	0 0.00%	11 5.34%	0 0.00%	0 0.00%	0 0.00%	11 0.00% 100.00%
Class4	0 0.00%	4 1.94%	0 0.00%	0 0.00%	0 0.00%	4 0.00% 100.00%
SUM	98 90.82% 9.18%	108 80.56% 19.44%	0 0.00% 0.00%	0 0.00% 0.00%	0 0.00% 0.00%	176 / 206 85.44% 14.56%

Figure 7:Confusion matrix of DNN

The confusion matrix of the RF and MLP classifier, where diagonal values are correctly classified, is displayed in Figures 4 and 5. Figure 6 displays the outcomes of the ML model in the second phase of experiments. Models performed admirably. Compared to the LSTM model, the DNN model achieves maximum accuracy. DNN model's accuracy, precision, recall, F1 score, and score are 85.04%, 90.05%, 96.02%, and 93.03%, respectively.

To acquire final findings in this study, an RF and MLP stacked classifier and a machine learning ensemble classifier are employed. Out of all the classifiers, this one has the highest accuracy (85%). However, the stacked classifier did not function well due to the lack of data. Figures 7 and 8 display proposed ML Ensemble classifier's confusion matrix. Findings demonstrate that using the Cardiovascular Disease dataset, the suggested ML ensemble classifier can effectively identify the existence of cardiovascular disease. Findings of the ensemble machine learning model that uses ML to identify cardiovascular illness are illustrate in Table 4.

Table 2: ML Ensemble performance of CDV

Metrics	**DNN**	**LSTM**
F1 Score	93	69
Precision	90	63
Recall	96	76
Accuracy	85	49

The stacked LSTM classifier obtained an F1 score of 69.01%, accuracy of 49.05%, precision of 63.05%, and recall of 76.02%. The DNN classifier obtains 85.04%, 90.05%, 96.02%, and 93.03% accuracy, precision, recall, and F1 score. In conclusion, when it came to identifying cardiovascular illness, the ML model performed the best.

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Machine Learning Ensemble Classifier.

Researchers employed ensemble learning to handle a variety of ML challenges [22, 23]. To differentiate

between various diseases and properly classify data, an ensemble learning approach is utilized because each dataset has a diverse spectrum of issues. Every classifier in the ensemble makes a class labe prediction whenever a new data point is received. Using a weighted majority approach, the suggested ML ensemble classifier develops the results based on estimation of many classifiers. The best findings are presented after each classification model has been adjusted. However, the ensemble approach was employed in this study to identify the weak classifier and enhance accuracy. DNN and LSTM yielded the best comparative results in the ensemble approach.

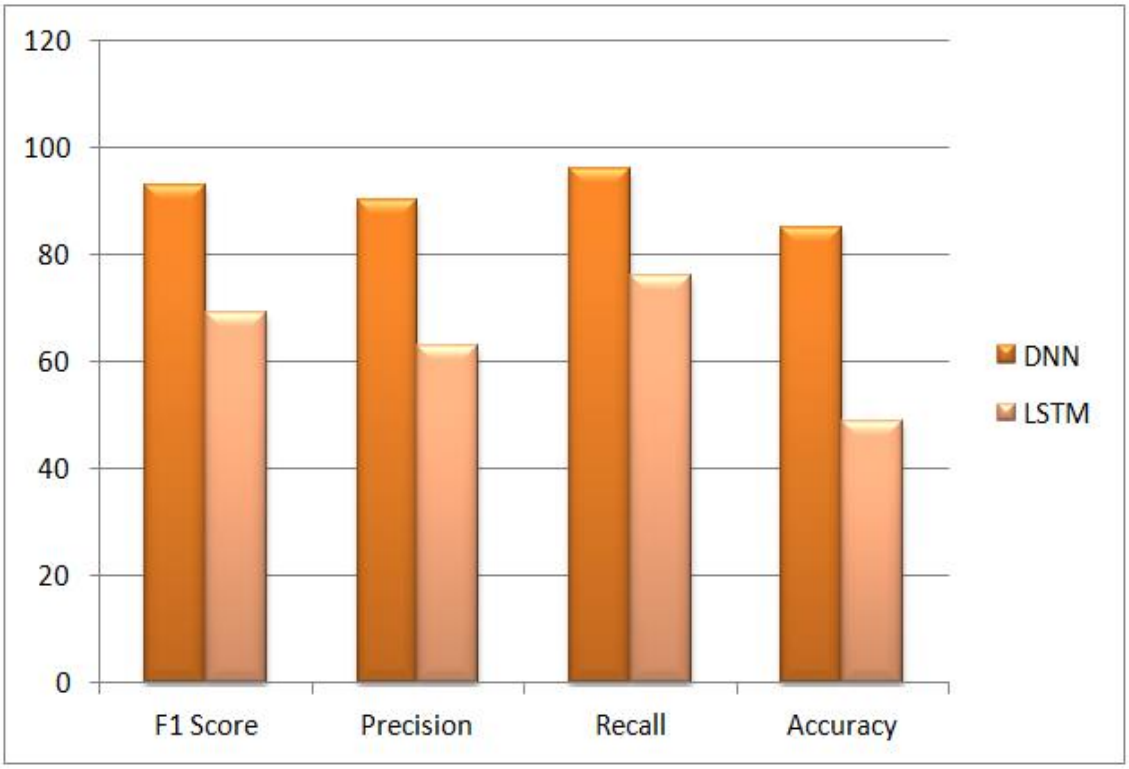


Figure 8: Improvement in accuracy of classifier with bagging

CONCLUSION

This research analyzes precision of predicting cardiac disease using an ensemble of classifiers. Training and testing were conducted using the Kaggle heart dataset. For the experiments, the bagging ensemble techniques were used. The accuracy increased by up to 85.04% when bagging was utilized. Using DNN to ensemble the weak classifiers boosted accuracy by up to 10.04%, and using LSTM stacking enhanced accuracy by up to 4.93%.. The greatest increase in accuracy is achieved via majority voting, according to a comparison of outcomes.

Feature selection approaches were used to further improve the performance. The feature selection strategies improved ensemble algorithms' accuracy. Highest accuracy was achieved by majority voting using the feature set SMOTE method.

Data Availability: The article contains the data on cardiovascular disease that were utilized to support the study's conclusions.

Conflicts of Interest: NIL

Disclosure: NIL.

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