# An Approach of Predicting Heart Disease Using a Hybrid Neural Network and Decision Tree

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## ABSTRACT
Heart disease is one of the leading cause deaths of worldwide. Prediction of cardiovascular infection is a critical challenge in the area of clinical data analysis. Data mining techniques are providing an effective decision and significant results on data that are used widely for predicting. The purpose of this paper is to propose a novel approach with aims to find a noteworthy method to diagnose heart disease prediction. In this research, a unique dataset was created by combining the Cleveland dataset and Stalog heart disease datasets collected from the UCI ML repository. The new dataset contains 14 medical parameters such as age, sex, blood pressure, and 568 instances for training and prediction heart disease. This paper offers a novel methodology of NNDT (Neural Network and Decision Tree) that uses Neural Network for training model and Decision Tree to test classification for better heart disease prediction. The performance of the proposed approach have been compared with Naïve Bayes, Support Vector Machine, Neural Network, Voted Perceptron, and Decision Tree algorithms. The results showed that the accuracy and performance improved as compared to other techniques and methods. This study enables the researchers to analyze the heart disease data with a new approach to predict heart diseases to maintain human health.

## CCS Concepts
**•Computing methodologies→Machine learning→Machine learning approaches→Classification and regression trees**

## Keywords
Data Mining; Neural Network; Decision Tree; Prediction method; Heart Disease; Prediction Heart disease.



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## 1. INTRODUCTION
Heart disease according to WHO statistics is the number one killer [1]. Every year several millions of people die from heart disease, and a large population of people suffers from heart disease.

Medical research has identified several factors that increase the risk of a heart attack. These includes two categories, one of which cannot be changed, such as gender, age, and family history, other categories depend on people's lifestyles, such as smoking, high cholesterol, high blood pressure, and physical inactivity that can be changed. The latter are risk factors that can be remedied by changing lifestyle and medication, and in some cases, can be eliminated [2].

Predicting heart disease plays a crucial role in its treatment. Prediction can help to predict heart diseases earlier, avoiding the death of many patients and providing more accurate and efficient treatments. The need for improving the medical diagnosis system is increasing day by day. Furthermore, the main reasons for medical diagnostics systems are cost savings and getting more accurate rates efficiently.

Invasive-based for diagnosing heart disease are based on patient history analysis, physical examination reports, and symptom analysis by medical professionals. Often due to human errors, the results are delayed. Besides, it is more expensive and computationally complex and takes much time in evaluations [3].

To address these complexities in the aggressive-based diagnosis of heart disease, a non-invasive medical decision support system based on Data Mining prediction models such as Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), Artificial Neural Network (ANN), Decision Tree (DT), Logistic Regression (LR), Adaboost (AB), Naive Bayes (NB), and rough set [4, 5]. It has been extensively developed by various researchers to diagnose heart disease, which is used to diagnose heart disease. This has reduced mortality from heart disease [6]. In a comparison between a neural network, Naïve Bayes, and decision tree algorithm, Soni et al. found that the decision tree was the most accurate of the three in CHD prediction [7].

In the last decade, different hybrid diagnostic systems based on features preprocessing and ANN have been developed to improve the classification accuracy. These diagnostic systems have improved the quality of decision making during the diagnosis of patients by physicians. The study of these automated diagnostic systems also motivated us to propose novel approaches for predicting heart disease by using a neural network with a decision tree.

The remaining parts of the paper are structured as follow: in section 2, related work regarding heart disease and prediction are highlighted. In section 3, the proposed approach and experiments are discussed. In section 4, there is evaluation of experiment results. Finally, in section 5, this work is concluded.

## 2. LITERATURE REVIEW

In the last few decades, data has been generated in large scale of volumes from diverse fields, including health care services (HCS) and medical fields [8]. State of the art machine learning techniques has been applied to obtain knowledge from the health care data for research and make effective predictions and decision for heart disease diagnosis. Machine learning (ML) methods have drawn that aim to solve the different medical and clinical problems [9].

Detrano et al. [10] proposed a logistic regression classifier-based decision support system for heart disease classification and obtained a classification accuracy of 77%. The Cleveland dataset used [11] with global evolutionary approaches and achieved high prediction performance in accuracy. The study used feature selection methods for the selection of features. Therefore, the classification performance of the approach depends on the selected features. Gudadhe et al. [12] used multilayer perceptron (MLP) and support vector machine algorithms for heart disease classification. They proposed a classification system and obtained an accuracy of 80.41%. Kahramanli and Allahverdi [13] designed a heart disease classification system that used a hybrid technique in which a neural network integrates a fuzzy neural network and artificial neural network. Furthermore, the proposed classification system achieved a classification accuracy of 87.4%. Palaniappan [14].

The data of heart disease patients collected from the UCI laboratory is used to discover patterns with NN, DT, Support Vector machines SVM, and Naive Bayes. The results are compared for performance and accuracy with these algorithms. The proposed hybrid method returns results of 86.8% for F - measure, competing with the other existing methods [15]. The classification without segmentation of Convolutional Neural Networks (CNN) is introduced. This method considers the heart cycles with various start positions from the Electrocardiogram (ECG) signals in the training phase. CNN is able to generate features with various positions in the testing phase of the patient [16], [17]. A large amount of data generated by the medical industry has not been used effectively previously. The new approaches presented here decrease the cost and improve the prediction of heart disease in an easy and effective way. The various different research techniques considered in this work for prediction and classification of heart disease using ML and deep learning (DL) techniques are highly accurate in establishing the efficacy of these methods [18], [19].

Olaniyi and Oyedotun [20] proposed a three-phase model based on the ANN to diagnose heart disease in angina and achieved a classification accuracy of 88.89%. Moreover, the proposed system could be easily deployed in healthcare information systems. Das et al. [21] proposed an ANN ensemble-based predictive model that diagnoses the heart disease and used statistical analysis system enterprise miner 5.2 with the classification system and achieved 89.01% accuracy, 80.09% sensitivity, and 95.91% specificity. Jabbar et al. [22] designed a diagnostic system for heart disease and used a machine learning classifier multilayer perceptron ANN-driven backpropagation learning algorithm and feature selection algorithm. The proposed system gives excellent performance in terms of accuracy. In order to diagnose heart disease, an integrated decision support medical system based on ANN and Fuzzy AHP were designed by the authors in [23], which utilizes a machine learning algorithm, artificial neural network, and Fuzzy analytical hierarchical processing.

The decision tree appears to be one of the most accurate algorithms among data mining tools in CHD. Alizadehsani et al. used four different algorithms for the classification of 303 CHD records with 54 attributes. They found that among the Bagging, SMO, Neural network, and Naïve Bayes methods, the highest accuracy was 89% for the Bagging or SMO methods [24]. In a comparison between a neural network, Naïve Bayes, and decision tree algorithm, Soni et al. found that the decision tree was the most accurate of the three in CHD prediction [7].

## 3. PROPOSED APPROACH AND EXPERIMENT

Figure 1. Depicts the conceptual diagram of proposed approach.

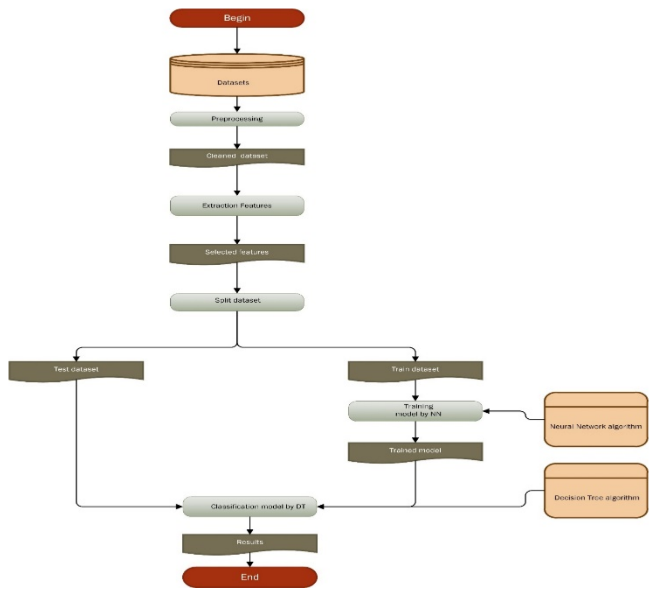


**Figure 1. Proposed Approach.**

As shown in Figure 1, the input of the approach is a collected dataset, the main 5 steps are preprocessing, extracting features, splitting dataset, training model by NN, and classification model by DT. The different parts of the modules will be described in more detail in the following.

### 3.1 Dataset

This work used two different datasets from the UCI Machine Learning repository [26], one is Cleveland heart disease, another is Statlog Heart disease dataset. The StaLog heart disease dataset consists of 270 records, and Cleveland Heart Disease has 303 records. The datasets are in a different format, and data separated in different ways. The Cleveland dataset uses the "," as the separator while the Stalog dataset uses the "space." In Stalog dataset, the number attribute is showing by values 1 and 2. Value 1 is <50% diameter reduction (meaning 'no heart disease'), and value 2 is >50% diameter reduction ('meaning have heart disease'). In Cleveland, there are values '0' and 1-4, value 0, meaning the absence of heart disease and values 1-4 showing the presence of heart disease.

## 3.2 Preprocessing

The datasets are merged together and the format of the combined dataset is changed to rdf. All data separated by space and the dataset consist a total of 573 records. Initially, dataset had 76 attributes for this paper only 14 attributes are required others will be ignore. The description of values attributes is displayed in table 1. The heart disease datasets include six records with some missing values. Those six records have been removed, and the remaining 567 records are used.

**Table 1. Dataset with standard attributes after combining.**

| Num | attribute | Description | values |
|---|---|---|---|
| 1 | age | age in years | continuous |
| 2 | sex | Male or female | male =1, female=0 |
| 3 | cp | chest pain type | Value 1= typical angina<br>Value 2= atypical angina<br>value 3= non-anginal pain<br>Value 4= asymptomatic |
| 4 | trestbps | resting blood pressure | Measured in mm Hg |
| 5 | chol | Cholestoral | serum cholestoral |
| 6 | fbs | fasting blood | 1 = true, 0 = false) |
| 7 | restecg | resting electrocardiog raphic results | Value0: normal restecg<br>Value1:ST-T wave is abnormal. T wave or ST elevation is bigger than 0.5 mV<br>Value2: probable or definite left ventricular hypertrophy criteria is given |
| 8 | thalach | maximum heart rate achieved | Continuous values |
| 9 | exang | exercise induced angina | 1 = yes, 0 = no |
| 10 | oldpeak | ST depression induced by exercise relative to rest | Continuous values |
| 11 | slope | the slope of the peak exercise ST segment | Value 1= upsloping<br>Value 2= flat<br>Value 3= downsloping |
| 12 | ca | number of major vessels | Values from 0 to 3 |
| 13 | thal | thallasemia | Value3= normal<br>Value6= fixed defect<br>Value7= reversible defect |
| 14 | num | diagnosis of heart disease | Diagnosis of heart disease<br>Value1= smaller than 50% diameter<br>Value2= over 50% diameter |

## 3.3 Feature Extraction

There are two features age and gender among 14 features that are used for personal identification information of the patient. The remaining features are considered essential because they contain critical clinical records. The patient's clinical records for the diagnosis and learning of the severity of heart disease are vital. As before mentioned in this experiment, a new method that is hybrid of decision tree and neural network is used. Also, the same features are used in this experiment for traditional methods like Naïve Bayes, Support Vector, Neural Network, Voted Perceptron, and Decision Tree.

## 3.4 Split Datasets

The heart disease dataset for this research after preprocessing includes a total of 567 instances. Here, the dataset needs to be split into two parts: testing dataset containing 40% and training dataset containing 60% of the total dataset.

## 3.5 Neural Network (NN)

A first neural network is applied to trained data for the training model. The training process began with the observation of the training error curves, and as soon as the training error decreased, the training process ended. In this work, there are 13 attributes for the input layer; input layer nodes are equal to the number of input features. The number of hidden layers started by two nodes, and it increased one by one until it reached to the number of nodes of the input layer. Then the hidden layer error stopped to decrease has been selected. The hidden layer with seven numbers is stopped to decrease error, and it has been selected for the experiment. Figure 3 is the trained model visualized with seven hidden layer.

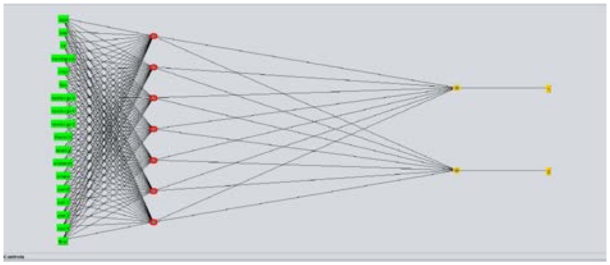

**Figure 3. Training model visualized with seven hidden layer.**

The results from the training process create the weight of the link between the input node and the hidden layer. They are specifying the intrusion power that input properties helps the nodes in the first hidden layer. The output layer includes 2 nodes that are displaying whether it has heart disease or not have heart disease. The result produced a transfer to the decision tree.

## 3.6 Decision Tree (DT)

Then model was applied decision tree C4.5 rule for testing quality of classification. In this work decision tree specify the information obtained from attributes in the dataset, sort the information obtained in decreasing order, select best attribute of the dataset as the root of the tree, calculate obtained information with the same formula, divide the nodes by the highest amount of information obtained, and repeat this process to set each attribute as a leaf node in tree branches. Figure 4 is showing the visualization of a decision tree with nodes and their relationship classification.

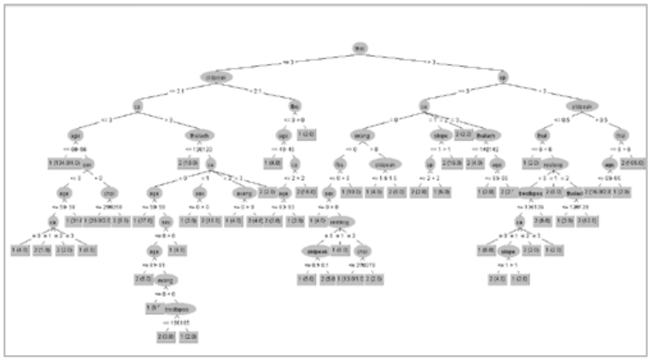

**Figure 2. Decision tree rules.**

Nodes shows us the attributes, the root node is Thal, and branches are showing the relationship between attributes. There is a direct relationship between age and the risk of heart disease. Older men have a higher risk of developing heart disease. There is a relationship between the type of chest pain, resting blood pressure, maximum heart rate, and risk of heart disease. However, if chest pain is type 4, there is no correlation between resting blood pressure, maximum heart rate, and risk of heart disease. There is also a hypothesis that resting blood pressure is only related to the maximum heart rate and risk of heart disease. Cholesterol, fasting blood sugar, and exercise-induced angina are associated with a risk of heart disease. There is a relationship between resting ECG, oldpeak, slope, and the risk of getting heart disease. The number of vascular traits, thalassemia, and type of chest pain is associated with the risk of heart disease.

# 4. EVALUATION

## 4.1 Performance of Various Methods

In table 2 and figure 5, there are the results of performance details of naïve bayes, support vector, voted perceptron, neural network and decision tree, and the performance details of the proposed method, which are experimented using datasets on Weka 3.8 version. Accuracy is not always a real measure of the performance of a classifier. The proposed approach needed to look at some other criteria like precision, recall, f-measure, and ROC, to make sure the model is reliable. Precision-Recall is a useful measure of success of prediction. In information retrieval, precision is a measure of result relevancy, while recall is a measure of how many genuinely relevant results are returned. F-measure is a harmonic mean between precision and recall [21, 22].

Sensitivity is defined as the ratio of people who are correct to heart disease and the number of people who have heart disease. Specificity is defined as the ratio between the number of people who are correctly identified as healthy and the number of actually healthy people. The amount of people having heart disease is the amount of true-positive test results plus the amount of false-negative test results. The amount of actually healthy people is the amount of true-negative test results plus the amount of false-positive test results. The ROC curve plots the true positive rate on the y-axis versus the false positive rate (attribute) on the x-axis (sensitivity). The true positive rate (TPR) is the recall, and the false positive rate (FPR) is the probability of alarm.

**Table 2. Performance of various methods**

| Models Name | precision | Recall | F-measure | Sensitivity | Specificity | ROC area |
|---|---|---|---|---|---|---|
| Naïve Byes | 84.4 | 89.8 | 87.0 | 89.8 | 79.0 | 90.4 |
| Support vector | 82.4 | 88.2 | 85.2 | 88.2 | 76.0 | 82.1 |
| Voted perceptron | 69.1 | 81.1 | 74.6 | 81.1 | 54.0 | 68.6 |
| Neural Network | 87.3 | 86.6 | 87.0 | 86.6 | 84.0 | 88.9 |
| Decision Tree | 87.3 | 86.6 | 87.0 | 86.6 | 84.0 | 88.9 |
| NNDT | 99.2 | 98.4 | 98.7 | 98.4 | 99.0 | 99.9 |

## 4.2 Confusion Matrix

The confusion matrix represents the performance display information about the number of correctly and incorrectly instances for each classifier [23]. Table 3 shows that in confusion matrix for each method, each classifier generate a 2*2 confusion matrix for two possible outcomes (one is Positive, and another is Negative). True positive (TP) is showing the number of instances classified as true when, in reality, they are true. True negative (TN) is displaying the number of instances classified as false when, in reality, they are true. False-positive (FP) is showing the number of instances classified as true when, in reality, they are false. True negative (TN) is displaying the number of instances classified as false when, in reality, they are false [24]. To analysis the confusion matrix, need to be consider the following performance parameters:

Precision= (TP) / (TP+FP)

Recall = (TP) / (TP + FN)

F-MEASURE= (2 * Precision * Recall)/ (Precision + Recall)

Sensitivity = (TP)/ (TP+FN)

Specificity = (TN)/ (TN+FP)

**Table 3. Confusion matrix**

| | | | | |
|---|---|---|---|---|
| **Naïve Byes** | TP | 114 | FN | 13 |
| | FP | 21 | TN | 79 |
| **Support vector** | TP | 112 | FN | 15 |
| | FP | 24 | TN | 76 |
| **Voted perceptron** | TP | 103 | FN | 24 |
| | FP | 46 | TN | 54 |
| **Neural Network** | TP | 110 | FN | 17 |
| | FP | 16 | TN | 84 |
| **Decision Tree** | TP | 110 | FN | 17 |
| | FP | 16 | TN | 84 |
| **Proposed method** | TP | 126 | FN | 2 |
| | FP | 1 | TN | 98 |

## 5. RESULT

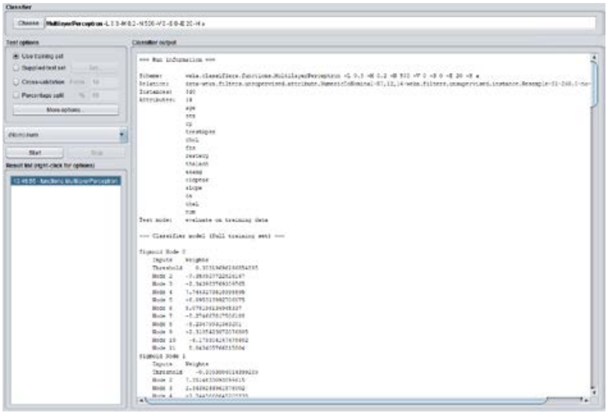

**Figure 6. Trained model by Neural Network.**

Figure 6, shows details of training model with neural network. The training model with neural network has been started with initial 340 instances which is 60% of total dataset. The training model has 11 nodes and every node contain inputs. There is a sigmoid function for every node and size of weights for inputs in sigmoid function are initialized automatically by Weka. There are two class and their inputs are node 1 and node 2.

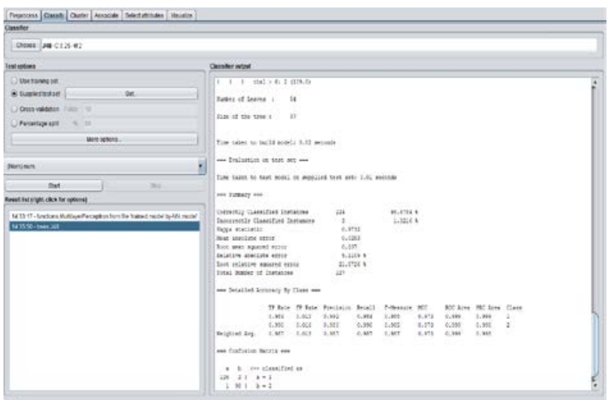

**Figure 7. Classified by decision tree.**

In Figure.7 the result of classifying test model by decision tree is shown. Test model has been started by loading the trained model and supplied test dataset. Test dataset includes 227 instances which is 40% of total dataset. In the result of testing classification there are 224 instances correctly classified and 3 instances are incorrectly classified. The decision tree algorithm built the model in 0.01 seconds and the time to taken test on supplied test dataset is 0.01 seconds. Here, the size of tree is 97 and it contain 54 leaves.

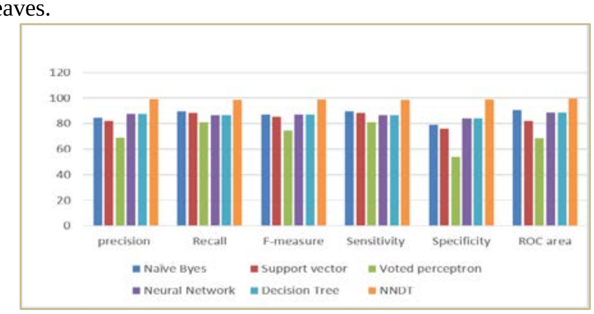


**Figure5. Performance of various methods.**

Table 2, in details, and figure 5 visualize further validation of the improved performance of our proposed method (NNDT) and results of comparison with other methods of data mining like: naïve bayes, support vector, voted perceptron, neural network and decision tree by using the same dataset. Figure 5, shows that the performance of the proposed method (NNDT) is higher than others and voted perception is lowest.

## 6. CONCLUSION

Predicting and early detection of heart disease can prevent dangerous consequences. It allows physicians to do this at the right time if treatment is needed. This saves the lives of many people who suffer from heart disease. In this work, we proposed a novel approach for improving performance and increasing the accuracy of prediction by collecting data from the UCI repository. The novel approach for predicting heart disease is combining neural networks with a decision tree. The comparison result of this research shows that the proposed method has the highest performance result compared to other methods and the voted perceptron has the least performance. Future work in this approach can be used for actual real-time data from hospitals that can be built using big data. Researchers can use this technique for analyzing and predicting real patients. Furthermore, the future work of this research can use different data mining techniques for improving implementation and increasing the accuracy of prediction.

## 7. ACKNOWLEDGMENTS

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