Heart Failure Detection Using Artificial Neural Network and Decision Tree Model

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A B S T R A C T

Heart failure is one of the leading causes of death in the world. The function of the heart is directly impacted by this illness. This disorder results in ineffective delivery and circulation of nutrients and oxygen. In this work, a deep learning (DL) model that uses patient checkup records to forecast heart failure states is developed. Compared to machine learning models, deep learning can produce more accurate results since it can handle complex and massive amounts of data.Because of its excellent compatibility with numerical and categorical data, we employ artificial neural networks (ANNs), which can be helpful in obtaining optimal features from patient data.

Keywords: Deep Learning, ANN, Machine Learning, Heart Failure

1. INTRODUCTION

The heart is a vital component of the human body that is responsible for pumping blood throughout the circulatory system. It works as a muscle pump that removes waste materials and carbon dioxide from the blood while ensuring that oxygen-rich blood reaches all of the organs and tissues. The heart, which is positioned somewhat to the left of the chest, is essential to maintaining life. Heart failure (HF) is a disorder in which the heart is unable to pump blood efficiently, resulting in cardiac issues [1][2]. Forecasting and early diagnosis are essential for improving patient outcomes and survival rates. Conventional techniques for predicting heart failure frequently struggle to handle complicated medical data and identify nonlinear correlations. Nevertheless, deep learning methods have surfaced as viable substitutes, providing improved predictive power. However, it is important to distinguish between heart failure (HF) and a heart attack. A blood clot blocking one of the heart's arteries causes HA, which hinders the heart's capacity to pump blood efficiently. Oxygen deprivation may occur throughout the body as a result of the heart's inability to pump oxygenated blood to tissues in such circumstances. Usually, the severity of the heart attack determines how severe this circulatory insufficiency will be. One of the most common causes of heart failure is a heart attack (HA). Hypertension (high blood pressure), coronary artery disease, inflammation of the heart, cardiomyopathy, or abnormal heart rhythms are major causes of heart failure. Other factors, such abrupt shocks or high levels of stress, can also cause heart failure or a heart attack. By their very nature, these occurrences are unexpected. An AI subfield called deep learning is used to identify patterns in big datasets. Artificial neural networks (ANNs), which function similarly to the human brain, are the most crucial component of the deep learning idea. Each layer of neurons in the network that makes up an ANN processes information before sending it on to the next layer. Artificial neural networks (ANNs) are able to extract complicated characteristics, such as image identification, natural language processing, and in this case, heat failure prediction, thanks to their hierarchical structure. In addition to handling large and diverse datasets and accounting for a wide range of clinical variables, the primary benefit of artificial neural networks

(ANNs) is their ability to capture the non-linear association between the various factors, which results in a more accurate depiction of the underlying biological process involved in heart failure.

2. LITERATURE REVIEW

To increase model accuracy, a range of machine learning and deep learning techniques have been ext ensively researched in the literature. These techniques include support vector machines, decision tree s, and artificial neural networks.

C. B. Rjeily :- In this study[2] the author uses CPT+ algorithm for predicting the heart failure based upon the Cleveland dataset, which is consists of 207 rows, This dataset size may not sufficient to predict the heart failure in all cases worldwide and the CPT+ algorithm may takes high computational cost when worked on larger datasets. The CPT+ reported an accuracy of 90.5%.

Shouman M :- This study[4] uses the Cleveland Heart Diseases Dataset with only 297 records, which may not applicable to larger population. Finding the initial K value in K-Means is challenging, affecting the clustering performance. However, the author uses inlier, outlier and range methods for selecting the initial centroids. These methods may lead's to mixed cases being grouped together, because this methods finding the initial centroids based upon on the smallest and largest values of attributes, increasing the risk of misclassification. However the model accuracy obtained is 83.9%.

Priyanga :- This study uses the heart diseases dataset with only 303 records, limiting generalization. It relies on the naïve Bayes model, which assumes feature independence, a potentially unrealistic assumption for correlated medical data. The reported accuracy of 86 % is not compared with more advanced models[5].

Abdalla Mahgoub:- This study proposes two different comparative machine learning approaches to predict heart diseases cases in unknown data[1]. The reported an average accuracy of Multilayer perceptron is 85.49%. more specifically, the Relu activation functions gives better accuracy than other activation functions. According to the author analysis the Multi Layer perceptron yields better performance than other machine learning algorithms such as KNN, Logistic Regression and Naïve bayes.

Marbaniang :- The study compares six machine learning for cardiovascular disease prediction, showing that KNN delivered the highest accuracy of 72.91%, succeeded by Random Forest at 72.12%. The drawbacks include computational time variations, with SVM being computationally expensive in terms of and naïve bayes having lower accuracy of 60.1%. Adding BMI and Blood Pressure as features improved accuracy slightly [9].

H. Agrawal :- This study uses an ensemble model combining 10 Classifiers for heart failure prediction, achieving 85.2% test accuracy and 87.5% recall, while the ensemble improved recall, drawbacks include computational complexity and possible overfitting due to multiple models. Individual classifier performance varied, with logistic regression(86.4%), XGBoost(86.1%),and Random Forest (86.2%) showing high accuracy, whereas Naïve bayes has lower accuracy(82.5%)[9].

3. PROPOSED SYSTEM

The proposed system is designed to detect the risk of heart failure in patients by analyzing various medical parameters using machine learning models—specifically, an Artificial Neural Network (ANN) and a Decision Tree classifier. The goal is to provide a reliable and efficient method for early diagnosis, which is essential for timely treatment and improved patient outcomes.

System Description

The system functions in a sequential pipeline that includes data acquisition, preprocessing, model development, evaluation, and performance comparison.

1. Data Acquisition

The first step involves collecting a medical dataset that includes patient health records with features related to cardiovascular health. These features may include age, sex, blood pressure, cholesterol levels, diabetes status, ejection fraction, serum creatinine, smoking habits, and other clinical indicators relevant to heart health. A suitable dataset for this purpose is the “Heart Failure Clinical Records Dataset,” which is publicly available from reputable sources such as Kaggle or PhysioNet.

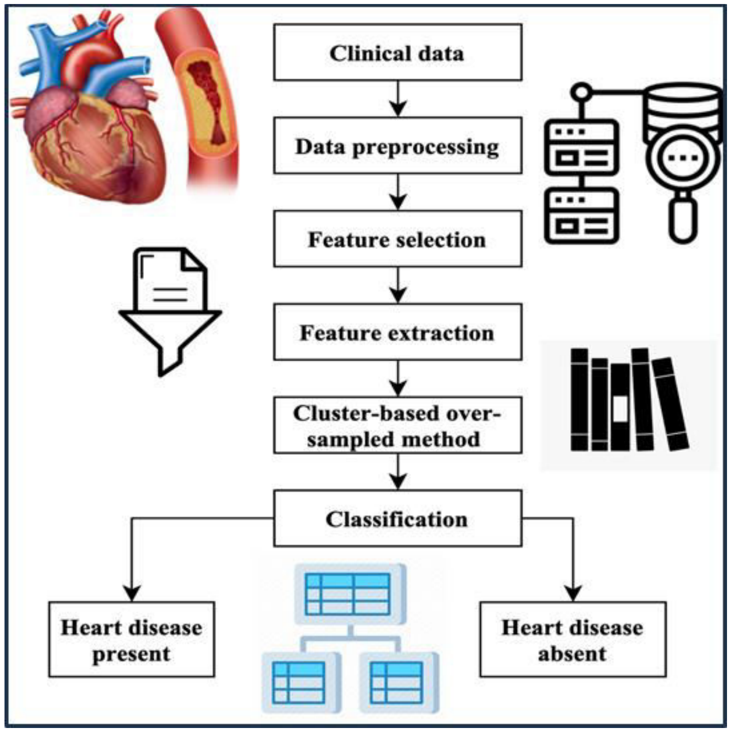


Figure 1.1 Heart Failure Detection Model

2. Data Preprocessing

Raw medical data often contains inconsistencies, missing values, or noise that can affect model performance. Therefore, preprocessing is crucial to ensure the data is clean and ready for model training. The preprocessing phase involves:

- Handling missing or null values appropriately
- Encoding categorical variables (e.g., gender, smoking) into numerical formats
- Normalizing or scaling numerical features to ensure uniformity
- Splitting the dataset into training and testing subsets, typically in an 80:20 ratio

3. Model Development

The system employs two different machine learning models to perform the prediction task:

a) Artificial Neural Network (ANN)

An ANN is a computational model inspired by the structure of biological neural networks. It consists of an input layer, one or more hidden layers, and an output layer. Each layer contains neurons (nodes) connected by weighted edges. In this system:

- The input layer receives the normalized feature values
- Hidden layers perform non-linear transformations using activation functions like ReLU
- The output layer uses a sigmoid function to predict a binary outcome: presence or absence of heart failure
- The model is trained using a backpropagation algorithm and optimized with techniques such as gradient descent

b) Decision Tree Classifier

A Decision Tree is a flowchart-like structure where internal nodes represent tests on features, branches represent decision outcomes, and leaf nodes represent final classifications. It is a simple and interpretable model that splits the dataset based on feature values that maximize classification performance. It provides transparency in decision-making, making it particularly useful in healthcare applications.

4. Model Evaluation

After training, both models are evaluated using the testing dataset. The performance of each model is assessed using several evaluation metrics:

- Accuracy: Overall correctness of the model
- Precision: True positive rate among predicted positives
- Recall (Sensitivity): True positive rate among actual positives
- F1-Score: Harmonic mean of precision and recall
- Confusion Matrix: Visual representation of prediction errors
- ROC-AUC Curve: Measures the trade-off between true positive and false positive rates

These metrics help in understanding the effectiveness and reliability of each model in predicting heart failure.

5. Performance Comparison

The final stage involves comparing the ANN and Decision Tree models based on their evaluation metrics. The comparison highlights the strengths and weaknesses of each model in terms of:

- Predictive accuracy
- Computational complexity
- Interpretability
- Suitability for clinical deployment

In most cases, while ANN may offer higher accuracy due to its ability to learn complex patterns, the Decision Tree model provides better explainability, which is crucial in medical decision-making.

4. METHODOLOGIES

In order to classify the heart failure into distinct groups based on the patient's severity levels, we utilize an Artificial Neural Network (ANN) as a suggested model to identify significant aspects in the data. In order to create a prediction system for heart failure that works, we will also take a few crucial actions.

4.1 Data Collection
4.2 Data Cleaning And Preprocessing
4.3 Model Selection
4.4 Feature Selection
4.5 Model Evaluation
4.6 Visualization

4.1. Data Collection

We used the most well-known dataset, the Cleveland dataset for heart disease prediction, which was made available by the "Kaggle" website. Although there are 76 characteristics in this dataset, only 14 of them are used in all described experiments. Thirteen characteristics out of these fourteen attributes inform us whether or not we have heart failure, and the remaining property, or target variable, does the same. This dataset has the form (1025,14), which indicates that there are 1025 distinct instances and 14 characteristics. Age, trestbps, chol, thalach, Old peak, ca, thal, and targets retain integer values, but the remaining attributes—sex, cp, fbs, restecg, exang, and slopes—are categorical in character. All of the data will be in integer and category values.

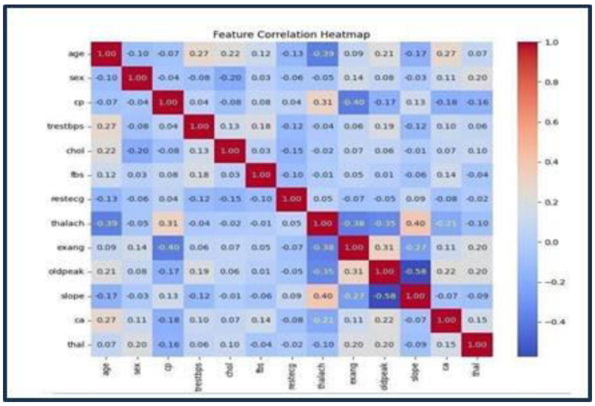
2. Data Cleaning and preprocessing :
- The Cleveland Heart Disease dataset was utilized, and it was acquired from the UCI repository. Two features out of all the characteristics have missing values: ca and thal. The data must be noise-free in order to rule out the overfitting and underfitting conditions of the ANN model. Otherwise, the patient's cardiac condition was not accurately predicted by the model. After using Python approaches to address all missing values, all missing values have been removed. We'll use KNN, mean imputing, and one-hot encoding to turn the missing values and NaN values into categorical values.Model Selection We have several machine learning algorithms for classifying cardiac disease, but they typically fail when dealing with unstructured data. In contrast, supervised learning algorithms may categorize cardiac disease using a target variable in the dataset; nevertheless, this method performs best when dealing with labeled data. Deep learning algorithms provide more accuracy than traditional learning algorithms and can handle both structured and unstructured data. There is a vast array of deep learning models, and we may choose the optimal one by examining the problem statement and the type of data we wish to manage

Attributes	Description
Age	Patients age in terms of years.
Sex	Patients Gender (male:1,female:0)
Cp	Patient's chest pain category: 0 for (typical angina), 1 for (atypical angina), 2 for (non- anginal pain), 3 for asymptomatic
Trestbps	The blood pressure level of the patient at rest (in mm/Hg)
Chol	cholesterol content in the blood in mg/dl
Fbs	Blood sugar levels during fasting above 120 mg/dl denoted as 1 for true and 0 for false
restecg	The resting ECG results are classified into three categories : 0 (Normal), 1(ST-T wave abnormality-T wave inversions or ST elevation/depression exceeding 0.05 mV), and 2 (probable/definite left ventricular hypertrophy by Estes criteria).
Thalach	peak heart rate achieved
Exang	Angina induced during exercise 0 indicates NO, 1 indicates Yes
old peak	ST-depression caused by exercise , measured against the resting state
Slope	During peak exercise, the ST segment slope is recorded as : 0- up sloping, 1 – flat, 2- down sloping
Ca	The total number of main vessels (0- 3)
Thal	A blood disorder thalassemia is indicated as : 0- NULL 1- normal blood flow 2- fixed defect (no blood flow in some part of the heart) 3- reversible defect (a blood flow is observed but it is not normal)
Target	target value: 0-no heart failure 1-heart failure.

Figure 1.2 Heart Disease Predection Using Different Algorithms

3.Feature Selection

An artificial neural network (ANN) was utilized to process and improve the dataset's 14 properties.To identify the most important patterns, Ann uses a variety of layers. Weights are changed while Ann is being trained, which lowers the prediction error for heart failure. Features that contribute the most to the model's performance are given greater weights. A feature extractor is employed in the ann's penultimate layer. This layer reduces the high-dimensional input data to an optimal collection of characteristics that aid in heart failure prediction. Certain parameters, such learning rate, step size, and optimizer, might alter feature patterns, which can have a detrimental effect on the model's effectiveness. In addition to increasing computational efficiency, the penultimate layer's dimensionality reduction reduces the chance of overfitting.



5. Model Evaluation

The performance of the Artificial Neural Network (ANN) and the Decision Tree (DT) classifier under various scenarios is analyzed in order to evaluate the proposed hybrid model. Evaluating how well the ANN extracts optimal features and how well the DT classifies using these extracted features is the main objective.

5.1. Performance of ANN

To extract features, the proposed model uses a sort of feedforward neural network known as a MultiLayer Perceptron (MLP). The feedforward architecture directs data from the input layer to the output layer via hidden layers

. 5.2. Network Architecture

✓ Network Type: Multi-Layer Perceptron.

✓ Total Layers

✓ Input Layer: Receives 14 attributes from dataset as input features

✓Hidden Layer: Includes neurons with ReLU activation function to introduce nonlinearity and learn complex patterns.

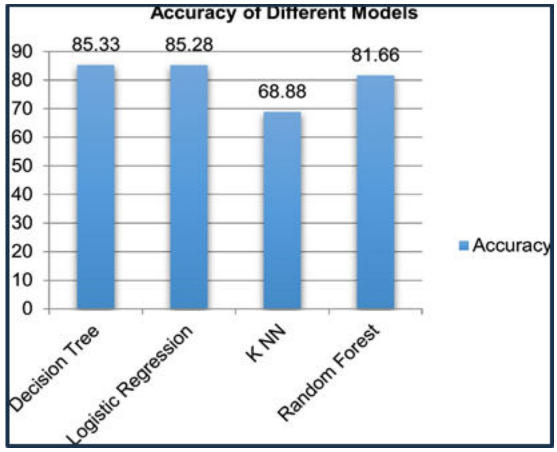
✓ Output Layer: Extracts 8 optimized features from the penultimate layer. For the hidden layers, the network design employs the Rectified Linear Unit (ReLU) activation function as it has been demonstrated to have the highest average accuracy when compared to other activation functions.The results from the base study, where the authors showed that ReLU performs remarkably well because it can effectively manage nonlinearity and avoid the vanishing gradient problem, are consistent with this conclusion. These observations led to the selection of ReLU as the activation function for all hidden layers in this investigation..

Discussion of Results with Existing Systems To assess the benefits and strengths of utilizing the suggested model, the outcomes obtained from the hybrid model (ANN+DT) are contrasted with the current system. Key elements like accuracy, feature optimization, and computational efficiency are examined in this comparison to show how the suggested approach overcomes the drawbacks of conventional techniques and boosts predictive performance.

Table 3 : comparing the accuracy of hybrid proposed model with existing system accuracies.

Model	Accuracy
Naïve Bayes	79%
Logistic Regression	81%
K-nearest Neighbour	86%
Support Vector Machine	89%
Traditional Decision Tree	85.95%
Artificial Neural Network	86%
K-Means	76%
AdaBoost	89%
Proposed Hybrid Model (ANN+ DT)	98.54%

The results showned in table With an accuracy of 98.54%, the results in the table demonstrate how well the suggested hybrid approach performs in comparison to current findings for the prediction of heart disease.



With accuracy ranging from 85% to 92%, the hybrid model outperforms conventional methods like decision trees, svm, k-means, and cpt+. Ann is the only way to get this improvement. its capacity to efficiently extract pertinent and optimal characteristics from the collection while reducing redundancy. Accuracy and efficiency are guaranteed when feature extraction and classification are combined into a hybrid technique. These results demonstrate the usefulness of the suggested system.

Conclusion:

The proposed hybrid approach, combining ANN for optimized feature extraction and a Decision Tree classifier for heart disease prediction, provides a reliable and efficient solution for early detection. The ANN effectively extracts noise-free and relevant features, enabling the Decision Tree to deliver accurate and interpretable predictions. Another key reason to use ANN for selecting features is among all Traditional methods the decision tree gives around 90 to 99% but disadvantage is unable to handle noise data and there is no overfitting techniques are available in traditional techniques. By using Ann we just pass 8 features instead of 13 features to handle the noise data and overfitting conditions

Future Scope:

The prediction of project successfully implements machine learning algorithms to predict heart failure with high accuracy. By leveraging data preprocessing techniques, Label_encoder and standard scalar the performance of models such as ANN(Artificial Neural Network) and Decision tree clasifier was significantly enhanced. Among the models tested, the optimized hybrid models achieved the high accuracy of 98.56% demonstrating its effectiveness in predicting heart failure. The activation function was implemented to explore non-linear relationships in the data. The study highlights the potential of machine learning in heart failure prediction, offering a more efficient, automated, and data-driven approach compared to traditional diagnostic methods. Identification of Key Risk Factors analyze significant medical parameters contributing to heart failure.

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