



Predicting and Analyzing Cardiovascular Disease through Ensemble Learning Approaches

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Abstract: Among the toughest assignments for medical professionals is discovering heart illness indicators as quickly as attainable. Coronary artery disease is an urgent issue and should be treated promptly. The diagnosis of heart illness is complicated by a number of factors affecting health, including high pressure, situated cholesterol levels, inconsistent heartbeat, and several more. Therefore, AI can be helpful in recognising and dealing with ailments at an early stage. This research suggests an ensemble-based method to estimate an individual's risk of heart disease using Deep Learning (DL) and Machine Learning (ML) models. In order to forecast cardiovascular disease, we use six classification methods. A large collection of cardiovascular disease cases that is made open to the world is used to train models. To identify key characteristics related to cardiac illness, we employ Random Forest (RF). The research's results show that the ML ensemble model obtains the highest accuracy of 92.75% in predicting diseases. When compared to conventional machine learning methods like K-nearest neighbor (KNN), Random Forest (RF), and Multi-Layer Perceptrons (MLP), the suggested methodology's uniqueness is evaluated by showing a 5.52% increase in efficiency.

Keywords: Heart Failure, ML Model, Deep Learning, Ensemble Techniques, Random Forest

1. Introduction

The system of circulation, which includes arteries, veins, and capillaries, connects to the hearts [1]. The other the more essential structures in the human organism is the heart, but it is also susceptible to sickness and accident; as a result, its condition is unavoidable. The heart's circulation are impacted by cardiovascular disease, which results in cardiac dysfunction [2]. A specific set of illnesses is cardiac disease that can be triggered by issues with the heart. Feeling short of oxygen, fatigue, enlarged toes, and collapse are some of the symptoms that might be used for the identification of cardiac disease. High cholesterol, High blood pressure, cigarette use, and inactivity are some of the risk factors for heart attacks and strokes [3]. The World Health Organisation states that cardiac disease is the primary cause of mortality [4], causing over eighteen million deaths annually, or nearly 35% of all fatalities. The least typical type of cardiac arrest is caused by a blockage in the coronary arteries. Stroke as well as Heart disease are therefore serious issues for the whole population. Cardiovascular illness is frequently diagnosed by clinicians using angiography. The testing process is lengthy and costly since it necessitates looking at a lot of variables, especially in developing countries where there are few doctors, diagnostic tools,

and additional assets. Due to the rising death rate from arterial illness, cardiac disease has emerged to be among of its most important medical concerns in the last few decades. Making predictions helps find the best course of action for treating a medical condition and detecting it early.

More and more ML is being used for health diagnosis. This could be attributed in part to maintaining the well-being of humans, lowering the death rate, helping medical professionals recognise and treat ailments, and enhancing the classification and detection of conditions. One of the main objectives of ML research is now to make predictions based on past performance. Neural networks are among the most widely used techniques in machine learning. This is the initial stage of supervised learning, where test data is used to evaluate the model's effectiveness once it has been constructed using labelled information. Machine learning classification techniques are frequently employed in assessing the probability of a disease occurrence [5, 6]. The aim of this effort is to develop an algorithm for classification capable of forecasting heart disease. One of the main objectives of machine learning investigations is now too used to recommendations based on past performance. Neural networks are among the most widely used techniques in machine learning. This is the

initial stage of supervised learning, where test data is used to evaluate the model's performance once it has been constructed using labelled data. Problems with categorization and regression are frequent in supervised learning. Another kind of modelling involves using unlabelled info and having an algorithm look for concealed trends in it. The outcomes of an information exploration lead to conclusions regarding the type information that may be hidden. Using the clustering method presents evidence of informal learning [7]. The third strategy, dubbed "improved teaching," does not employ tagged data and does not relate the conclusions to the facts. The investigation is centred on autonomous systems in the context [8]. Build a sorting model using a real-world dataset of patients with heart failure. The chance of an illness occurring is frequently predicted using the machine training approach. It uses a structure that has been developed on information for training to forecast the number of new samples [9, 10]. Another concept in supervised learning is classifying data [10]. This prediction will save billions of lives and save millions of individuals worldwide who suffer from cardio ailments. Although cardiovascular disease is predicted to save millions of lives, it is known to cause large losses to the financial sector as a whole.

This approach contributes to greater precise and cost-effective detection of heart problems. Here is a summary of the investigation's main findings.

- i. A voting-based decision-making technique utilising a number of classifiers in a collaborative learning strategy for the detection of heart disease is suggested.
- ii. In order to evaluate the effectiveness of the suggested methodology contrast it with conventional machine learning techniques as K-nearest neighbour (KNN), Random Forest (RF), multi-layer perceptron's (MLP).
- iii. The suggested method's results from the study demonstrate an efficiency rise in 5.52% when contrasted with previous modern facilities research and conventional ML methods.

The next segment offers a summarised of the pertinent research. The next chapter contains information about the data collection and the suggested method; Part 4's analytical section contains the results and evaluations. The fifth part wraps up this task and offers an in-depth overview of the investigation that will be conducted in the future.

2. Related Work

Many industries, particularly medical and healthcare, are very interested in data mining [11]. Several workable methods for employing ML to identify heart disease have been put forth by experts. As a result, research on creating medical apps with different

algorithms for ML has been released. A study [12], built-in artificial home monitors may be utilised in conjunction with ML techniques to assess and forecast an individual's mental state. Participants considered 179 people to be donors in total.

The computer task assessment of quality rates and the observational evaluations were discovered to be correlated, with $a=0.79$. Using ML techniques, the mental condition of those who took part could be anticipated with an area under the curve of 0.64. Analysing individual's diagnostic data, ML can be utilised to identify heart disease, claims [13]. The model with the greatest precision was the RF model, which had an accuracy rating of 86.60%. A computational technique was created by Motarwar *et al.* [14] to estimate the chance of heart failure. Their results showed that RF were extremely precise, at 95.08%. Sabarish and Parvati employed a number of techniques, such as K-nearest neighbour (KNN), Naive Bayes (NB), Decision Tree (DT), and Random Forest (RF) [5]. The technique known as KNN has the best rate of accuracy (90.7%), based on the data. Furthermore, a Convolutional Neural Network (CNN) model with a 71% overall precision was employed to identify photos of Chinese herbal medications. It also came to light that ANN might be used to detect lung tumours, with an amazing efficiency rate of 96.7% [15]. A few studies focus on creating new categories and strategies to enhance the current state of affairs. Studies by [16] suggested, for instance, using the use of Natural language processing (NLP) to train and evaluate an illness forecast model. Artificial Neural Network (ANN) with a success rate of 87.3% has been suggested by [17], for the forecasting of insulin. The suggested technique improved the neural network's score by 91% in trained and 86% in test when contrasted with the original achievement of 89% and 81%. The Particle Swarm Optimisation (PSO) technique was put forward in [18] as a potential means of improving an artificial neural network's performance even more. The set of data used for this study comprised 303 examples of both mentally and physically unwell individuals. Out of the 72 variables in the collection, only 13 had been utilised in the PSO feature choice procedure. This data set was pre-processed before selecting features and ranking were done using the PSO. Ranked findings showed the 8 most beneficial solutions from a list of 13 possibilities for increasing the accuracy the neural network instruction through feedback back propagation.

The hybrid PSO-FFBP NN was 91.94% efficient in forecasting cardiac disease, in line with the research study's outcomes. Additionally, it showed that an enhanced form of the A deep neural network (DNN) employing PCA and the Grey Wolf Optimisation (GWO) method may be able to predict diabetes-related retinopathy. Chowdhury *et al.* [19] created an online survey and went numerous medical institutions in the Bangladeshi district of Sylhet to gather information. There are 18 attributes and 564 incidents in the set of

data. With a 91% efficiency pace, Support Vector Machine (SVM) is more effective. The technique developed by Mohan *et al.* [20] for discovering essential features through neural network methodologies has improved the efficacy of the disease's forecast. The accuracy of the suggested combined RF and linear model approach in detecting heart attack was 88.7%. Heart failure can now be diagnosed using a hybrid method that was given by Au *et al.* [21]. It has been demonstrated that the successful rate of the logistic regression method for forecasting cardiovascular events is 89%. A mixed approach to forecast heart disease was proposed by researchers in [22]. To build the model, they employed 3 neural network algorithms: RF, DT, and a combination of both. The mixed approach, which had a success rate of 88.7%, is extremely precise. They detected cardiac illness using independent AI techniques, as stated [23]. To increase their forecasting algorithm's precision they employed several mixed-learning models. They cited emissions, insomnia, and poor control of stress as characteristics. We use information about heart conditions for our investigation.

They think this is the best piece of experiment to use, with about seven million clients and eleven features in this data set. In order to determine what deep learning and machine learning model is optimal for forecasting cardiac illness, we additionally validate a number of them.

3. Proposed Method

The techniques for predicting heart failure are covered in this subsection. The seven stages of the suggested strategy for this research. The first step in the suggested method is choosing a set of data for the study. This study uses the heart disease collection for its investigations. After learning the model, a number of activities in the preparation phase must be finished. After assessing the characteristics' importance using an attributes extractor technique, various machines learning algorithms and deep learning classes are used in experimentation. This investigation also assesses the use of deep learning approaches for the diagnosis of the heart illness.

3.1 Dataset

This study makes use of the heart failure dataset from the Kaggle database (<https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-dataset>). The assortment has 13 characteristics and 70,000 instances. Machines are trained on 70% of the information provided, with the remaining thirty percent utilised to evaluate the strategy efficiency. Dataset is available on <https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-dataset>.

3.2 Pre-Processing Methodology

In order to evaluate the level of accuracy of data at hand and extract essential details that may affect the efficiency of the model of learning, deep learning depends on data processing. Processing is a must before learning an individual. Scaling, Standardisation, empty value management, and treating a variety of information properties are all handled within the pre-processing step. This entails handling massive, chaotic, tiny databases, name storing, class disparity, and excessive fitting prevention. This paper suggests pre-processing techniques including removing oddities (outliers) and running the raw data through a conventional scaler to show how well the model works and obtain a respectable level of performance for illness forecasting. To normalise the data inside the specified range, we use a conventional scaling. To get a median of 0 and an average of 1, it modifies properties such as its geographical distribution. The typical scaler is defined by equations (1), while F is Z_i standardised expression.

$$F = \frac{D_i - \mu}{\alpha} \quad (1)$$

Here, μ is the mean of the training samples and α standard deviation of the training samples. According upon the way labelled are utilised, machine learning algorithms are capable of producing superior results. In order to boost the detection of diseases, the 'Data Coder' converts the desired words into mathematical representations that computers are able to read. Additionally, we modified the collected data on the ways listed below to clarify the traits that influence cardiovascular diseases (CVD).

- I. Although the details is kept, attributes are changed to improve the dataset's comprehensibility. In this collection of data, the age range has been transformed between days into years and the sex characteristic is changed to binary.
- II. Remove the date, weight, height, and id entries from the collection of data.
- III. Finding anomalies and eliminating the columns that include them by comparing the greatest and lowest intervals.
- IV. Body Mass Index (BMI) is a metric that assesses the body's fat proportion based on height and weight by combining height and weight into one attribute.

In Pearson's coefficient (PCC) is analysis to determine the connection among the attributes in order to eliminate unnecessary, inapplicable, and duplicated elements in the information at hand. The range of the relationship score is from -1 to 1. If the value is near -1, the parameters are negative associated; if the score is near 1, the characteristics are strongly linked and have a substantial effect on the simulation's efficiency. In

order to find the PCC, we set the thresholds to 0.85%. The attribute is retained if the correlation score is within the limit and neglected if it is over the limit. Following attribute correlation assessment, all characters remain identical.

3.3 Feature Selection

Significant characteristics that support categorisation must be chosen. Its objective is to find an especially relevant features that might increase the reliability of the framework in order to reduce multiplicity. We discovered that the key aspects are identified by the RF choice method. It is a well-liked decision-making strategy in ML techniques in addition, and it functions effectively in practical settings.

3.3.1 Correlation-Based

The interconnection based choice of features technique is independent of the previous categorization approach because it is a screening mechanism. As the title makes abundantly evident, it just takes into account the correlation between the intrinsic attributes of the data when assessing subsections of features. Finding a particular group of features with low feature-feature association and strong characteristic-class connection will either preserve or enhance prediction ability, preventing duplication. Naturally, we will examine the subgroup with the highest quality. A better score can result from both a tiny feature-feature correlation in the denominator and an enhanced feature-class association in the total of each feature [24]. Figure 1 shows the Correlation Matrix, where 'fbs' shows less relevant with target value.

$$Score = \frac{N\overline{Ffc}}{\sqrt{N+N(N-1)Fff}} \quad (2)$$

Here N is number of components used in data set while ff is feature-feature association with main feature F

3.3.2 Chi Square Test

In a categorizing situation, this measure works well for evaluating variables by category. Based only on negative variables (booleans or frequencies), it assists in determining which of the n_features variables have the largest scores according to the chi-squared statistic produced from X. Remember that the chi-square test measures the degree of dependency across unpredictable variables. Applying this technique aids in eliminating traits that are probably insignificant for classifying because they are unrelated to a category [25]. To examine correlations between categorical data, one often used method is the Chi-Square analysis.

$$X_i^2 = \sum \frac{(O-P)^2}{P} \quad (3)$$

Here O is observed value while P is expected value. X_i^2 is chi squared is indicated in equation 3.

3.3.3 Mutual Information

Mutual Information assesses shared data between recognized sections, such as an ongoing parameter in predicting scenarios or a query about the organization. The intricacy of the settings determines how similar sharing functions [26]. An official declaration of understanding that the two unidentified variables, A and B, share is as follows:

$$M(A, B) = H(A) - H(A|B) \quad (4)$$

Here H[A] is the amount of entropy for A and A & B are mutual information. The result is given in binary

3.4 Category of Algorithm

To enhance our categorization outcome, we suggest an ML and DL-based stacked model (DNN, ML, KDNN and ensemble model) and a set of models that uses ML (XGB, KNN, and DT). During our study, we used two deep learning theories, DNN and KDNN, together with four ML approaches: DT, KNN, RF, and XGB. The next section demonstrates methods to successfully assess the efficacy of our strategy by identifying heart disease using the machine learned group classification and the DL technique.

3.5 Mixture Classification for ML

A variety of difficulties with ML have been resolved by academics using collaborative learning [27, 28]. Since every dataset has an array of issues, the information is suitably categorised and distinct illness are identified using an ensemble learning approach. With each new data point that is received, every algorithm in the community forecasts its category label. For that particular occurrence, the group tag featuring the greatest number of approval, or which is anticipated by a greater number of classification algorithms, is utilised. A variety of classification and voting methods should be used to try to increase effectiveness [29]. These tactics provide superior generalisation outcomes over the traditional single-learning method. The suggested ML group classifier develops the outcomes by using an equal vote approach to combine the forecasts of many classes. The best outcomes are presented following the fine-tuning of each categorization model. To obtain the largest number of scores in formula (2), the procedure in the formula is applied.

$$Max f(i) = [i \in Z : f(i) = \max f(x)] \quad (5)$$

The fundamental machine learning technique for both classification and regression is called nearest neighbour (KNN).



Figure 1. Correlation Matrix

The information is employed in KNN calculations, whereby identify novel points using metric of similarity (such as the length function). The KNN computation depends on how comparable the objects under comparison are. The KNN classifies a region based on an overwhelming vote of its nearby neighbours. On the information's point, the category with the greatest number of neighbours is labelled [30]. The option of k and precision may get better as the quantity of nearest neighbours rises. The sklearn library's standard setting for parameters were employed.

The utilisation of storage and efficiency are both enhanced by severe gradient boosts. XGBoost is used in this ensemble learning strategy to enhance the efficacy of classification. To improve categorization efficiency, the classifier called XGBoost is employed. A machine learning approach called XGBoost is used to a sizable database. It provides a forecast in the form of a boosted ensembles of weakly tree classifications and optimises the reduction in function via gradient descent [31]. This approach is distinct in that it combines an agile methodology for learning with inadequate machine learning techniques. Gradient boosting is a rare example of its kind. Gradient boosting modifies the prior forecast using the remaining error in order to maximise the loss functions.

$$G'(i) = L(i) + \alpha(i) \tag{6}$$

Equation (6) shows the settings that can be calculated using oplus and derived from the supplied data. The regularisation factor (alpha) and the function

of loss (Loss) serve as indicators of the the model's intricacy. The following are the XGBoost algorithmic variables used in this study: The XGBoost model makes use of the highest depth parameter. The maximum depth that may be attained is 6. XGBtree is the boost, and the μ value is 0.3 plus to the subsequent criteria: scale positioning size, min-children-weight, and accelerator are all set to 1, with the remaining values staying at their default values. Data that is both quantitative and category can be sorted using decision trees. In terms of framework, it is similar to a tree. When it comes to collaborating with health data, DT is the single most widely used method. Making and evaluating a tree chart is really simple. We used the DT classifying approach, which is among the many popular and successful strategies for controlling development [32]. For a given set of data, creating a trustworthy decision tree is easy. During development with the provided dataset, this algorithm also employed its standard settings.

3.6 Classifier with Deep Learning

DL-based classifications have been implemented using deep neural networks (DNN). Additionally, RNN (Recurrent Neural Network) models like LSTM were also used; however, due to the large amount of numerical data in the data set, LSTM failed to operate well. To provide a comprehensive analysis, we evaluated cardiac diagnosis and categorization performance using DL-based algorithms. The CNN model starts with a layer of inputs that has an activation

function for the ReLU of ten dimension and a unit value of 16. It is subsequently followed by three layers of density, each possessing a unit appreciate of 12, 8, and 4. Finally, there is a fully interconnected layer that has an activated sigmoid that is immediately linked to a particular value that the machine learning system is attempting to forecast. The data input layer has 176 characteristics in altogether. There are 204 attributes in this component, and each one has an integer of 12. The subsequent layer that is hidden has 104 parameters with 8 units, while the ultimate hidden layer has 36 characteristics with 4 units. The DNN algorithm has a rate at which it learns of 0.001, and its dual cross-entropy is used to compute the loss. Each value can be learned, and the suggested model did well on the test set. We employed a form of neural network called KDNN, a reliable method for sickness identification, to avoid excessive fitting. After eliminating outliers from the dataset, we used an infection identification neural network (KDNN) to effectively reduce over fitting. To calculate the cost and make fine-tuning easier, the Keras Deep Neural Network (KDNN) architecture uses an optimizer based on Adam with Binary cross-entropy. The design of the suggested KDNN model consists of only one input layer. Numerous hidden layers are eventually exposed in order to reveal a single, completely integrated layer. Many concealed layers eventually give way to the disclosure of a single, completely integrated layer. The input portion of the layer displays the 132

variables. The next layer contains a hundred and 30 variables.

The last hidden layer has 54 characteristics with 411 train variables, and the third hidden layer contains 88 variables. The heart attack database is used for effectively test and train the improved KDDN classifier.

4. Result & Discussion

In this part, the initial approaches are compared and outcomes are explained in some detail. This study's primary objective is to assess the efficacy of proposed machine learning and deep learning classifiers for cardiac failure prediction. The present research's tests are conducted using the Cardiovascular Disease dataset. In this work, deep learning and machine learning are both applied. Two methods are used to conduct experiments. Using ML models is the first stage towards improving outcomes. On the data set given, our machine learning combination model yielded good results. To obtain more dependable outcomes, this is done. We experimented with deep learning techniques in the subsequent phase. Deep learning models performed poorly due to a lack of data, thus we created a stacked collective model to improve deep learning performance. Precision, confusion matrix, recall, F1 score, accuracy, and area under the ROC curve (AUC-ROC score) were among the outcomes metrics employed in this study.

Table 1. ML Classifier Performance

| Algorithm | Accuracy | Precision | Recall | F1 score | ROC-AUC |
|-----------|----------|-----------|--------|----------|---------|
| RF | 89.65 | 91.13 | 89.33 | 89.22 | 93.14 |
| KNN | 87.55 | 88.54 | 87.24 | 87.27 | 91.25 |
| DT | 87.39 | 87.43 | 87.25 | 87.52 | 89.65 |
| XGB | 89.49 | 89.45 | 89.81 | 89.01 | 94.25 |

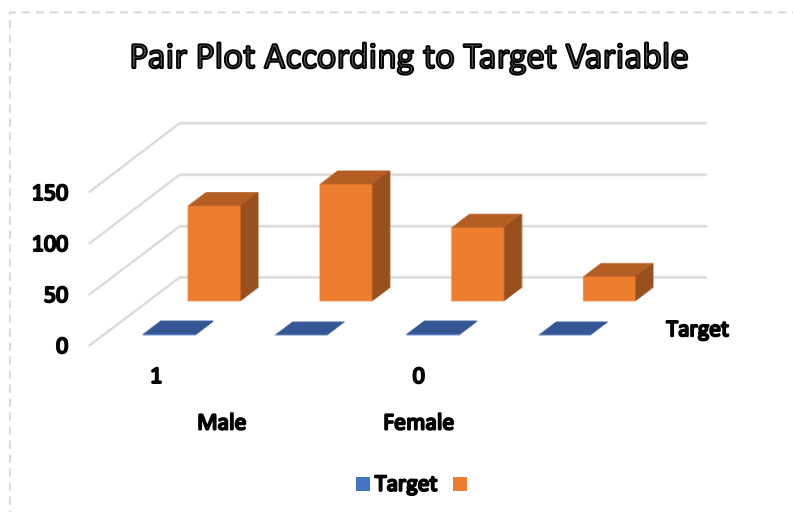


Figure 2. Pair plot according to target variable

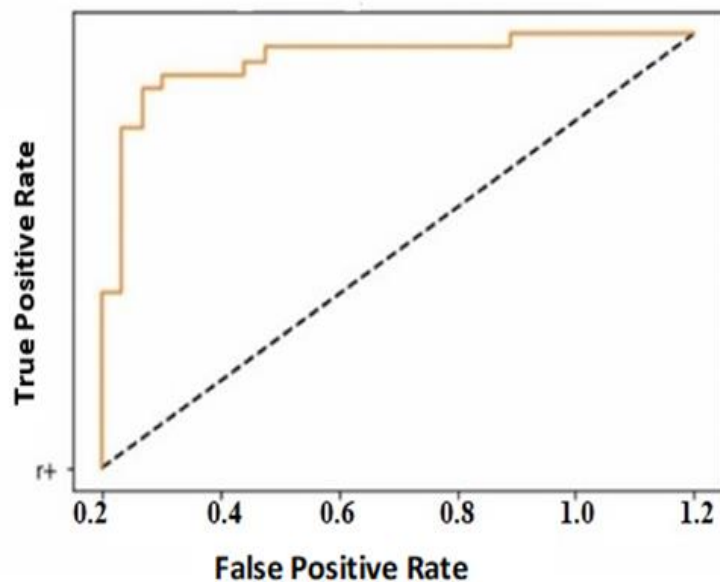


Figure 3. Random Forest ROC Curve

The collection of data is divided into two sections: 30 percent is utilised for model testing, while the remainder, or 70%, is employed to train the model.

4.1 Experimental Results

The results of the machine learning classifiers that identified coronary sickness in a heart disorder sample are shown in Table 1. In this investigation, RF, KNN, DT, and XGB are utilised. Table 1 shows that the RF classification algorithm achieved the best reliability rate of 89.65% in contrast to other predictive models. The results for RF's recall, F1, AUC, and precision are 89.33%, 89.22%, 93.14%, and 91.13%, in that order. Comparing with XNN we got accuracy of 87.55%, Precision is 88.54% and F1 score is 87.27%. We additionally show the RF classifier's confusion matrix. Figure 2 displays the pair plot based on the target parameter.

This plot describes the male and female numbers using a bar chart. Furthermore, the ROC Curve figure in Figure 3 (with a ROC score of 93.14%) suggests the RF classifier did exceptionally well on the heart disease datasets. The outcomes of the deep learning model are displayed in the following phase of the research. Table 2 displays the outcomes of the deep learning system. Each of the deep learning systems gave very good performances. The precision rating of the two models is nearly identical, however lower than the ML model's since the deep learning model outperformed the latter on a substantial volume of data. Compared to the KDNN model, the DNN model achieves the maximum efficiency. The F1 score, ROC AUC, accuracy, precision, recall, score of the DNN model are 67.54%, 93.42%, 89.54%, 98.51%, 77.57%. Figure 4 displays the DNN model's learning and validation loss,

while Figure 5 displays the model's accuracy in training and validating in excess of 400 epochs.

Figure 6 displays a graph of the ROCAUC curve. The research's final conclusions are derived from an ML and DL stacking predictor and an ML ensembles classification. Of all the classification methods, this one has the highest accuracy, at 89.85%. Yet, the stacked classification was unable to function well due to the paucity of data. The ML Ensembles has a 93.42% ROCAUC, and 67.54% F1 score, and 77.57% recall and accuracy rate. The outcomes demonstrate that the suggested machine learning combination classifier is capable of effectively identifying heart disease from a heart attack dataset.

The findings of the group machine learning model, which uses ML and DL stacked classifiers to identify cardiovascular illness, are shown in Table 3. The ML combined model produced the following results: the following: precision of 91.03 %, accuracy of 92.75%, recall of 91.22 %, ROC-ACU of 94.25 % & F1 score of 91.35%; the stacked classifier achieved these results with precision of 89.55%, accuracy of 88.46%, recall of 88.22%, and F1 score of 88.51%. In conclusion, the ML model produced the greatest findings when it came to heart disease detection. Table 4 presents a comparison of the suggested and base techniques. We make a general comparison with two reference studies [33, 34]. The suggested study's methodology is nearly identical to that of the baseline investigation. An ML Ensemble approach was utilised in this study to identify heart disease.

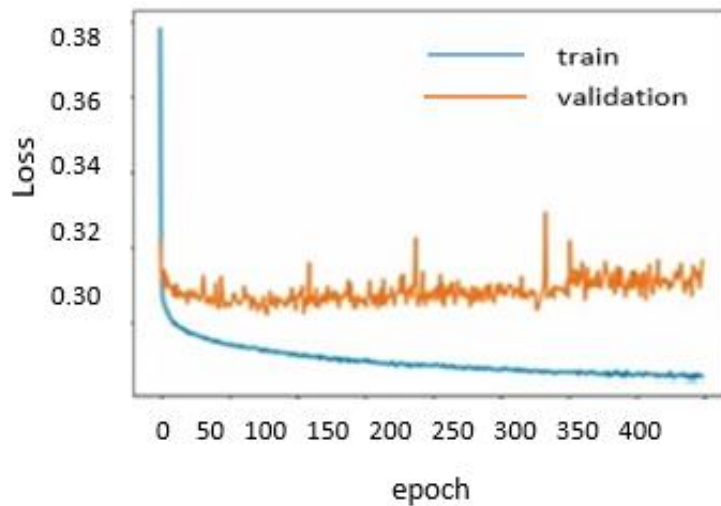


Figure 4. The DNN model's validating and training losses

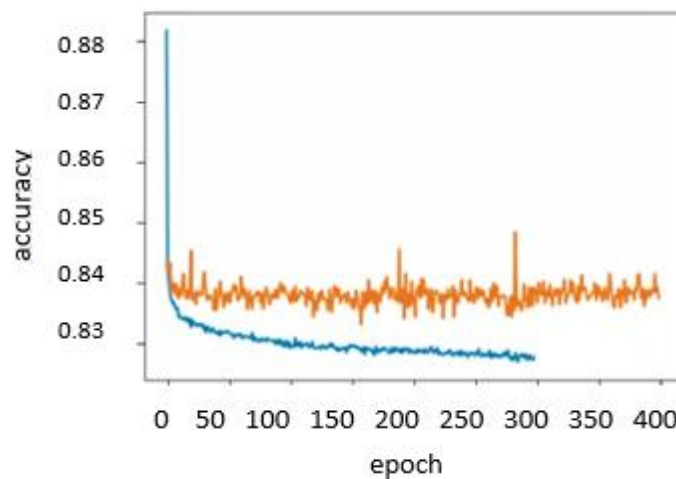


Figure 5. The DNN model accuracy for training and validation

Table 2. Deep Learning Performance

| Algorithm | Accuracy | Precision | Recall | F1 Score | ROC Curve |
|-----------|----------|-----------|--------|----------|-----------|
| KDNN | 89.54 | 98.51 | 77.57 | 67.54 | 93.42 |
| DNN | 89.85 | 97.98 | 78.37 | 67.56 | 93.58 |

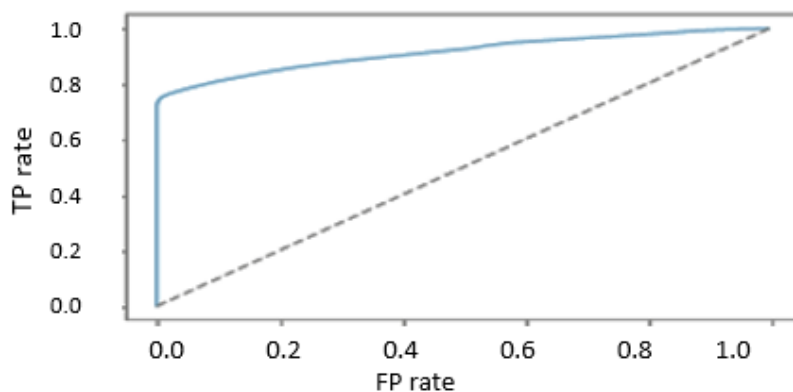


Figure 6. DNN Model ROC AUC Curve

Table 3. Comparison performance of ML Ensemble & DL Stacked

| Model | Accuracy | Precision | Recall | F1 Score | ROC Curve |
|-------------|----------|-----------|--------|----------|-----------|
| ML Ensemble | 92.75 | 91.03 | 91.22 | 91.35 | 94.25 |
| DL Stacked | 88.46 | 89.55 | 88.22 | 88.51 | 98.65 |

Table 4. Comparison of proposed system with baseline methodology

| Method | Model | Accuracy |
|---------------------------------|---------------------|--------------|
| A.Alfaidi et al [30] | LR | 85.54 |
| | RF | 86.03 |
| | DT | 85.93 |
| | KNN | 84.56 |
| | MLP | 87.23 |
| J. C. T. Arroyo et al [31] | GA-ANN | 73.43 |
| | ANN | 68.35 |
| | Logistic regression | 72.35 |
| | DT | 61.72 |
| | RF | 68.94 |
| Our Proposed Methodology | ML Ensemble | 92.75 |

4.2 Comparative Analysis

The results of this investigation are contrasted with our baseline methodology in Table 4. Alfaidi *et al.* used several different machine learning models, with the MLP model yielding the best results with an accuracy rate of 86.03% and 87.23 % for RF & MLP respectively [34]. Three ML models and two artificial neural networks were employed by Arroyo et al [33]. With the GA-ANN model, this study's accuracy rate was the greatest at 73.43%. By creating an ML Ensemble model using an overall polling strategy, the suggested method outperformed the original findings in terms of accuracy. The accuracy score for the ML Ensemble model was 92.75%. By exhibiting a 5.52% improvement in accuracy over conventional machine learning approaches like K-nearest neighbour (KNN), random forest (RF), and multi-layer perceptron's (MLP), the suggested technique is judged to be novel.

5. Conclusion

The present research suggested techniques using deep learning and ML utilising ensembles to forecast cardiovascular illness. We utilised data from 70,000 individuals who have a variety of cardiovascular diseases for this investigation. The models' effectiveness was evaluated based on how accurate

they were. Furthermore, we have chosen supplementary informative attributes that impact the models' functionality. The ML Ensemble model proved to be most reliable for forecasting heart attack and stroke, based on the findings. To prepare the data set for examination, we have included a few steps. Various techniques may be used to identify the ideal attributes for our next projects. More datasets might be used to provide an even more precise judgement. Ultimately, the prediction problem for more effective cardiovascular disease detection may be addressed using deep learning and reinforcement learning techniques.

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Competing Interests

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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