Enhancing Heart Disease Prediction Through a Heterogeneous Ensemble DL Models

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Abstract. Accurate and highly effective forecasting approaches for timely detection and management are imperative given that cardiovascular illness is one of the biggest causes of death world wide. Machine learning (ML) and Deep learning (DL) methodologies have produced promising outcomes. In particular, ensemble DL models have gained attention for their ability in order to capitalize on the advantages of many models to enhance predictive performance. This study focuses on applying a cardiovascular disease prognosis with a DL ensemble. The model combines the predictions of multiple DL models, networks of neurons, such as supervised DL Models (CNN and RNN), to magnify accuracy and robustness. In this research, the effectiveness of an ensemble model is measured using an ample dataset, comparing it with individual DL models. The model's prediction skills are evaluated by utilizing a verity of Evaluation metrics. The findings highlight the effectiveness of cardiovascular disease ensemble DL models prediction, showcasing their potential for enhancing diagnostic accuracy in clinical settings and aiding healthcare professionals in making informed decisions for patient care.

Keywords: Heart disease prediction · Ensemble DL · ML · CNN · RNN · healthcare decision-making

1 Introduction

According to mortality rates, heart disease is the deadliest ailment afflicting humans today. Heart disease happens when the heart is unable to Diagnosing cardiac disease might be complicated by coexisting disorders such high blood pressure, diabetes, and abnormal cholesterol levels. These additional symptoms can make it more difficult to pin down the root cause of the cardiac problem, which can then make it more difficult to treat. In order to recognize cardiac illness early and accurately is crucial for preventing and treating heart failure [1].

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Diagnostic criteria for coronary heart disease according to antiquity have been discredited for various reasons. A vast volume of intricate medical records and a selection of ML and DL methodologies, support forecast heart illness with less involvement from clinicians. Mainly, we want to save people's lives by recognizing irregularities in heart conditions, which would be accomplished by finding and analyzing raw data derived from heart disease data. Non-invasive measures and also ML and DL techniques are effective in differentiating between healthy individuals and those who have cardiac illness.

ML is both a type of AI and a method for accomplishing AI tasks for developing algorithms that take providing inputs such as historical data and then employing statistical analysis to make predictions about future output. ML is an effective method for developing complex algorithms for analyzing high-dimensional and biomedical data [2]. DL is a subset of ML that uses numerous layers of expert systems to process and calculate a plethora of data. The human brain's activity and operation are the basis for the DL algorithm. The DL algorithm is capable of erudition without the need for human intervention and can handle both organized and unstructured information. It is useful for extracting valuable information from a huge clinical data set [3] and helping the health care professionals to make decisions quickly. Deep learning is currently implemented in various other domains, including but not limited to finance, banking, and e-commerce. Information extraction, representation learning, and outcome prediction, are some of the DL techniques and frameworks used in healthcare applications [4]. DL algorithms are based on expert systems, just as how the human brain uses millions of neurons to process information.

Heart disease is a common and dangerous disorder that needs precise and effective prediction models for quick diagnosis and treatment. ML and DL techniques emergently become formidable tools in healthcare, showing promise in areas related to heart disease prediction. Ensemble DL models, in particular, have gained attention for their ability to harness the strengths of multiple models, leading to improved predictive performance. This study focuses on utilizing an ensemble DL model for cardiac disease prognosis. The model combines predictions from various DL models, such as CNN and RNN to ameliorate both accuracy and robustness. A substantial data set serves as a gauge for the ensemble model's efficacy, and comparisons are formed against individual DL models. When evaluating the capacity for prediction of an ensemble model, evaluation measures such as accuracy, precision, recall, and F1-score are used. The study's findings demonstrate the effectiveness of ensemble DL models for heart disease prediction, showcasing their potential to enhance diagnostic accuracy in clinical settings and provide valuable support for healthcare professionals in making informed decisions for patient care.

In order to acquire reliable results from ML and DL methods, the heart disease dataset undergoes a number of adjustments. First, the basic data on heart disease is analyzed and inserted into either the machine or DL model. In the second step, preprocessing techniques are applied to remove irrelevant, noisy and inconsistent data. Then, applying the feature selection method, select the significant features for analysis. Finally, categorization methods are used to the extracted data and the prediction is made. These steps are shown in below Fig. 1.

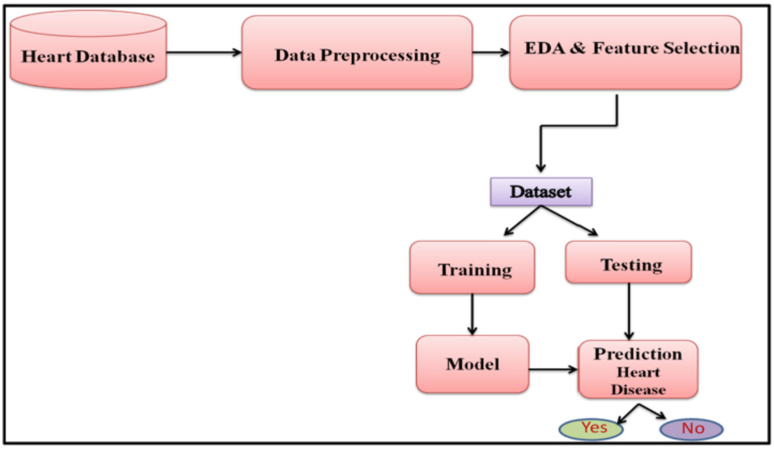

Fig. 1. The Heart Disease Prediction Model

2 Background

Different types of ML and DL approaches are covered in this section along with a brief discussion of each.

2.1 Machine Learning Techniques

All three of these types of learning—supervised, unsupervised, and reinforcement has their uses add these three categories used to classify ML algorithms. In a supervised learning method, a target or dependent variable must be predicted from a collection of independent factors. A model that maps inputs to target outputs is developed using a set of variables. The model is trained on the training data until it gets the required level of accuracy. Regression, Decision Tree (DT), Random Forest (RF), KNN, Logistic Regression (LR) etc. are few examples of supervised learning. In unsupervised learning, there is no desired outcome or outcome variable for which predictions or estimates must be made. Unsupervised learning is used to find patterns from data sets that have neither been classified nor labelled. Unsupervised Learning examples are K-means and Apriori algorithms. The machine is trained to make certain decisions using the Reinforcement Learning method. To make accurate decisions, the computer learns from its past experiences and works to acquire as much information as possible. Markov Decision Process and Q learning are examples of this type of algorithm.

2.2 Deep Learning Techniques

DL techniques employ neural networks to compute information in the same way that the human brain uses millions of neurons to do so. It uses multiple layers of neural networks to do data processing and computations on a large amount of data [5]. Because so much computing occurs between the input and output layers, this learning process is referred to as DL. It requires more time to train a model on a huge amount of data, but it requires much less time to execute than other ML methods [6]. This is the main reason for DL becoming more popular day by day than ML. It comprises both supervised and unsupervised learning algorithms because it is a subset of a ML algorithm. Supervised learning uses ANN, CNN, and RNN as examples. AutoEncoders and Boltxmann machines are used in unsupervised learning.

Ensembling is a well-established algorithm that has been shown in Fig. 2. to increase the precision of machine learning models, reduce overfitting, and increase the robustness of the system.

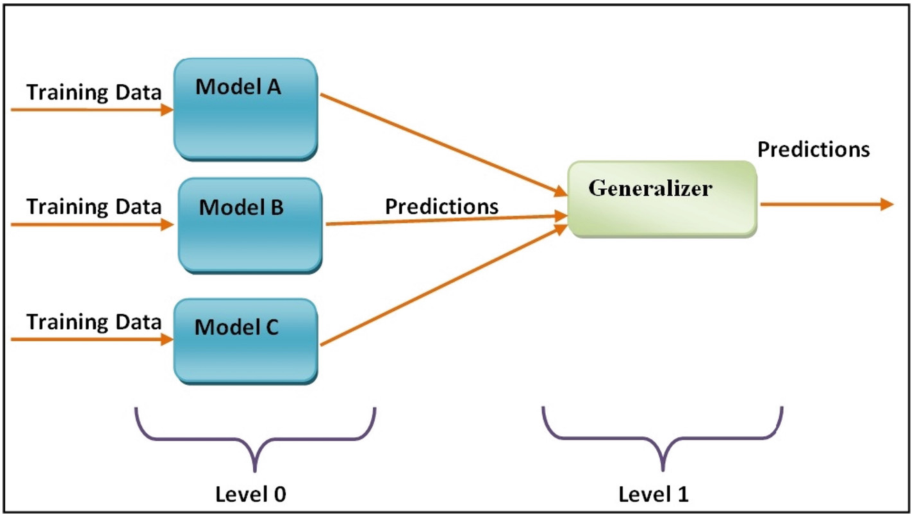

Fig. 2. The organization and mechanisms of ensemble learning

There are several ways to combine multiple deep learning models for ensemble learning. Here are a few examples:

Bagging: In bagging, multiple deep learning models are trained independently on various subset of the training data. The outputs of various models are averaged to get the final projection. Bagging can improve the robustness of the system by reducing the variance of the models.

$$\hat{y} = (\hat{y}_1 + \hat{y}_2 + \ldots + \hat{y}_n)/n \tag{1}$$

where $\hat{y}$ is the final ensemble prediction, $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are the predictions from individual models, and n is the number of models.

Boosting: The process of boosting includes training many DL models in succession, with each subsequent system concentrating on the errors generated by the models that came before it. The ultimate forecast is arrived at by adding up the results of all of the models. By decreasing the inherent bias of the models, boosting has the potential to make the methodology more accurate.

$$\hat{y} = \alpha_1 \hat{y}_1 + \alpha_2 \hat{y}_2 + \ldots + \alpha_n \hat{y}_n \tag{2}$$

Here $\hat{y}$ is the final ensemble prediction, $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are the predictions from specific models, and $\alpha_1, \alpha_2, \ldots \alpha_n$ are the weights provided to individual predicted model.

Stacking: Multiple deep learning models are trained independently using training data in stacking, and the results are then used as features in a meta model that generates the final prediction. Stacking can improve the accuracy of the system by integrating the benefits of various models. The mode of ensembling is shown in Fig. 3 (Table 1).

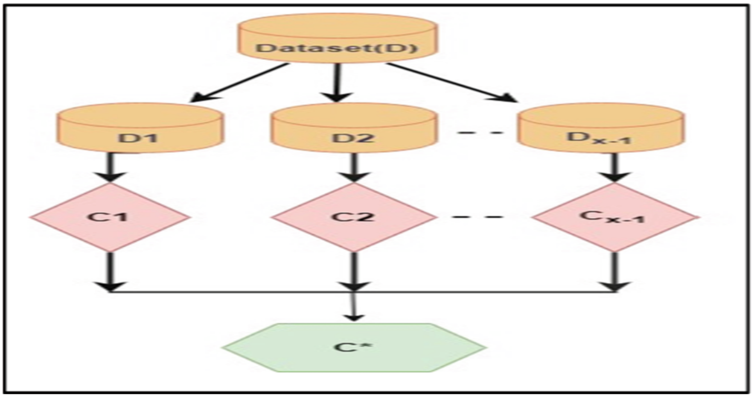

Fig. 3. Ensemble Stacking

3 Literature Review

The proper diagnosis of patients and the identification of potential dangers are essential components of heart disease study. In such a context, it is essential to consider different evaluation metrics to assess the performance of the models accurately.

While precision, recall, and F1 score are important metrics to consider, accuracy is also a crucial measure that should not be overlooked. Accuracy is a metric that quantifies the proportion of correctly predicted instances in the dataset, relative to the total number of instances. It serves as an indicator of the model's capability to correctly classify both positive and negative instances.

In the case of heart disease analysis, accuracy is important because misdiagnosis or misclassification can have serious consequences. False positives and false negatives can lead to unnecessary procedures, missed diagnoses, or wrong treatment plans, which can affect patient outcomes.

Despite their significance, precision and recall do not account for a model's total accuracy. A high recall score indicates a low false-negative rate for the model, but it may classify some negative cases as positive.

In summary, the choice of metric in heart disease analysis should depend on the specific goals and priorities of the analysis. While accuracy is a valuable metric for overall performance, precision and recall are important in situations where false positives or false negatives can have serious consequences. The F1 score can be a overall measure of model performance that combines both precision and recall.

M. Kavitha et al. [7] developed a mixed-method model by fusing RF and DT techniques. In comparison to the RF tree model and the DT model, the proposed hybrid model demonstrates superior accuracy. The experimental results indicate that the hybrid model achieves an accuracy of 88.7%, outperforming the other models.

Hager Ahmed et al. [8] compared the accuracy of various Supervised ML classification algorithms, including DT, RF, SVM, and LR Classifier, was measured using both a selection of features and the entire set of features. The suggested approach exhibits a notable benefit in its capacity to effectively handle Twitter updates that encompass patient information. The framework's fundamental design involves the integration of Apache Kafka and Apache Spark. In comparison to the other designs, the RF classifier received the best with 94.9% accuracy. To extract essential features from the dataset, both the univariate feature selection and Relief methods were employed.

Pooja Anbuselvan [9] analyzed a range of various supervised ML models such as LR, NB, SVM, K-NN, DT, RF and the ensemble technique of XGBoost. Among these models, the proposed approach utilizing RF achieved the highest accuracy of 86.89%, surpassing the performance of other models.

Mohan et al. [10] created a novel approach to identifying and grouping critical characteristics to enhance the precision of cardiovascular illness prognosis. This suggested approach, a Hybrid RF with a Linear Model (HRFLM), for predicting cardiovascular disease showed an accuracy of 88.7%.

Considering the reason of making accurate predictions about cardiovascular illness, Budholiya et al. [11] created an XGBoost Classifier using a Bayesian optimization approach. With an impressive 91.8% accuracy for predictions, this approach outperforms the two most popular current tree-based concepts, RF and Extra Tree.

Spencer and colleagues [12] employed multiple ML techniques and feature selection algorithms to generate diverse tasks. The overall performance of the chi-squared feature choosing process and the BayesNet classification method for the model that was recommended was 85.0%.

The CHI-PCA approach, built by Escamilla et al. [13], when combined with RF, demonstrated remarkable precision. It was determined that the Cleveland database had a precision of 98.7%, the Hungarian database had an accuracy of 99.0%, whereas the Cleveland-Hungarian (CH) database had a reliability of 99.4%.

In [14], ApurbRajdhan et al., utilizing a RF method, introduced a novel model. When compared to other ML techniques, the suggested model's preciseness of 90.16% comes out as very excellent.

When compared with various categorization methods, such as K-NN, SVM, Naive Bayes, and RF classifier, Youness et al. [15] proposed an ANN model with impressive accuracy of 99.65% was developed by incorporating Particle Swarm Optimization (PSO) technique and Ant Colony Optimization (ACO) approach.

Haq AU et al. [16] developed a hybrid intelligent ML-based predictive system was evaluated using complete and reduced feature sets. The utilization of the Relief feature selection technique in conjunction with 10-fold cross validation and LR resulted in the attainment of an overall accuracy rate of 89%.

Awais Mehmood et al. [17] used deep learning to present a novel heart disease prediction model. Convolutional Neural Networks (CNN) algorithm, giving an accuracy of 97%.

Kazeem et al. [18] developed the models using hybrid algorithms like Boruta Algorithm and Deep Neural Network Algorithm (BADNN), Genetic Algorithm and Deep Neural Network (GADNN), and Boruta Algorithm and Neural Network Algorithm(BANN) all achieved two-way hybrid accuracy of 97%, 87%, and 100%, respectively.

FarmanAli et al. [19] developed a model that has an accuracy of 98.5% in predicting heart disease and proved that proposed system accuracy is higher than the existing traditional classifier model. The comparison is carried out based on metrics such as weighting techniques, feature selection and feature fusion.

To produce predictions based on learnt records, Mienye et al. [20] suggested an improved sparse auto encoder-based ANN framework. When using Adam's improved approach and batch normalization, the model's accuracy on processed data was 90%. The proposed model is more accurate than ANN and other standard methods.

Sumit Sharma et al. [21] used Talos optimization, a new DNN optimization technique, to implement a model using deep learning neural networks (DNN). Talos provides better accuracy of 90.76% to other optimizations.

Simanta et.al. [22] Proposed a Deep Learning Modified Neural Network (DLMNN)-based IoT-centric prediction model for heart disease classifier aimed to identify the heart disease of the patient more accurately. When results from this model are contrasted with those from other models, it is discovered that it has a 95.87% accuracy level.

P. Ramprakash et al. [23] proposed a new heart disease prediction model constructed by applying Deep Neural Network and chi-square statistical model. The accuracy of the developed model is compared with the accuracy of the existing models using DNN and ANN and stated that the proposed model more efficiently predicts the presence of heart disease than the other models.

The summary of prediction accuracy of both Machine and Deep Learning models are shown in Table 2.

Table 1. Classifying Ensemble approaches

Techniques Used	Fusion methods applied	Model Dependent	Type of Heterogeneity
Boosting	Weight Voting	Sequential	Homogenous
Gradient Boosting	Weight Voting	Sequential	Homogenous
AdaBoost	Weight Voting	Sequential	Homogenous
Bagging	Weight Voting	Parallel	Homogenous
Random Forest	Weight Voting	Parallel	Homogenous

Table 2. Machine and Deep learning models with accuracy

S.No	Authors	Methods	Accuracy
1	PoojaAnbuselvan	Random Forest	86.89%
2	Arabasadi	NN-Genetic algorithm	89.04%
3	Sumit Sharma	DNN optimization technique	90.76%
4	Doppala	Hybrid Machine Learning	94.20%
5	Hager Ahmed	DT, SVM and Logistic Regression	94.90%
6	Simanta Shekhar	Deep Learning Modified Neural Network (DLMNN)	95.87%

Table 3. Implementation of CNN and RNN Model with accuracy

Model	Input	Units/Layer1	Units/Layer2	Units/Layer3	Accuracy
Model-1	1025×7	64 units	32 units	1 unit	81.46
Model-2	1025×7	32 units	16 units	1 unit	80.48
Model-3	1025×7	128 units	64 units	1 unit	83.41
Model-4	1025×7	64 units	1 unit	-	96.58

4 Methodology

In this section a brief description about the feature selection is discussed. In heart disease analysis, the feature selection phase plays a crucial role as it allows users to identify the vital variables or features that have a substantial impact on predicting heart disease. The primary objective of feature selection is to enhance the accuracy and efficiency of the prediction model by eliminating irrelevant or redundant features, thereby improving the overall performance of the analysis (Fig. 4).

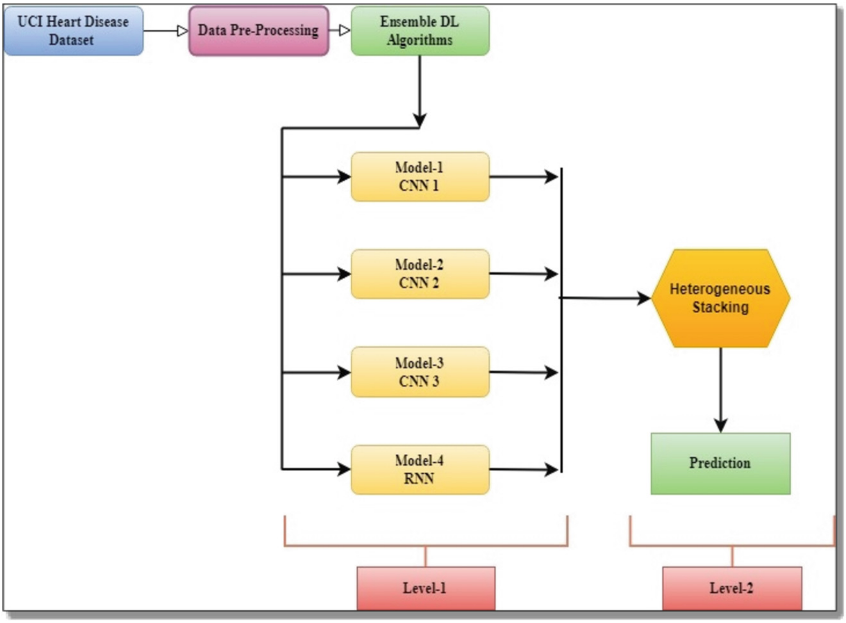

Fig. 4. Heterogeneous Ensemble DL Model

4.1 Information About the Dataset

Public Health Dataset was the dataset used in this study and exploratory data analysis is shown in Fig. 7.

1. **Span(age)** - the patient's age, quantified in years, and sex (one for males and zero for females).
2. **Chest Pain(cp)** - chest pain type.
3. **RBP(Trestbps)** - arterial pressure at rest (in millimeters of mercury (Hg)) at the time of patient admission to the clinic. The typical range for blood pressure is 120/80; if your reading is within that range, everything is great; however, if it is slightly higher than expected, we need to try to bring it down. Alter your way of living in a healthy way.
4. **Cholesterol(chol)-**A person's serum cholesterol will reveal their triglyceride level.
5. **Fasting glucose levels (fbs)–**Fasting blood sugar (FBS) refers to the measurement of blood sugar levels after a period of fasting. A value of 120 mg/dL or higher is considered indicative of elevated blood sugar (1 true). Normal blood sugar levels typically range from below 100 mg/dL (5.6 mmol/L) to 125 mg/dL (5.6 to 6.9 mmol/L), which serves as the threshold for prediabetes.
6. **Resting(Restecg)-**electrocardiogram findings while at rest.
7. **MaxHeartRate(thalach)-**The maximum achievable heart rate is determined by subtracting your age from 220.
8. **Exercise-**angina pectoris:exercise-induced angina (1yes).
9. **ST depression(Oldpeak)** - During exercise, there is a notable occurrence of ST depression in comparison to the resting state.

10. **Slope** - the angle of the exercise's ST segment peak.
11. **Ca** - Fluoroscopy-colored main vascular count (0–3).
12. **Thalassemia(Thal)-**No reason was given, although thalassemia categorization includes 3 instances of normal findings, 6 instances of fixed defects, and 7 instances of reversible defects is most likely the cause
13. **Target(T)** - (Angiographic disease status) No Heart Disease = 0, Heart Disease = 1.

4.2 Data Preparation

Once data is collected, it should be prepared for analysis. This includes cleaning and organizing the data, filling in any missing values, and transforming any categorical variables into numerical ones.

The ensemble DL model is made from the multiple models, containing multiple structures of layers. The heart analysis is made from the data containing multiple features co-related to rate of heart analysis. Initially, the data is pre-processed by handling null values of the dataset chosen which results to get much accurate results. Exploratory data analysis (EDA) is done on the data to select the features that are contributing much to the chance of heart attack. In the model, the correlation value $> \ = 0.3$ is termed to be preferably chosen. So, the feature selection is made based on the moderately correlated features. The training and testing data are splitted with a test size of 20% of the entire dataset. To avoid outliers of the data, robust scaling is used for the data.

4.2.1 Data Pre-Processing and Feature Selection

By using the robust scalar during data pre-processing, EDL for heart disease prediction benefit from improved performance and stability. The scalar normalizes input data, making it less sensitive to outliers and non-normal distributions. This robust normalization enhances the models' ability to learn and generalize from features, resulting in increased

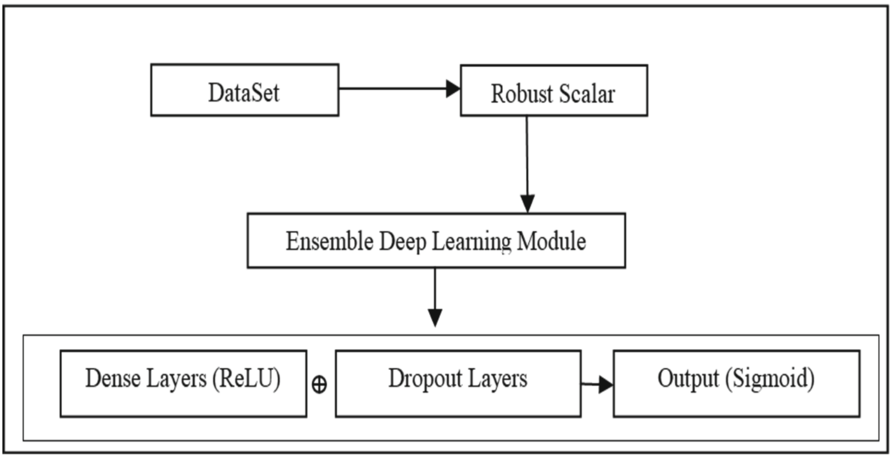

Fig. 5. Data Preprocessing

accuracy and reliability in heart disease prediction shown in the Fig. 5. In order to prevent the model's generalizability from being compromised, it is important that the duplicates be safely eliminated.

4.3 Hypothesis Testing

The null hypothesis that there is no correlation between a certain variable and the occurrence of heart disease can be tested using the chi-square test. If the estimated chi-square statistic is larger than the crucial value, then you can conclude that cardiac disease is occurring and reject the null hypothesis.

4.4 Model Building

After performing hypothesis testing, we can use the significant variables to model cardiac disease. One common method is logistic regression, which estimates the important predictors; estimate the likelihood of getting heart disease.

In ensembling multiple models, the stacking method is used in which entire training data is used to train each and every model (Table 3).

Performance Analysis

See Fig. 6.

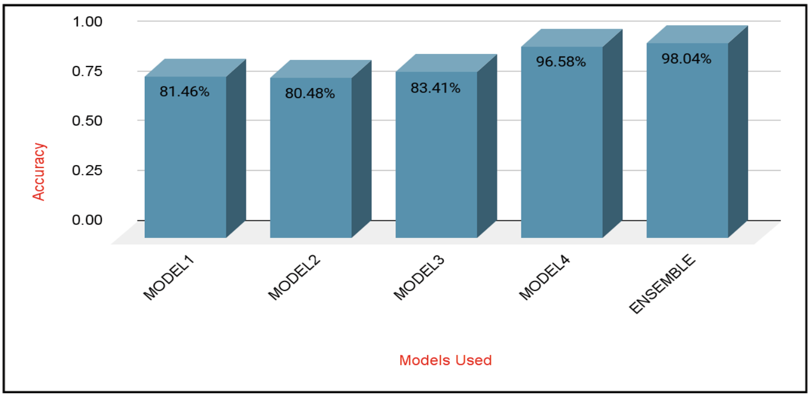

Fig. 6. Performance analysis between selected algorithms.

Evolution Metrics

1. Accuracy Processing

Accuracy is a term used in evaluation metric for classification problems in machine learning. It measures the percentage of the test dataset that was correctly labeled.

Mathematically, accuracy is defined as:

$$\text{Accuracy} = (\text{No of Positive Prediction})/(\text{Total no of Prediction})$$

2. Weighted Average Ensemble:

Weighted average ensemble combines the outputs of multiple models in ensemble deep learning. It assigns weights based on model performance, allowing accurate models to have a larger influence. This improves performance compared to other methods, especially in heart disease prediction for image recognition. Some of the Metrics or Activation functions used in Convolutional Networks are as follows.

Evaluation Process Used

Evaluation metrics include the confusion matrix, precision, accuracy score, recall, sensitivity, and F1 score. The confusion matrix consists of TP, TN, FN, and FP representing true positives, true negatives, false negatives, and false positives, respectively.

Table 4. Binary Classification Confusion Matrix

	Predicted Value 0	Predicted Value 1
Actual Value 0	TN	FP
Actual Value 1	FN	TP

In Table 4. P = positive, N = negative. The accuracy score evaluates model performance by considering the ratio of correct predictions to total predictions. It is calculated as

$$(\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{3}$$

Specificity, or the true negative rate, evaluates the classifier's performance by identify negative cases accurately and is given by

$$\text{TN}/(\text{TN} + \text{FP}) \tag{4}$$

According to the research on ML and DL techniques, rather than using just one strategy, assembling a number of techniques results in increased accuracy, which in turn results in better performance for the model (Figs. 8 and 9).

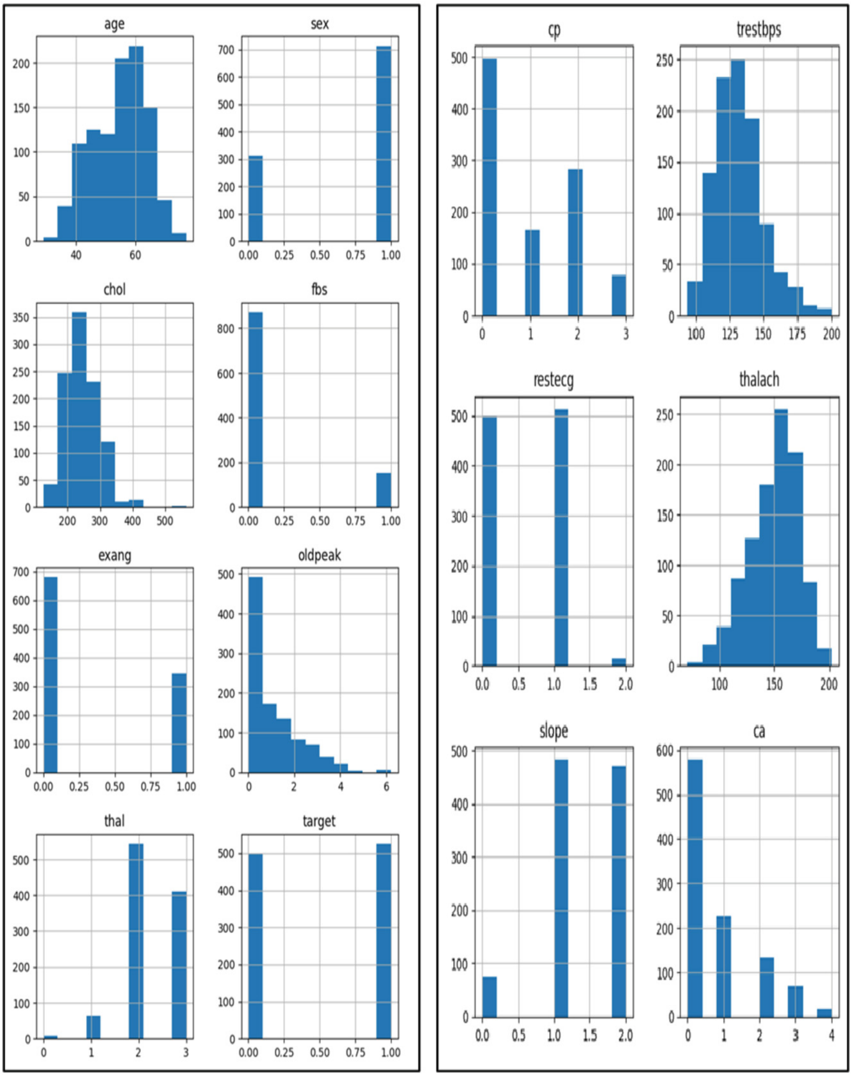

Fig. 7. DataSet Features Distribution

By employing the proposed ML method outlined in this study, the analysis of real time patient data can be significantly improved. Based on CNN's 97% accuracy, Generic and Deep neural network's 87%, Sparse auto encoder based ANN's 90%, DNN and Talos optimization's 90.76%, and IoT centered DLMNN's 95.87% accuracy, Ensembled deep learning model is the most accurate mode. Ensembling of multiple deep learning models achieves higher accuracy (98.04%) with multiple layers in each of the models.

Some of the limitations of ensemble learning can be overcome or mitigated in the future with advancements in technology and research. Researchers can develop more

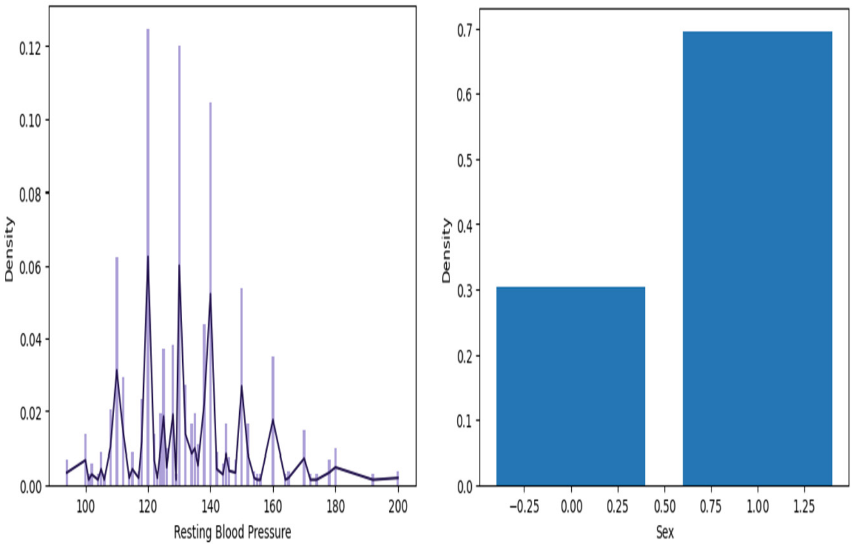

Fig. 8. Distribution of BP and Sex

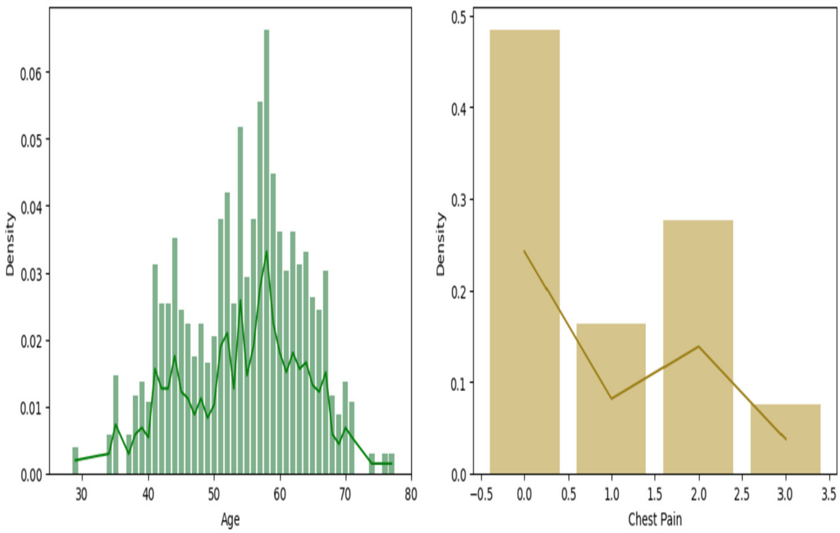

Fig. 9. Distribution of Age and Chest Pain

computationally efficient ensemble methods that require less training time and computational resources. One approach could be to use approximate methods such as random projections or sketching to decrease the amount of input data and the quantity of base models.

5 Conclusion

In this paper, we looked at the fundamental ideas behind the DL and ML models to prognosticate the onset of cardiovascular problems. Analysis of studies aimed at predicting cardiovascular disease by employing a selection of ML and DP techniques. Different models' performance was discussed and reviewed. Obstructive on the tools, dataset and the techniques, the models have varied accuracy. In recent years the usage of DL algorithms on huge datasets yields better accuracy in heart disease prediction models. This article will be beneficial for the researchers to get an idea of the present and existing models and work to design future models that are more accurate.

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