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Predictive Modeling for Early Detection and Risk Assessment of Cardiovascular Diseases Using the Ensemble Stacked Neural Network Model

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Abstract: Medical experts feel difficulty in making the right decision about cardiac arrest. Early detection of cardiovascular disease means a better chance of survival for the patient otherwise it can lead to death. This study proposes a state-of-the-art model named Ensemble Stacked Neural Network (ESNN) that combines both machine learning (ML) and deep learning (DL) techniques for early detection and risk assessment of cardiac disease. Our model pools multiple widely recognized cardiac disease datasets (Cleveland, Hungarian, Switzerland, Long Beach VA, and Statlog) to create a comprehensive dataset for training and evaluation. The ESNN model begins with extensive data pre-processing, including the elimination of null values, outliers, and duplicates, followed by Z-score normalization to standardize the feature scales. We address class imbalance using the Randomized Oversampling technique. Principal Component Analysis (PCA) is applied for feature reduction, ensuring the most informative components are retained. We employed a diverse set of nine ML algorithms, consisting of XGBoost and naïve Bayes, achieving individual accuracies ranging from 69% to 89%. ESNN model integrates a neural network that is trained and validated on the processed data, producing predictions that serve as additional features for the subsequent ML models. The chosen nine classifiers are used as base models and these are tuned using GridSearchCV for optimal Hyperparameters. The base models consist of a DT, RF, LR, gradient boosting, XGBoost, AdaBoost, SVM, KNN, and NB. RF is used as a meta-model in a stacking ensemble framework. The proposed model (ESNN) was carefully trained and tested and achieved an accuracy of 95%. This integration of machine learning and deep neural network methods within the ESNN framework establishes strong predictive modelling. It provides a reliable tool for cardiologists to diagnose heart disease risk.

Keywords: Cardiac Disease Diagnosis; Machine Learning Algorithms; Deep Learning; Cardiac Healthcare; Neural Networks; Ensemble.

1. Introduction

The world is facing several health issues due to a shortage of resources and medical facilities for many people. There are, many cases of heart disease that cannot be treated in time and it increases the mortality rates. It accounts for approximately one-third of all mortalities worldwide, with more than seventeen million expiries annually as reported by the WHO (World Health Organization) [1]. Early detection and accurate risk assessment are crucial for improving patient health and reducing the load of heart disease. Medical experts use multiple techniques to identify cardiac issues, relying on medical reports available in the form of images and text. However, the accuracy of their predictions is inconsistent and may lead to incorrect decisions. Therefore, an automated system is needed to avoid such anomalies. Artificial Intelligence (AI) is making significant progress in the area of health. ML and DL, subfields of AI, are renowned for their high performance. Various ML and DL techniques provide optimal solutions for disease diagnosis, especially for cardiac disease.

This disease directly damages the heart which is very important for the smooth working of humans. Its primary duty is to drive the blood and oxygenate other body parts [2]. Cardiac disease prediction is a hot research area that can be evaluated using the algorithms of ML and DL Most of the famously used ML and DL methods in cardiac disease prediction are LR, DT, XGBoost, KNN, and NB. Machine learning techniques were modified to build NN (neural network) models. These are some of the sub-categories of artificial intelligence that perform multiple jobs at a time [3]. These algorithms perform best with the huge available dataset. The disease diagnostic process relies on the data provided by the hospitals. Medical experts are trying their best to build an error-free system. It is necessary to utilize advanced methods and techniques for data analysis for accurate and precise results [4]. The importance of accuracy cannot be neglected as it saves not only a patient's life but also reduces the financial burden and time for diagnosis [5].

This study proposes a state-of-the-art model named Ensemble Stacked Neural Network (ESNN) that combines both machine learning (ML) and deep learning (DL) techniques for early detection and risk assessment of heart disease. Our model combines five widely recognized datasets. It includes Cleveland, Hungarian, Switzerland, Long Beach VA, and Statlog to create a comprehensive dataset for training and evaluation. This study includes the pre-processing for the removal of unnecessary information from the dataset by using standard methods of data normalization. This research implements the Randomized Sampling technique for the balancing of datasets. It also finds the best Hyperparameters through GridsearchCV to tune up the system to get improved results. The working of the model was assessed on benchmark datasets via certain metrics like F1 score, recall, and ROC. Our research makes several key contributions:

- Identifying the most influential attributes from the pool of multiple (Cleveland, Hungarian, Switzer Land, Long Beach VA, and Statlog) datasets for predicting cardiovascular diseases (CVDs)
- Determining the most effective ML techniques (out of 9 classifiers) when applied to these key Attributes
- Developing a hybrid (integration of DNN and ML) technique that offers improved prediction performance
- Enhancing current diagnostic systems to better predict CVDs in clinical settings

This work is managed as Section 2 gives the detailed process of conducting the review of previous related work, which was used to identify relevant material. Section three explores the applied method and structure of ESSN. Section 4 elaborates on the results and discussions, including answers to the research questions. Section 5 outlines the limitations of this study and presents the conclusion.

2. Related Work

Heart disorder is a type of illness that occurs due to cardiac issues, which may be predicted based on multiple factors. These include symptoms such as chest pain, breathiness, faintness, inflamed feet, and fatigue. The causes of cardiac disease can stem from inactive lifestyles, high cholesterol, smoking, and high blood pressure. Cardiac disease risk can be reduced by addressing these causes. Scientists are working to develop improved models for predicting heart disease. There are many datasets available on the internet for research purposes, and scientists utilize these to predict disease by applying various ML and DL techniques. Researchers choose different modalities from these datasets to identify the illness.

For example, a study used a dataset of 303 heart patients, which included test reports, previous history, lifestyle, and angiographic data. The authors in this study used ML methods to improve the diagnosis accuracy of heart disease [6]. Several researchers have been using multiple techniques, combining machine learning and deep learning. They applied ensemble classifiers to obtain improved results [7]. In another study, the authors used an ensemble classifier with multiple classifiers including RF, LR, and SVM as base learners. They used SMOTE for bata balancing and got an accuracy of 93%. They used a dataset of 303 patients from UCI and 4238 records of cardiac patients from Kaggle [8]. Cardiac disease can be managed through exercises and physiotherapy. A study was conducted leading to the invention of an automated rehabilitation training model focused on Human Activity Recognition (HAR) techniques [9].

Many researchers have used recurrent neural networks (RNNs) to predict heart disease. The authors in [10] modified the RNN network to build a Long Short-Term Memory (LSTM) model. It was developed to minimize memory problems encountered during training. It gave better results. Cardiac disease is not only predictable by applications but it can also be predicted by an electronic stethoscope [11]. In [12], authors used the Generative Adversarial Networks (GAN) model to balance their heart dataset for predicting cardiac disease. They claimed improved accuracy after dataset balancing. In another study, conventional machine learning classifiers (LR, DT, RF, K-NN, SVM, and XGB) were applied, and the logistic regression classifier achieved an accuracy of 85.84% [13]. These conventional learners, such as DT, LR, SVM, and RF, provide extended results. They performed feature engineering to get the optimum results [14].

This was demonstrated in a study where a SVM classifier was used for heart disease prediction. They got an accuracy of 87% after applying principal component analysis for feature engineering [15]. A study utilized a dataset containing electrocardiogram information alongside other attributes for predicting cardiac disease [16]. Another study used a dataset featuring electrocardiogram arrhythmia characteristics to diagnose cardiovascular disease. They obtained promising results [17]. Researchers in [18] adopted the N2 Genetic-nu-SVM method for forecasting cardiovascular disease. They attained an accuracy of 93% on an Iranian dataset with over a hundred patients. In a different study, authors achieved 89% accuracy using six machine learning classifiers [19]. They used a dataset of more than 300 patients. They achieved the best results with the SVM classifier. The working of algorithms was measured through metrics such as precision, F1-score, and recall.

In [20], the study achieved 90% accuracy using multiple machine-learning techniques. They identified the random forest classifier as the best performer on a UCI dataset consisting of 303 records. The researchers in another model combined the random forest and linear regression classifiers. They achieved 88.7% accuracy for heart disease prediction [21]. Further researchers obtained the highest accuracy by applying DT, KNN, and K-Means classifiers. They found the decision tree gave the best results in a comparative analysis [22]. A different research proposed an SMO (sequential minimal optimization) classifier, achieving an accuracy of 86.4% [23]. In [24], machine learning techniques were applied to identify cardiac diseases. They identified the decision tree classifier showing optimal results. Another study used GNB, LR, and DT to diagnose heart disease. The authors decreased the attribute from 13 to four by applying single-value decomposition functions. They identified that GNB and LR classifiers achieved 82.75% accuracy [25].

A CNN model was used to build the multimodal disease risk prediction (MDRP) approach to identify cardiac disease [26]. In another study, neural network techniques were combined with a decision tree classifier for heart disease identification. They combined the Cleveland and Statlog datasets and achieved 99.9 on the Receiver Operating Characteristic curve [27]. The research was performed on a dataset of South Indian hospital dataset with 1,670 records. They identified that the RF algorithm showed a maximum accuracy of 93.8% among five classifiers, including AdaBoost, LR, NB, KNN, and RF [28]. In another study, authors applied LR and SGD techniques to 303 patient records from the UPI repository. They found logistic regression achieved an accuracy of 91.67%, while SGD reached 80.0% [29]. ML and image fusion techniques have also been found effective in predicting cardiac diseases [30]. A study using the Classification and Regression Tree (CART) model for heart disease prediction achieved 87% accuracy [31].

The researchers applied Minimum Redundancy Maximum Relevance (MRMR) after data pre-processing on the UCI dataset for feature selection. The support vector machine classifier reached 84.85% accuracy [32]. The authors conducted an analysis using multiple classifiers. Their technique approached an accuracy of 88% for both RF and LG classifiers [33]. A study on a Kaggle dataset was applied to seven ML learners for cardiac disease prediction. The random forest classifier approached to 83.53% accuracy. The authors also applied the Boruta algorithm to selected features after pre-processing the dataset [34]. In [35], Hyperparameters tuning was performed using Randomized CV and Grid CV methods for LR feature reduction. They analysed the different combinations of seven algorithms. The combination of logistic regression and Grid Search with the Kernel PCA ensemble technique achieved 100% accuracy. Cardiac disease prediction using logistic regression on the UCI dataset reached 87.10% accuracy with a 90% training and 10% testing ratio [36].

Another study combined ML and DL classifiers for heart disease prediction. They normalized the dataset with the Isolation Forest for outlier detection and used the Lasso algorithm for feature selection. They achieved an accuracy of 94.2% on four datasets (Cleveland, Hungary, Switzerland, and Long Beach V) [37]. A majority voting ensemble classification algorithm was used on the Cleveland dataset to detect heart disease with high accuracy. The dataset was pre-processed using min-max normalization, and the ensemble model combined the stochastic gradient descent, KNN, RF, and LR classifiers [38]. A machine learning system was designed for heart disease identification using real-time data. They proposed a cloud-based framework to monitor the patients at home. This system combined the Swarm Whale Optimization (SOW) algorithm with the LeNet model to achieve 99.2% accuracy on the Stulong dataset [39]. Another study applied weight learning based on density information, achieving 98% accuracy. They used the UCI dataset with additional features for training [40].

A model with a fuzzy set was applied to the UCI medical repository. The researchers achieved 93% accuracy [41]. They achieved 96% accuracy but faced challenges in managing big data [42]. A soft voting ensemble classifier was used on the Cleveland dataset achieving 93.44% accuracy. They faced increased training and testing complexity [43]. In [44], XGBoost and Optuna were applied to the Cleveland, UCI, and Kaggle datasets and achieved 94.7% accuracy. In another research, SVM, XGB, NB, and LR were applied to the Cleveland dataset and achieved 88.5% accuracy [45]. The MLP-PSO model was applied to the Cleveland dataset and achieved 84.61% accuracy. Their technique offered better timing but with a low prediction rate [46]. A new method called Grey Wolf Horse Herd Optimization-based Shepard Convolutional Neural Network (ShCNN) was developed for diagnosing heart disease using the VA Long Beach dataset. Their model achieved an accuracy of 93.25% [47]. Another study developed a Deep Neural Network for heart disease detection. They improved prediction accuracy by removing inappropriate features [48].

The Fuzzy Deep Convolution Network (FDCN) was introduced for diagnosing cardiac disease. This technique even avoided irrelevant features but system performance was not so impressive [49]. In another study, CNN was used to handle uncertainty in learning algorithms [50]. The researchers created the MD-RCNN, which was cost-effective but struggled with real-world applications [51]. In [52], a new machine-learning method was developed for predicting cardiac disease, involving data cleaning, transformation, and standardization. Four machine-learning classification algorithms were tested on the Cleveland and Statlog datasets. They included 138 instances of heart disease and 161 normal cases. Similarly, 150 cases of heart disease and 120 without disease were used from the Statlog dataset [53]. In another study, several algorithms were applied to the Cleveland dataset to predict cardiac issues. The ensemble method with these algorithms was used to predict cardiovascular disease (CVD). The system was evaluated using 10 performance metrics. The metrics showed that categorical features had a vital role in diagnosing cardiac disease and the system achieved an accuracy of 95.94% [54].

The application of the GWO-KELM technique for identifying cardiovascular disorders achieved an accuracy of 95.94% [55]. This study proved that combining AI with medical techniques has resulted in early diagnosis and improved patient care. The researchers have improved the performance of machine learning and deep learning methods by applying feature engineering. They select essential features from medical datasets to predict cardiovascular diseases [56]. A multi-model approach combining XGB, SVM, RF, and LR with PCA-based feature engineering achieved 97.1% accuracy. They applied the classifiers to the Cleveland dataset, though it required extensive computational resources [57]. Another study on the Framingham Heart Study dataset applied deep learning techniques for cardiovascular risk prediction, achieving an accuracy of 92%. Their study was focused on age, cholesterol levels, and blood pressure as primary predictors [58]. A study developed a CNN-based model for predicting heart disease using echocardiographic data. The researchers achieved 95% accuracy but faced challenges in generalizing across different patient populations [59]. In [60], researchers applied ensemble learning techniques combining RF, XGB, and DNN models on the Kaggle dataset. They approached an optimum accuracy of 94%. Another research effort utilized a hybrid approach combining genetic algorithms with deep learning for heart disease prediction. This approach obtained an accuracy of 93.5% on a dataset of 1,000 patients [61].

A study observed the use of wearable gadgets for real-time cardiac issues using machine learning models, achieving 91% accuracy [62]. Researchers applied transfer learning techniques on pre-trained CNN models for heart disease prediction using chest X-rays. They got an accuracy of 89%, with the need for further fine-tuning [63]. A novel approach Graph Neural Networks (GNNs) was developed to predict cardiovascular disease. It approached an accuracy of 96% on a multi-hospital dataset [64]. A study employed a federated learning approach to predict heart disease across multiple hospitals, achieving 94% accuracy [65]. Another research effort used reinforcement learning for personalized heart disease prediction. It achieved 92% accuracy, though computational complexity was a concern [66]. Lastly, a study was made to predict heart disease using explainable AI techniques. It enhanced interpretability and trust with an accuracy of 93% on the UCI dataset [67].

2.1. Research Questions

The existing literature review has led us to the following research gaps in terms of questions:

Q1. What are the main critical predictors used for predictions of cardiovascular disease?

Q2. Which Machine-learning techniques will perform best with the main attributes of a dataset?

Q3. Which hybrid technique (integrating two or more ML methods) will improve results?

Q4. How will the proposed system increase the efficiency of clinical practice?

Q5. What resources may be needed when healthcare professionals deploy the suggested system?

3. Research Method

This portion describes the details of the method used to build the proposed structure. This section presents the necessary steps taken to predict heart disease from the ensemble stacked neural network model (ESNN). It consists of the acquisition of datasets, combining datasets, preprocessing, data balance, splitting datasets, model training, performance evaluation, and model interpretation. The pre-processing step includes multiple stages of data normalization. After normalization of data choosing the right features is very important for predicting cardiac disease. Key features like blood pressure, cholesterol, age, gender, and other risk factors must be carefully chosen to ensure they impact the diagnosis of heart disease. Feature extraction is performed to assess the relevance of features. The next step is to apply multiple machine learning and deep learning classifiers for the prediction of heart disease. To identify cardiovascular disease, nine ML classifiers (logistic regression, decision tree, random forest, XGBoost, AdaBoost, gradient boosting, support vector machine, k-nearest neighbour, and naive Bayes) are used with a deep neural network model. Moreover, a Stack ensemble classifier was used to enhance the accuracy of the proposed model. Further, a model was designed to enhance prediction accuracy by introducing a deep neural network with nine machine classifiers.

The work starts by combining four datasets of heart disease taken from the UCI site as shown in Figure 1. Necessary preprocessing is performed to normalize the data to ensure consistency across all features, making it suitable for machine learning models. After preprocessing we performed feature engineering to enhance the predictive power of our models. The dataset was balanced by using 'RandomOverSampler' to maintain the balance among both classes (0 and 1). At the next level, we applied nine machine-learning classifiers to get individual results. After this, a stacking ensemble was used to find the best classifier among the nine and improved accuracy. Lastly, the proposed model Ensemble Stacked Neural Network (ESNN) was applied to get the best results. The detailed discussion of each step is discussed below.

3.1. Dataset Acquisition

For this research, several datasets were combined to increase the strength of the cardiac disorder prediction model. The datasets were retrieved from the UCI repository [21]. The datasets included "processed_cleveland_data.csv", "processed_switzerland_data.csv", "processed_va_data.csv", and "reprocessed_hungarian_data.csv", as shown in Table 1.

These datasets include a variety of patient records with diverse demographic and clinical features. This contributes to a comprehensive dataset for model training and evaluation. The acquisition and combining of these datasets involved reading each CSV file individually and then concatenating them into a single, unified data frame. This was achieved using a Python script that defines the path to the dataset files and iteratively reads each file into a separate data frame. Later, these individual data frames were combined to form a pooled dataset, ensuring consistency and completeness. The primary purpose of combining these datasets is to improve the diversity and information within each dataset. By integrating data from different sources, the resultant dataset provides a diverse sample of patient records. This integration lessens possible biases inherent in individual datasets.

Each dataset in the 'dataset frame' has a similar data type and instance format. It consists of 76 raw attributes out of which only 12 of them are used. The combined dataset contains the records of 920 patients and 12 attributes. The descriptions of selected fields are shown in Table 2. The dataset consists of 6 categorical and 6 numerical fields.

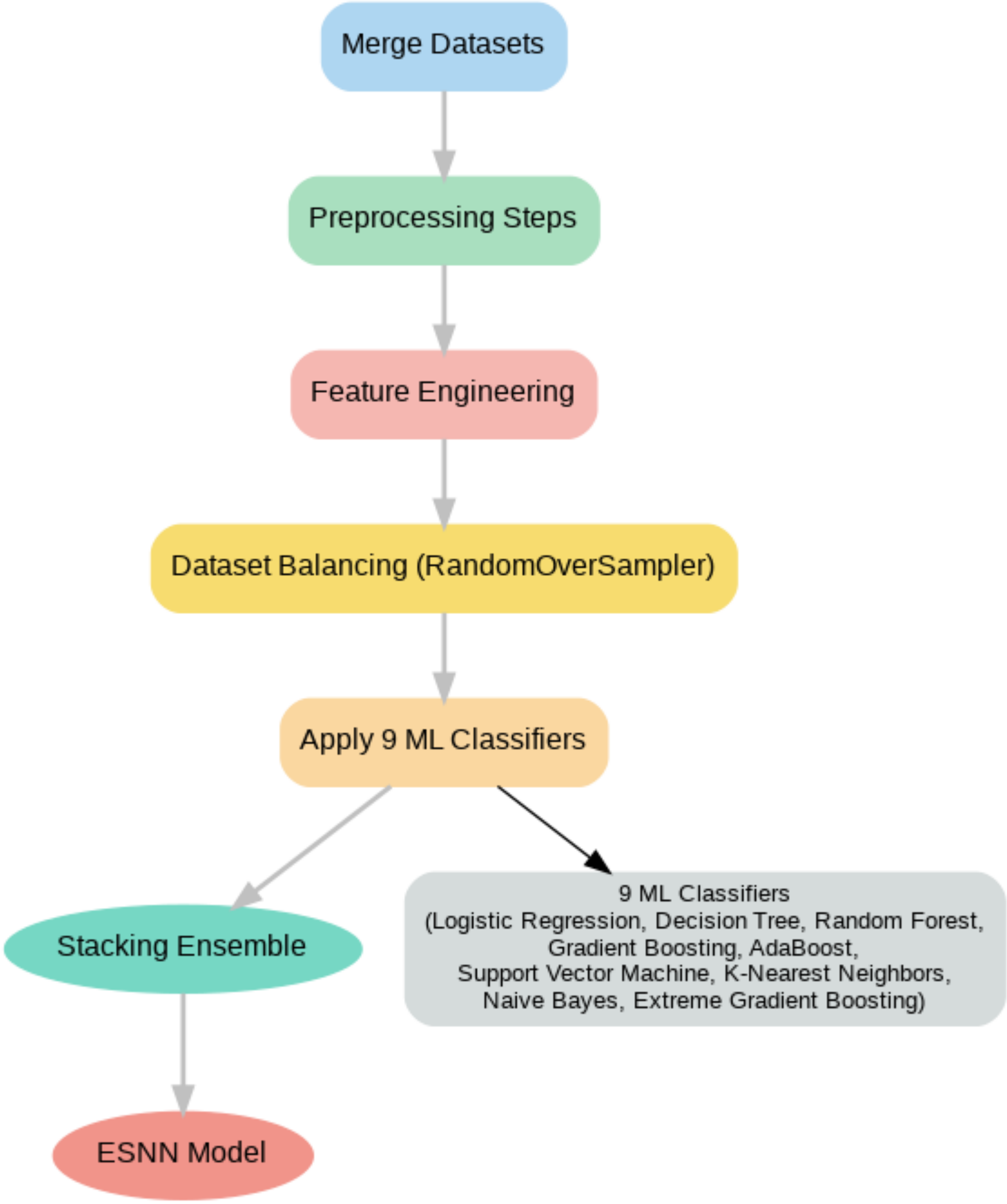

Figure 1. Flowchart of the Heart Disease Prediction System

The dataset includes patients aged 29 to 79. Males are indicated as 1 and females as 0. There are 4 types of chest pain pointing out cardiac disease:

1. Typical angina: Due to less blood flow due to narrowed coronary arteries
2. Atypical angina: Chest pain due to any pressure
3. Non-angina chest pain: Chest pain from various other causes
4. Asymptomatic: No symptoms indicating HD

The last attribute (Target) shows the patient has cardiac disease, with 0 representing no disease and 1 indicating the presence of heart disease.

3.2. Preprocessing

Various data preprocessing tasks are performed to ensure the dataset is clean and ready for model training. The application of the proposed model starts by importing the necessary library files and then after loading of concatenated dataset. Initially, the dataset information is displayed, showing the first few rows, shapes, detailed info, descriptive statistics, and checks for missing values and duplicates. Duplicates are then removed to maintain data integrity.

Table 1. Datasets for Concatenation

Sr#	Description	CSV File	Total Instances
1	Cleveland Clinic Foundation (Cleveland.data)	processed_cleveland_data.csv	303
2	Hungarian Institute of Cardiology, Budapest (Hungarian.data)	processed_switzerland_data.csv	294
3	V.A. Medical Center, Long Beach, CA (long-beach-va.data)	processed_va_data.csv	123
4	University Hospital, Zurich, Switzerland (Switzerland.data)	reprocessed_hungarian_data.csv	200

Table 2. Selected Attributes of Dataset

Sr #	Attribute	Type
1	Age	Integer
2	Sex	Integer
3	CP	Float
4	Trestbps	Integer
5	Chol	Integer
6	FBS	Float
7	Restecg	Integer
8	Thalach	Integer
9	Exang	Integer
10	Oldpeak	Float
11	Slope	Integer
12	Target	Integer

Two duplicate records were found and those were deleted from the dataset. Next, z-score normalization is applied to specific columns (‘age’, ‘sex’, ‘cp’) to identify and filter outliers. Rows with z-scores greater than 3 are considered outliers. The Z-score for a feature x_i in a dataset is calculated as:

$$z_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

Where μ is the mean of the feature and σ is the standard deviation. Rows with $|z_i| > 3$ are considered outliers and are filtered out. The outliers are removed to ensure the dataset is free from extreme values that can affect the analysis. In the next setp of preprocessing, columns such as ‘trestbps’, ‘chol’, ‘fbs’, ‘restecg’, ‘thalach’, ‘exang’, ‘oldpeak’, ‘slope’, ‘cp’, and ‘thalach’ are converted to numeric, with invalid entries replaced by NaN. Missing values in numeric columns are filled with the mean of the respective columns. For each numeric column with missing values, we replace the NaN values with the mean of the column. If x_{ij} is a missing value in column j, it is replaced with x_j and calculated by

$$x_{ij} = \frac{1}{N} \sum_{i=1}^{N} x_{ij} \quad (2)$$

It separates the features and target variables and the features are scaled using a standard scaler. The purpose of the scaler is to normalize the data and to have a mean of 0 and a standard deviation of 1. For each attribute (feature) x_i, the scaled value x_i' computed as

$$x_i' = \frac{x_i - \mu}{\sigma}$$
(3)

The performance of machine learning algorithms relies on this scaling of features. Overall, data preprocessing involves cleaning and transforming the dataset to improve the quality of the data. This process includes handling missing values, removing outliers, and scaling features. These steps help in managing noisy datasets, overcoming overfitting, addressing class imbalances, and ensuring that the model achieves reliable and accurate predictions for heart disease.

3.3. Feature Engineering

The dataset consists of 76 features (attributes), and only twelve of them are used for research purposes due to their key role. These attributes are used by applying feature engineering to improve model performance. It helps to capture complex patterns in the data. It creates new features and transforms them into new ones to better understand the data. For example, age attribute can be grouped into categories to simplify the data. Similarly cholesterol feature can be divided into multiple levels to process the data easily. Features can be combined to capture the important relationships among them. Interaction terms, like age and heart rate can be combined to get binding effects of features. Similarly, converting categorical data into binary fields ensures the model uses all the information effectively. These steps make the model more accurate and reliable for predicting heart disease as shown in Figure 2. The following steps were adopted to perform the feature extraction. New feature 'age_category' is created by grouping ages into different sections: 30-39, 40-49, 50-59, 60-69, and 70+. This is performed using the following bins.

Bins = [29, 39, 49, 59, 69, 100]

Each age is categorized based on these bins and assigned labels:

Labels = ['30–39','40–49','50–59','60–69','70+']

Next, a binary feature 'cholesterol_binary' is created based on cholesterol values. The feature is defined as:

1 if cholesterol > 1
0 if cholesterol <= 1

Relations are then created between certain attributes to capture the combined effects. For example:

Age * max-heart-rate = age x max-heart-rate
Oldpeak * exercise-angina = oldpeak x exercise-angina

These relational terms can reflect relationships between features that may improve prediction accuracy. Categorical variables such as 'chest pain type', 'ST slope', 'resting ecg', and 'age_category' are converted to a binary column:

0 If category is absent
1 If category is present

Lastly, the actual 'age' attribute is dropped as it is now represented by the 'age_category' feature. The updated dataframe is displayed to show the newly engineered features as shown in Figure 2.

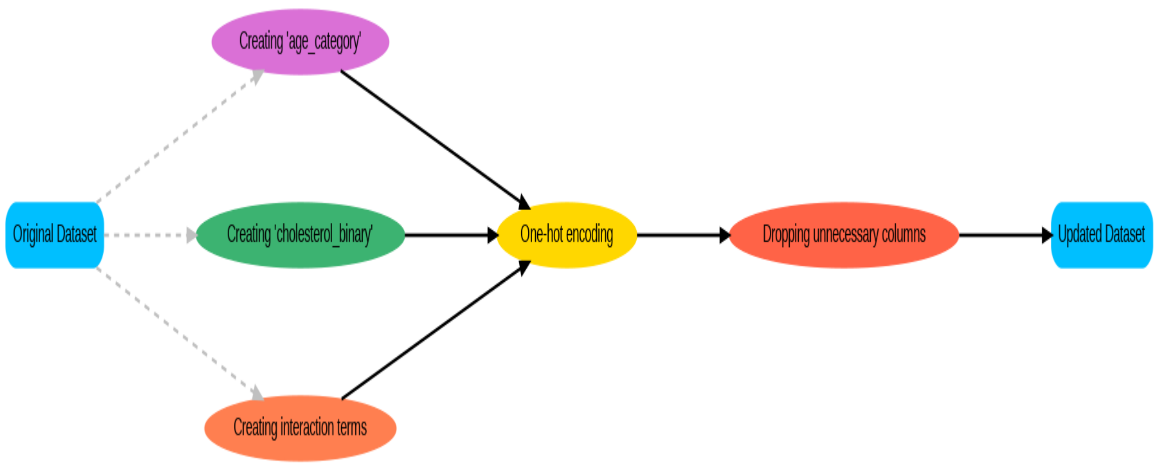

Figure 2. Feature Engineering Graph

These steps collectively enhance the dataset by adding meaningful features. It simplifies existing ones and prepares categorical data for the model's accurate predictions. Feature engineering is crucial for improving model performance. It helps capture complex patterns in the data. By creating new features and transforming existing ones, the model can better understand the data. Converting categorical data into binary columns ensures the model uses all the information effectively. These steps made the model more accurate and reliable for predicting heart disease.

3.4. Class Distribution Analysis

This step checks the class distribution of the target variable. It counts how many instances belong to each class. The results are printed to show the distribution. Next, it plots the class distribution using a bar plot. The plot shows how many instances belong to each class visually. The results indicate an imbalance: class 1(heart disease) has 508 instances, while class 0 has 410 records as reflected in Figure 3. This helps understand the balance of classes in the data.

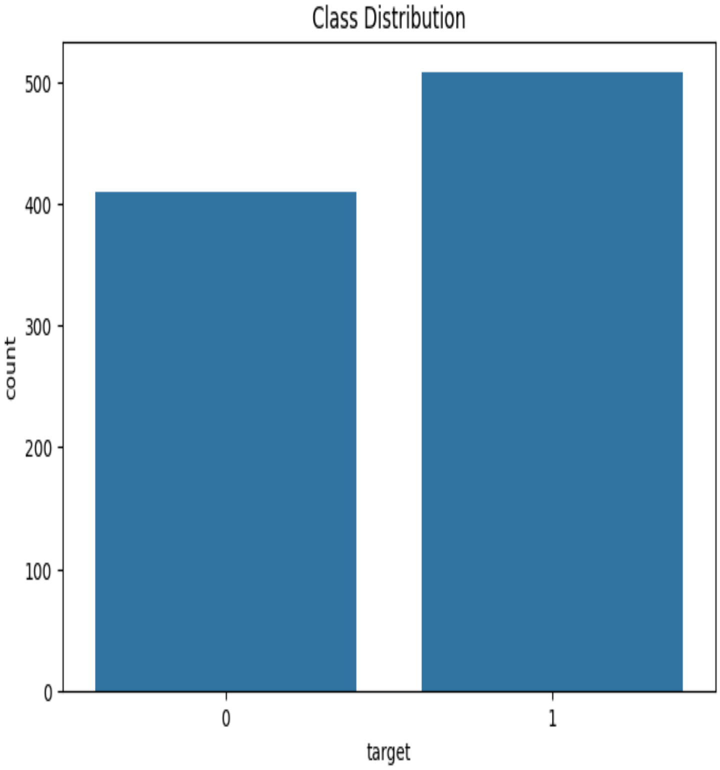

Figure 3. Class Distribution Graph

Splitting the dataset is an essential step in ML. We first separate the attributes and the target variable. The features are stored in 'X' and the target in 'y'. We then use 'train_test_split' to divide the data into training and test sets. Here, 80% of the data is used for training and 20% for testing. The 'random_state = 42' confirms the random selection of the split. This selection helps in evaluating the performance of the model on unknown data. Data balancing is necessary when coping with imbalanced data. We have used 'RandomOverSampler' from the sklearn('imblearn.over_sampling') for this task. It generates more samples for the minority class to balance the dataset. We initialized the sampler with a 'random_state' of 42 for reproducibility. We have used 'ros.fit_resample(X, y)', to resample the dataset. Finally, it results in balanced features 'X' and target 'y'. This step improves model performance on imbalanced data.

3.5. Machine Learning Classifiers

The process of analysis starts by importing the essential libraries. The necessary functions are used from Pandas and Numpy. We use 'train_test_split' from sklearn.model_selection to divide the dataset into 'train' and 'test' portions. The test set size is 20% of the entire dataset while 80% is used for training purposes. The 'random_state = 42' confirms the reproducibility of the split. We create a dictionary called 'classifiers' to store different machine learning models. Each 'key' is the name of a classifier, and the 'value' is an instance of the classifier. This allows us to easily iterate over multiple models and compare their performance. We initialize an empty dictionary called 'results' to store the performance metrics of each classifier. We then loop over each classifier in the 'classifiers' dictionary and perform the following important tasks.

- For each classifier, CLF.FIT is used to Fit and train
- Use CLF.PREDICT to predict

• Use ACCURACY-SCORE to find accuracy

The output in terms of metrics are stored in the results dictionary with the classifier's name as the key. After this, we print the performance metrics for each classifier. We iterate over the results dictionary and print the name, accuracy, confusion matrix, and classification report. This provides a comprehensive overview of how each model performed on the test data.

Through comparison of these results, we can judge which classifier works best for our specific dataset as shown in Table 3. The results of used ML classifiers lies between 69% and 89%. SVM gave the minimum accuracy of 69.60% while the random forest algorithm's accuracy was found 89.21%. This method ensures that we evaluate multiple models efficiently and effectively. A detailed discussion of used machine learning classifiers is given in the following subsections.

Table 3. Comparative Analysis of ML Classifiers

	Classifier	Accuracy	Precision	Recall	F1-Score
0	Logistic Regression	0.843137	0.843137	0.843137	0.843137
1	Decision Tree	0.848039	0.851124	0.848039	0.848582
2	Random Forest	0.892157	0.89218	0.892157	0.891817
3	AdaBoost	0.843137	0.845606	0.843137	0.843641
4	Gradient Boosting	0.882353	0.883586	0.882353	0.882628
5	Support Vector Machine	0.696078	0.71978	0.696078	0.696458
6	K-Nearest Neighbors	0.715686	0.721594	0.715686	0.716926
7	Naive Bayes	0.852941	0.852941	0.852941	0.852941
8	XGBoost	0.882353	0.882353	0.882353	0.882353

3.6. Stacking Ensemble Classifier

This study experimented on the dataset using a stacking ensemble classifier after getting the individual performance of machine learning classifiers. This model aims to predict heart illness using a stacking ensemble technique. The main objective of this research is to improve the strengths of various classifiers. That will cause to enhance the accuracy of cardiac disease prediction. The ESNN technique is designed to increase prediction accuracy by integrating nine machine-learning classifiers. The working of the stacking classifier is shown mathematically by the expression (15). In this expression, each model 'h1' makes individual predictions. These are then combined by a meta-model ('RandomForestClassifier') to get the results. The applied classifiers are $h_1, h_2, \ldots, h_n$, the final prediction $\hat{y}$ can be calculated by the meta-model H as:

$$\hat{y} = H\,(\,h_1(X), h_2(X), \ldots, h_n(X)\,) \quad (15)$$

This ESNN model consists of a set of 9 base learners including DT, LR, SVM, KNN, and Naive Bayes. Each classifier has unique strengths and weaknesses. The results of these classifiers are fed to the stacking classifier to strengthen the prediction process. It makes the prediction model stronger to overfitting and variance in the data. It takes the average of predictions of all machine learning classifiers and reduces the risk of overfitting. Therefore, it produces results in a more accurate and reliable format. This ensemble stacking model proved itself as a modern and effective approach for medical predictions. This approach is valuable for early detection and risk assessment of cardiac disease.

3.6.1. Working of Stacking Classifier

The working of an ensemble classifier starts from the split of the data into TRAIN and TEST. It divides the dataset into ratios of 80 and 20 percent. This confirms the training on the majority of data and evaluated on separate test data. This ensemble stacking model contains nine different machine learning classifiers as base models, each with certain parameters. Random forest is used as a meta-model while RF, LR, DT, XGB, AB, GB, SVM, KNN, and Naive Bayes play a role as a base model. An instance 'RandomForestClassifier' is used as the meta-model to combine the results of the base models. The ensemble stacking model is trained on the output of the base models to make the final prediction. It is constructed by combining the base classifiers and the meta-model. The stacking classifier is trained on the training dataset and used to make predictions on the test dataset. The results of the stacking classifier are evaluated using accuracy metrics. These metrics are used to show the well-being of the model. The ensemble stacking classifier achieved an accuracy of 90.68%. The results indicate a high level of precision in predicting cardiac disease. This model exposes the power of stacking ensemble classifiers. It builds a strong and accurate model for predicting cardiac disease with enhanced accuracy as shown in Figure 12.

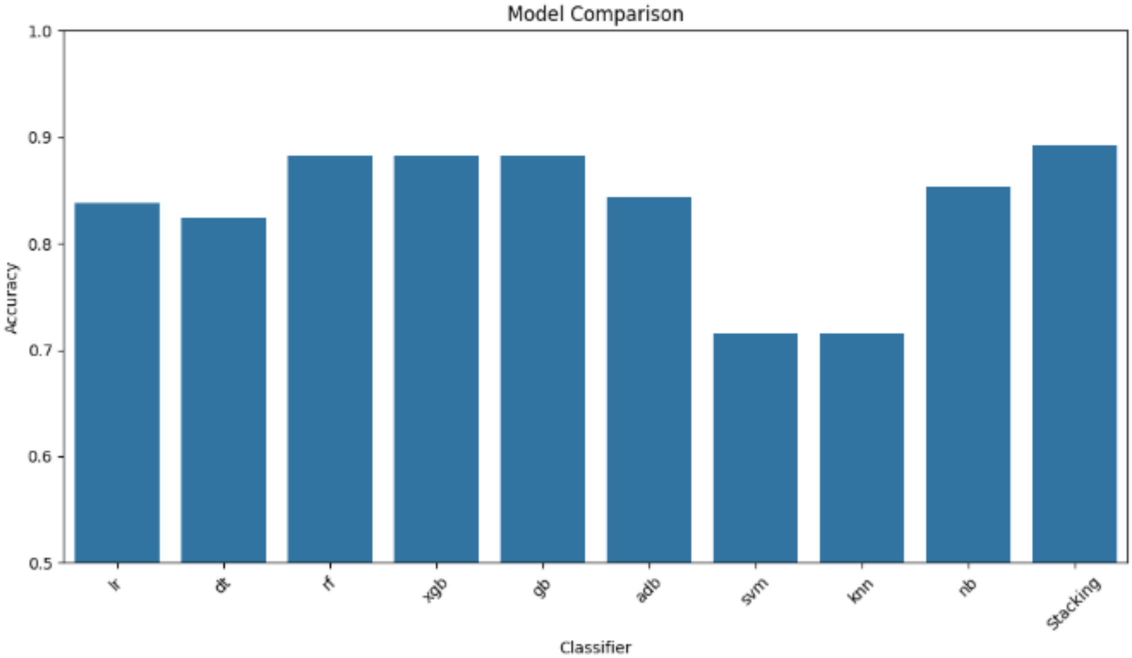

Figure 4. Stacking Classifier Comparison with ML Techniques

3.7. Ensemble Stacked Neural Network Model (ESNN)

The proposed architecture of the Ensemble Stacked Neural Network (ESNN) model is designed to predict cardiac disease. This research proposes a state-of-the-art technique to diagnose heart issues and their risk. It gathers homogeneous datasets of cardiac disease using ML and DL techniques. It combines multiple datasets of cardiac disease from the UCI site. Preprocessing is performed to normalize the dataset. The Ensemble Stacked Neural Network (ESNN) model applies multiple machine learning techniques to identify cardiac disease. It consists of 9 machine learning classifiers, a neural network, Principal Component Analysis (PCA), and GridSearchCV as shown in Figure 13.

3.8. Data Preparation:

The dataset, represented by 'X' and 'y', is split into TRAIN and TEST sets using 'train_test_split'. It is divided into X-Train and X-Test, with 80% for TRAIN and 20% for TEST. Additionally, 'X-train-pca' and 'X-test-pca' is used to smooth the features, retaining 10 principal components. This step simplifies the model and reduces computational cost.

3.9. NN (model) Creation and Training

The neural network layer is constructed by the function 'create_and_train_nn_model'. It builds and trains a neural network model using Keras. Certain layers are used in the model for binary classification. The logical construction of the neural network is reflected in Figure 14.

3.10. Neural Network Predictions as Features:

The neural network predictions are used as new features to enhance the original data. Predictions are obtained from the neural network model for both training and testing data. The trained neural network provides predictions on the training and testing sets, which are then, used as additional features ('nn_train_preds' and 'nn_test_preds'). These extended features ('X_train_extended' and 'X_test_extended') combine original PCA-transformed features and neural network predictions.

3.11. Hyperparameters Tuning with GridSearchCV

GridSearchCV is used to tune Hyperparameters for each base model. A parameter grid is defined for each classifier, specifying ranges for key hyperparameters. The base models include LR ('lr'), DT ('dt'), RF ('rf'), XGBoost ('xgb'), AdaBoost ('adb'), SVM ('svm'), KNN ('knn'), and GNB ('nb'). GridSearchCV performs an extensive search over the parameter grid for each base model, using cross-validation to evaluate performance. The best models from this search are observed for further use and stored in the dictionary 'best_models'. The best Hyperparameters of each classifier are shown in Figure

15.

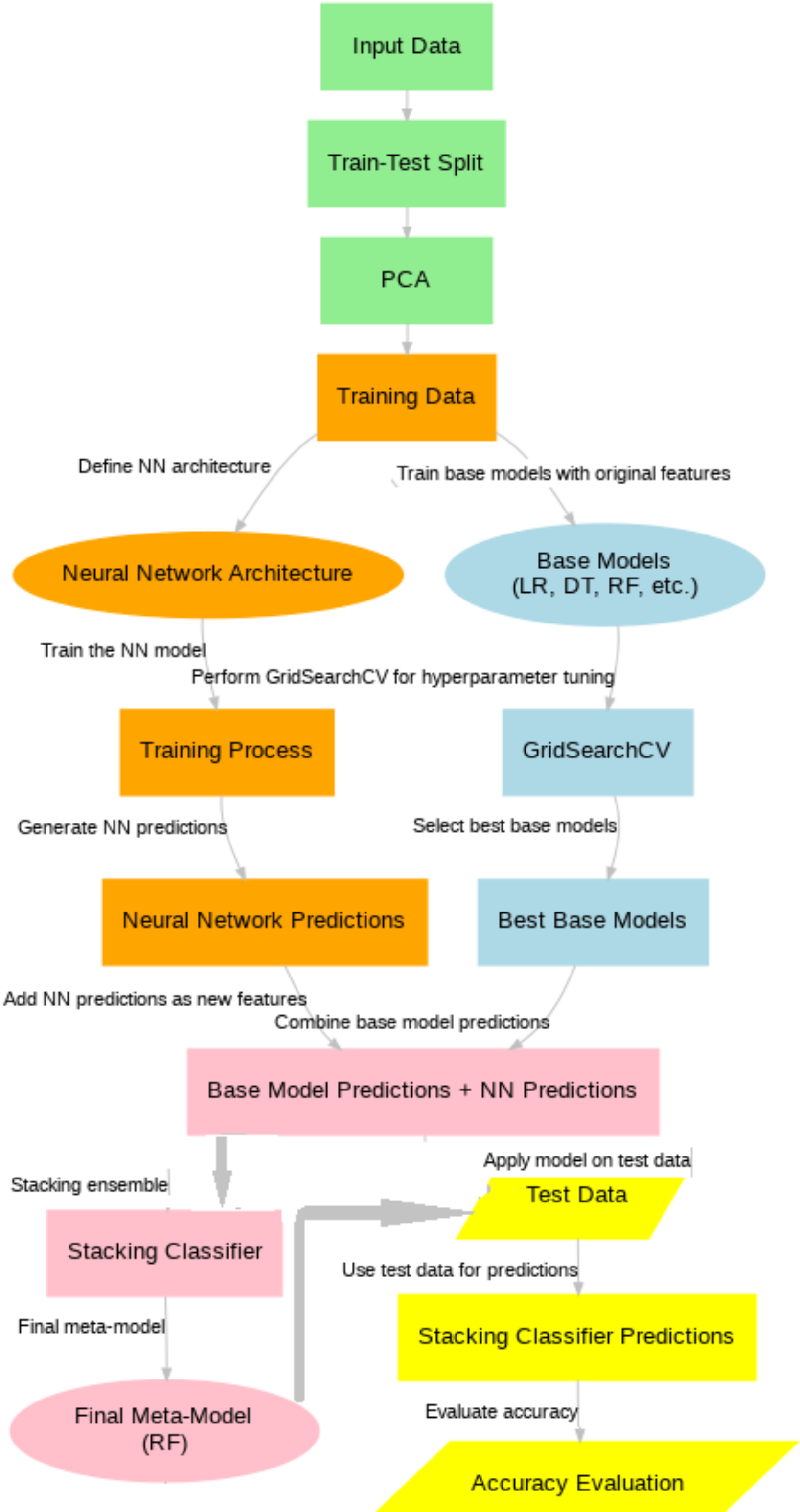

Figure 5. Flow of Ensemble Stacked Neural Network Model

3.12. Stacking Classifier

It is built using the best-tuned models. A stacking classifier gathers the results of these classifiers. The combined predictions help the meta-model to make the final prediction. The RandomForestClassifier plays a role as a final estimator or meta-model. It integrates the results from the base classifiers to finalize the results. This classifier works on the extended feature set.

3.12. Key Variables and Methods

The proposed study has used the following list of main variables and functions.

- X-TRAIN, X-TEST, y_TRAIN, y_TEST: Split for training and testing
- PCA, X-TRAIN-pca, X-TEST-pca: For feature reduction PCA split
- nn_model, nn_train_preds, nn_test_preds: Deep Neural Network and its predictions
- base_models, param_grid, best_models: Base Models with hyperparameters and best estimators
- stacking_classifier: The final ensemble model combining all tuned base models

The worth of the proposed ESNN model is reflected by the adopted systematic approach. The algorithm of the ESNN model is shown below.

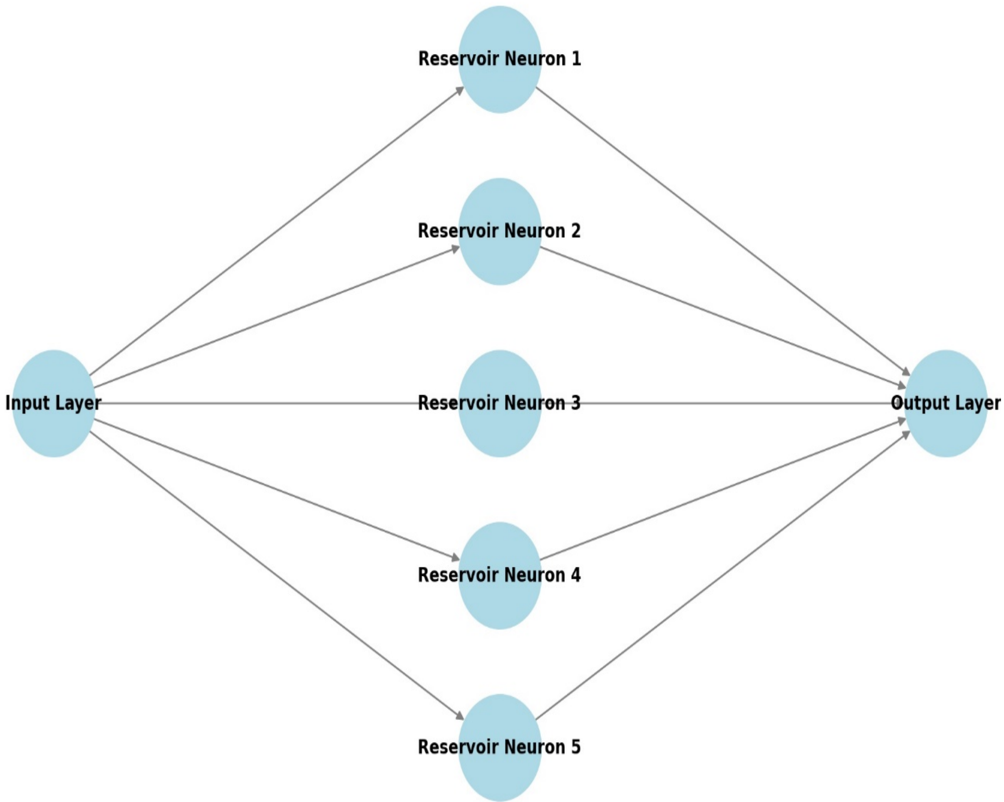

Figure 6. Echo State Neural Network (NN) Architecture

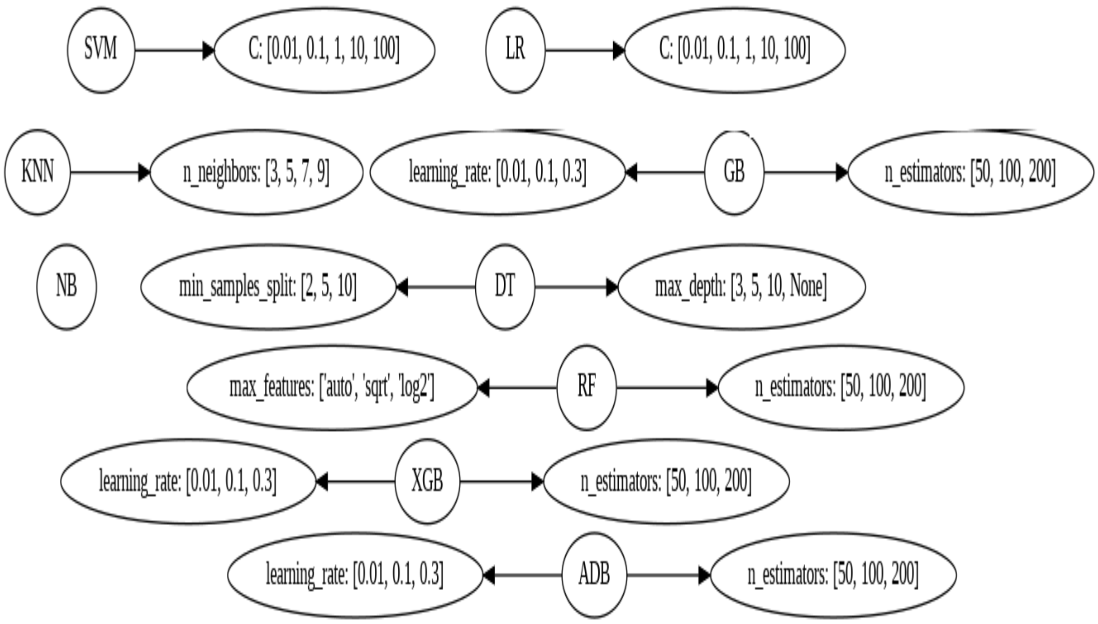

Figure 7. Bubble Graph of ML Hyperparameters

3.7 Algorithm: Ensemble Stacked Neural Network (ESNN) Model

Input: dataset, procedures, features , hyperparameters

Output: Cardiac disease Prediction

Start:

Input the X and y

Divide X and y into TRAIN and TEST

Apply PCA to reduce dimensionality of X_train and X_test

Define, compile, and train a neural network model using X-TRAIN-nn and y-TRAIN-nn, validating on X-VAL-nn and y-VAL-nn

Predict new features for training and test sets using the trained neural network

Concatenate neural network predictions with X_train_pca and X_test_pca to form X_train_extended and X_test_extended

For each base model(LR, DT, RF, XGBoost, GB, AdaBoost, SVM, KNN, GaussianNB)

Perform hyperparameter tuning using GridSearchCV

Train on X_train_extended and y_train

Store the best model

End For

Create and train a StackingClassifier using the best base models with RF as the meta-classifier

Predict on X_test_extended and evaluate accuracy

End

4. Experimental Results and Discussion

Here we explain and give an overview of the process used to achieve enhanced results with the proposed model and answers to the research questions. The first step starts with normalizing the merged dataset to ensure uniformity across the data. The dataset was balanced to address any potential biases. It was divided into TRAIN and TEST sets. The division was 80% for TRAIN and 20% for TEST. The data was analyzed by nine different machine learning classifiers. Each classifier was evaluated based on its ability to predict cardiac disease accurately. Random Forest appeared as the best performer, achieving an accuracy of 89% among others. The RF classifier outperformed the other classifiers, including LR, KNN, SVM, GNB, GB, DT, XGB, NB, and AB. The evaluation metrics were used to evaluate each classifier. These metrics prove the reliability of results that they are not only accurate but also consistent. The heatmap diagram is used to show the comparison of these metrics as shown in Figure 16.

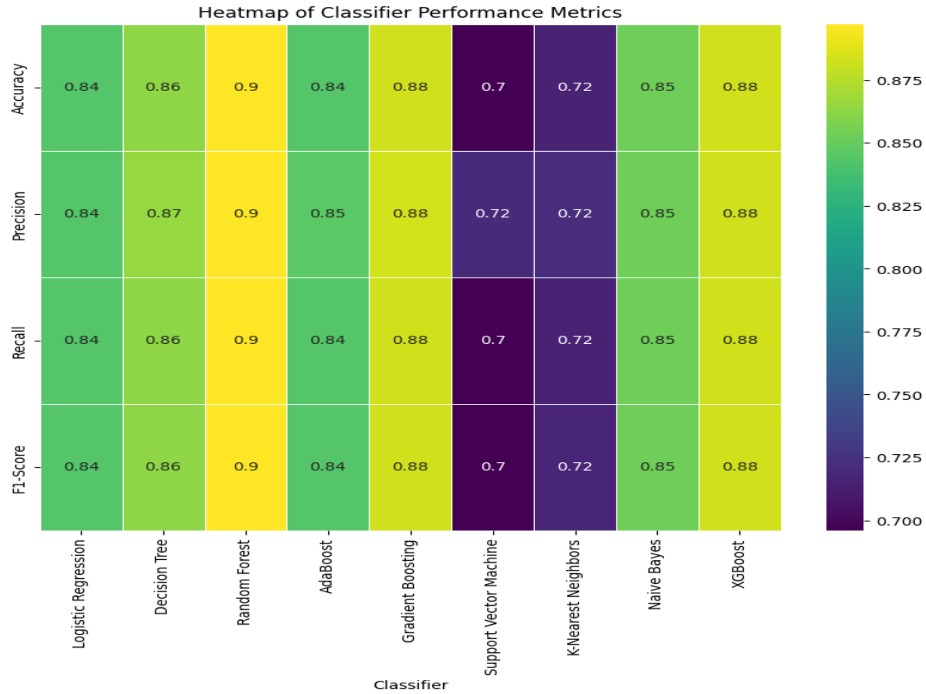

Figure 8. Heatmap of ML Classifiers Performance Metrics

After getting the individual performance of machine learning classifiers we used the stacking ensemble classifiers to improve the prediction performance. The result of each classifier was fed to the stacking ensemble and it was evaluated using its technique and gave a better accuracy of 90%. The comparison of this enhanced accuracy is reflected in Figure 17.

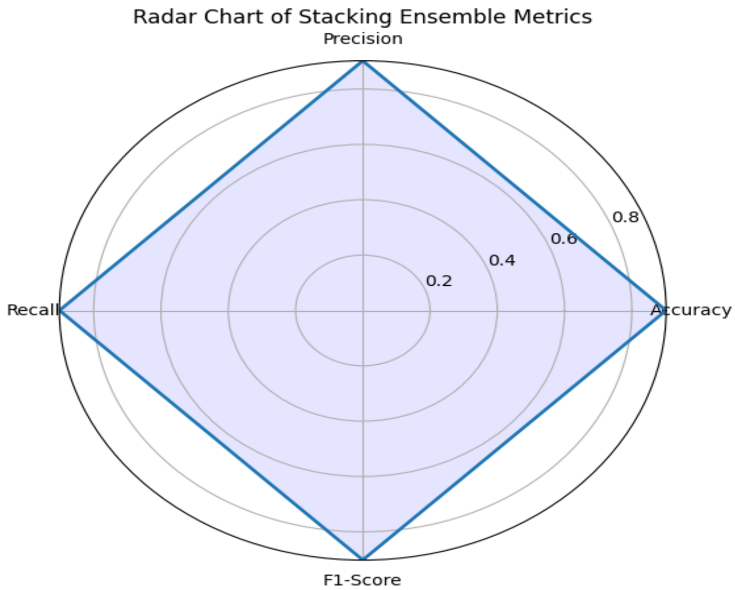

Figure 9. Radar Chart of Ensemble Stacking Metrics

The performance of the ensemble stacking classifier is better than individual classifiers as shown in Table 4. It demonstrates strong predictive capabilities across various metrics. This balance between metrics factors resulted in an F1-score of 0.8902, reflecting a strong overall performance for class 0. The support for this class was 88, meaning that the classifier evaluated 88 instances belonging to class 0. The result of 0.9191 of the F1-score indicates a strong and balanced performance for class 1. The contribution of class 1 in the dataset is shown by a support value of 116. Overall, the stacking classifier achieved an accuracy of 90.69%. It is consistent across the various metrics. Other parameters in the classification report show a consistent value of 0.9068 for a weighted average precision and recall score. This consistency reflects that the experiment performs consistently across different classes. It proves that it is a reliable tool for cardiac disease prediction.

Table 4. Classification Report of Stacking Classifier

	Precision	Recall	F1-Score	Support
0	0.905882	0.875	0.890173	88
1	0.907563	0.931034	0.919149	116
Accuracy	0.906863	0.906863	0.906863	0.906863
Macro Avg	0.906723	0.903017	0.904661	204
W. Avg	0.906838	0.906863	0.90665	204

The performance of the ensemble stacking classifier is reflected by a Matrix. Figure 18 briefly describes the efficient working of the classifier. It shows that the model correctly identified 109 instances belonging to Class 1. These true positives confirm the model successfully detected the condition it was designed to predict. Similarly, the model also correctly classified 76 instances as Class 0 which are true negatives. The confusion matrix discloses that the model made some errors. It misunderstood 12 instances as Class 1 while they belonged to Class 0. This wrong prediction of false positives indicates cases where the model signaled the presence of the condition. Moreover, the model missed 7 cases where the condition was present but predicted as Class 0. This incorrect prediction is known as false negatives where the model failed to detect the true condition. The overall performance of the experiment is strong, with correct predictions in both classes. The confusion matrix shows that the ensemble stacking classifier performed best. The ensemble classifier is effective at correctly identifying both classes. The matrix shows the maximum TP and TN.

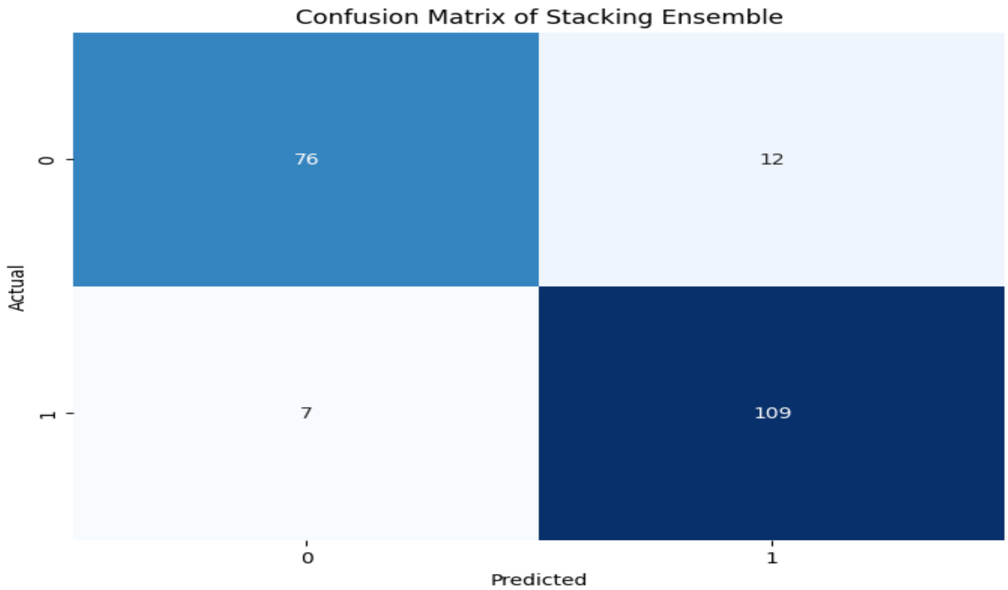

Figure 10. Confusion Matrix of Stacking Classifier

The proposed Ensemble Stacked Neural Network (ESNN) model was used to enhance the accuracy. The performance of ESNN was evaluated using measure metrics. The ESNN model performed best and showed an impressive accuracy of 95% as shown in Table 5.

Table 5. Classification Report of ESNN Model

	Precision	Recall	F1-Score	Support
0	0.9432	0.9432	0.9432	88
1	0.9569	0.9569	0.9569	116
Accuracy	0.9507	0.9507	0.9510	204
Macro Avg	0.9500	0.9500	0.9500	204

W. Avg	0.9510	0.9510	0.9510	204

It shows strong performance in identifying true negatives. It also performed well in class 1. The classifier got a high score of 0.9569. It reflects its ability to detect true positives accurately. The ESNN model got an accuracy of 0.9507. This indicates balanced performance across both classes 0 and 1. It demonstrates the consistency of the ESNN model. It confirms that ESNN has effectively predicted both positive and negative cases. The proposed study has shown exceptional performance in predicting HD. The efficiency of the ESNN model is demonstrated by key metrics in terms of different measures as shown in Figure 16.

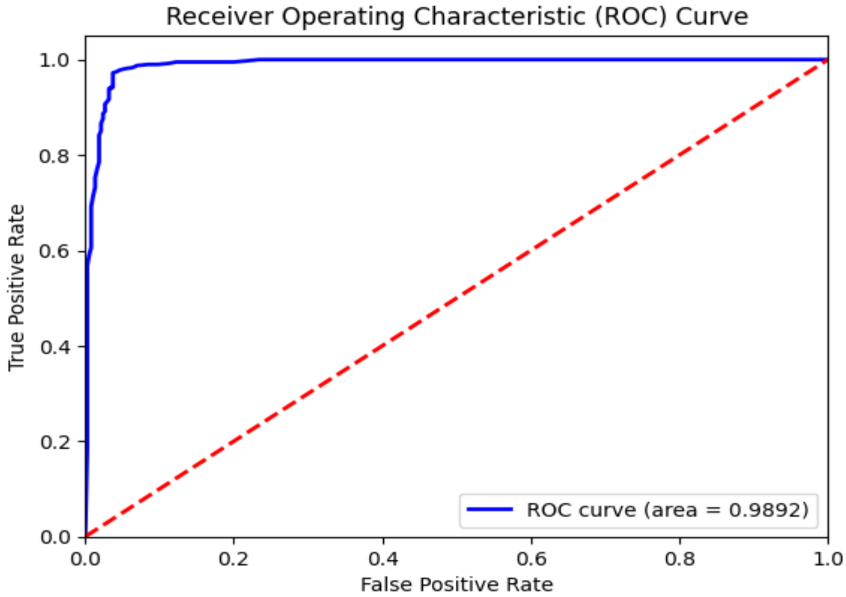

Figure 11. ROC Curve of ESNN Model

The ESNN model has shown amazing results that distinguish it from conventional models. Moreover, the confusion matrix further confirms the accuracy of model with 111 true negatives and 83 true positives out of 204 predictions as shown in Figure 17. The proposed architecture misclassified only 10 instances. It reflects the strength and reliability of model.

The ESNN model has proved its predictive capabilities across other classifiers, such as basic DT or logistic regression. The performance metrics have shown the higher performance and low misclassification rate of the proposed model. This outstanding performance discloses the importance of this model for the early detection of heart disease. The ESNN model can assist healthcare practitioners in making the right decisions. The proposed model can deliver better diagnostic results and more efficient use of medical resources.

All attributes of the dataset have played an important role in predicting cardiovascular disease. Few of them have a main contribution to the diagnosis process of disease. Specifically, the attribute “Resting BP S (PC3)” is the most important with a score of 0.2450. Its value shows that blood pressure is a key factor in heart disease prediction as shown in Figure 18. Other feature like “Chest Pain Type and Oldpeak (PC5)” also has a high impact of 0.1996. It means chest-pain-type and Oldpeak values are key indicators. The attribute “Age (PC4)” with a value of 0.1718 has a significant risk factor. The role of other attributes is also important to the model. The attribute “Resting ECG and Oldpeak (PC6)” has an impact of 0.1540. It shows that resting ECG and Oldpeak values play an important part in predictions. Another feature “Cholesterol (PC1)” has a value of 0.0648 and “Additional Component or Noise (PC9)” has a score of 0.0769. The values of these features indicate that cholesterol levels and other factors are less critical. But still, they influence the prediction process. The remaining attributes of the dataset have less importance in the diagnosis process. These are “Max Heart Rate (PC2)”, “Resting ECG (PC7)”, and “Exercise Angina and ST Slope (PC8)” which have a smaller role in the prediction of cardiac disease.

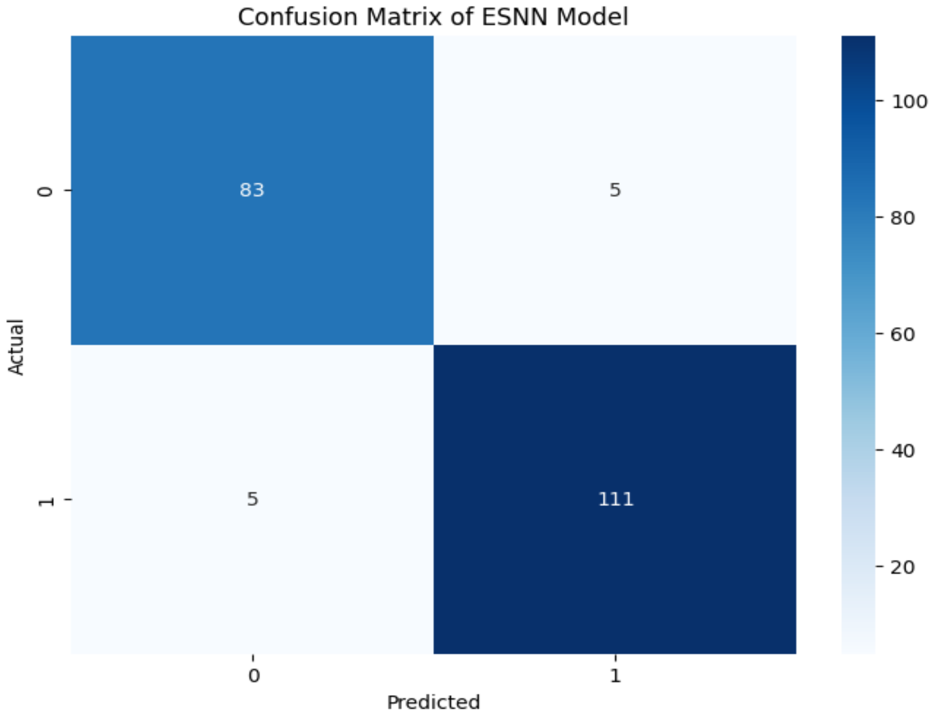

Figure 12. Confusion Matrix of ESNN Model

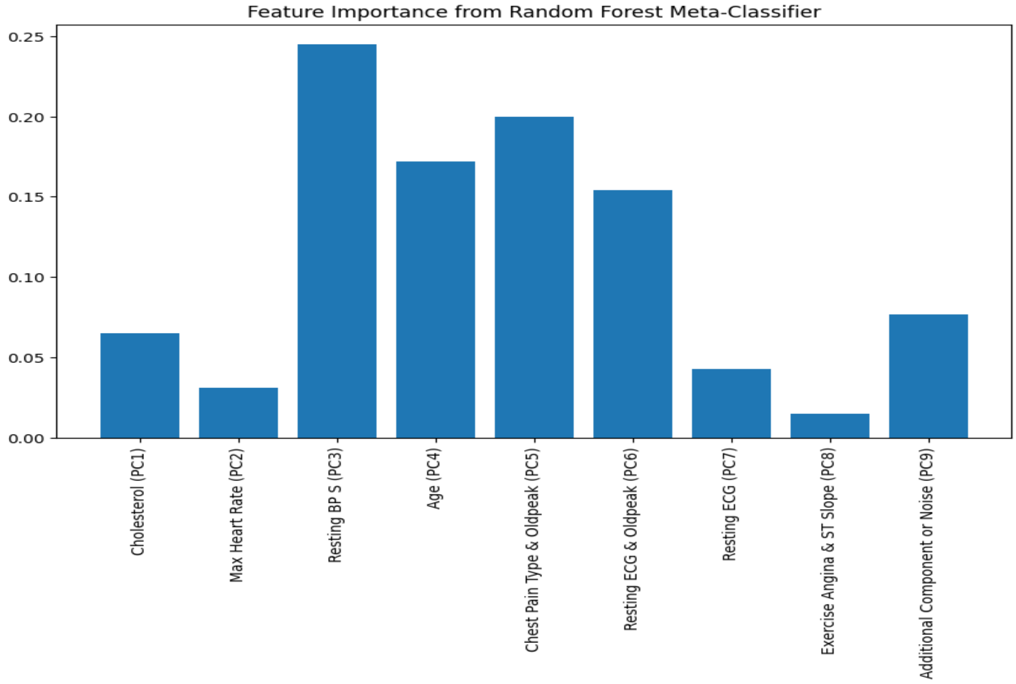

Figure 13. Feature Importance Graph of ESNN Model

4.1. Addressing Research Questions

The proposed study identified the main predictors of cardiac disease. These include age, cholesterol, and resting blood pressure of the combined dataset. The identified attributes were found to have a high impact on the diagnosis process of cardiac disease by the ESNN. Several machine learning techniques were applied to get the better accuracy on the dataset. The ESNN architecture achieved maximum accuracy among all classifiers. It combined multiple algorithms of ML and DL to get the optimum results. ESNN hybrid approach improved the overall accuracy, reaching 95%. The magnificent result of the ESNN model showed the potential to increase the efficiency of clinical practice. It proved itself to provide maximum accuracy in the diagnosis of cardiovascular disease. It could help healthcare professionals to make better decisions and identify high-risk cardiovascular patients sooner. The healthcare professional may need resources like computational power and access to patient data to deploy the system. These resources ensure the model can be effectively integrated into clinical settings.

5. Conclusion

This study proposes an innovative model, the Ensemble Stacked Neural Network (ESNN) model to diagnose cardiovascular diseases. The proposed model used several machine learning techniques combined with PCA. This model helped to increase the performance and efficiency of the diagnosis process. ESNN architecture obtained an accuracy of 95%. This shows its effectiveness in the diagnosis process of disease prediction. This research work identified key predictors for cardiovascular disease, such as RSTbp, Age, and cholesterol levels. These prime factors played a main role in the success of the model. Its complexity was reduced by Principal Component Analysis without losing important information. The PCA made the model faster and more reliable. Overall, the proposed ESNN model offers a promising tool for diagnosing cardiac disease. This model can help in early prediction and better risk assessment. The proposed ESNN model can be deployed easily in clinics to help cardiologists.

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