An Intelligent Predictive Framework for Early Diagnosis of Cardiovascular Disease Using Deep Neural Network

Mathan. S[1], Sunil Gupta[2]
[1]Research Scholar, School of Computer and Systems Sciences, Jaipur National University, Jaipur, Rajasthan, India
E-mail: mathansj@outlook.com
[2]Professor, HOD School of Computer and Systems Sciences, Jaipur National University, Jaipur, Rajasthan, India
E-mail: sunilg95@rediff.com

Article Info

Article History:

Received Oct 02, 2025
Revised Nov 04, 2025
Accepted Dec 01, 2025

Keywords:

Cardiovascular disease
Deep Neural network (DNN)
Random Forest
Accuracy
Imbalanced Data Handling
Risk Stratification

ABSTRACT

Cardiovascular disease (CVD) is a major cause of death worldwide. Congenital heart disease, arterial disease, heart failure, rheumatic heart condition, and cerebral disease are some of its most prevalent types. Early disease detection can help us avoid potentially fatal diseases and provide patients with better care than we could in later stages because prevention is always preferable than therapy. Those who are diagnosed may have a very high death rate because they are not accessible at an early stage. A variety of research techniques in the machine learning domains can assist in anticipating CVDs and identifying their behavioral patterns in enormous amount of data in order to solve these issues. The results of these estimates will help doctors make judgments and identify patients early, reducing the likelihood of death. This research covers the creation of an innovative, reliable, effective, and intelligent predictive system for early CVD detection using Deep Neural Network (DNN) model in order to optimize prevention and treatment for CVDs. Its goal is to automatically select significant features and detect heart disease in its earlier stages. The presented model's average accuracy, precision, recall, sensitivity, and F1-score are 99.98%, 98.78%, 97.86%, and 98.56%, respectively. Compared to other existing models, the presented method successfully achieved and maximized classification effectiveness with greater amounts of precision and pinpointing.

Corresponding Author:

Mathan. S,
Research Scholar, School of Computer and Systems Sciences,
Jaipur National University, Jaipur, Rajasthan, India.
E-mail: mathansj@outlook.com

1. INTRODUCTION

CVD is the collective term for conditions impacting the human heart and blood arteries. Organs like the kidneys, heart, eyes, and brain can also sustain artery damage. In many developed and industrialized nations worldwide, heart disease is a leading cause of death, even among young people [1]. In actuality, however, it can be significantly avoided by maintaining a healthy lifestyle. There are four primary categories of CVD. Angina, heart attacks, and heart failure result from the increased strain this place on the heart. Temporary ischemia attacks and seizures, which are caused by a brief disruption in circulation and blockage of the blood flow to the brain, fall under the second group. The third type, referred to as peripheral artery disease, is caused by a limitation in the limbs' blood flow. This leads to chronic ulcers, leg weakness, foot and leg hair loss, and excruciating leg pain. The last group, aortic disease, affects the aorta, the major blood vessel. When there is a risk of rupture, this causes a potentially fatal bleeding even though it shows no symptoms.

Deep Neural Network (DNN) model use several linked layers of neurons that can learn hierarchical data representations to replicate the organization of the human brain. When it comes to diagnosing CVD, this enables the network to find complex relationships between clinical indicators that would not be apparent using traditional statistical techniques, such as blood pressure, lipid profile, glucose level, electrocardiogram (ECG) signals, and demographic characteristics. In contrast to superficial machine learning algorithms that frequently rely on manual feature engineering, DNNs are highly proficient in automatic feature extraction, which enhances diagnostic precision and lessens human bias in the decision-making process.

Numerous studies have demonstrated the potential of using DNNs to diagnose CVD, especially in terms of forecasting the onset of the disease, categorizing patient risk, and supporting clinical decision-making. DNNs, for example, have been successfully used with time-series data, such as ECG signals, structured datasets, electronic health records, and medical imaging (such as CT scans and echocardiograms). Their applicability to a variety of diagnostic methods is demonstrated by this diversity. Furthermore, the viability of implementing DNN models into real-time clinical settings is becoming a reality because to the growing availability of big healthcare datasets and advancements in computing power.

Notwithstanding these benefits, issues including overfitting, model interpretability, and data imbalance continue to be major obstacles to their widespread use in the medical field. Therefore, the creation of therapeutically viable solutions requires the development of an intelligent prediction framework that incorporates strong preprocessing, efficient network layout, and performance evaluation techniques. In addition to improving diagnostic precision, such a framework would assist medical practitioners in reaching trustworthy, fact-based conclusions.

Reduced heart function and symptoms including coronary artery infarction and reduced blood vessel function are hallmarks of heart failure, a hazardous illness, can result from a chronic syndrome called CVD [2]. Approximately 18 million deaths globally, or 32% of all deaths, were attributed to CVD, according to statistics. 85% of all deaths were from heart attacks and strokes, and 38% of those killed were under the age of 70. Early detection is essential for the prevention and treatment of cardiac disorders, and machine learning can be a helpful method for diagnosing cardiac conditions.

The following techniques have been modified to meet the objectives of the research. They are used to research and understand different aspects of heart-related problems, which eventually help to develop accurate models for treatment and prediction. The general research technique design for the study is shown in Figure 1.

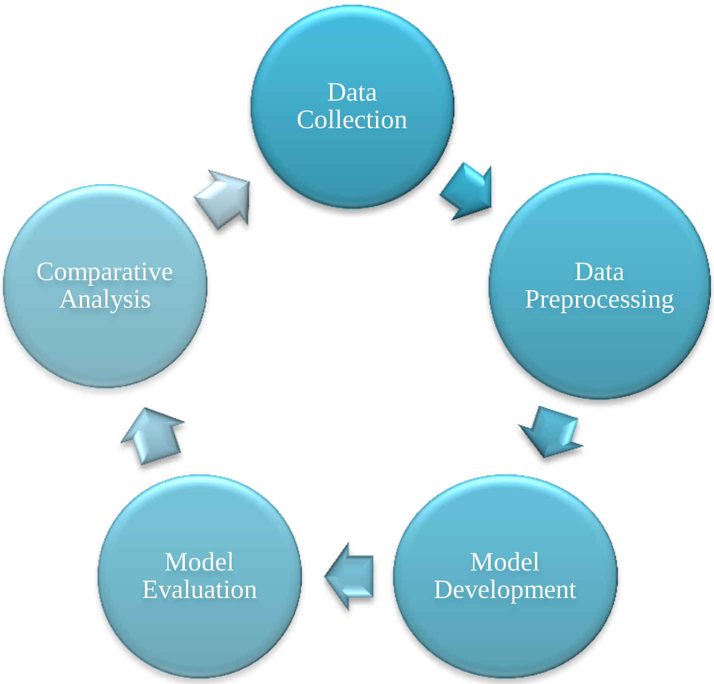

Figure 1. Workflow for the research methodology

Finding those who are vulnerable for CVD is essential. Scientists are now using more advanced methods for predicting illnesses, such as data mining, and deep Neural Network, due to the numerous disadvantages of manually identifying cardiac problems. These proved effective in aiding in forecasting and decision-making from the enormous volumes of data produced by the healthcare manufacturing [3]. The creation of one system from which organized information can be collected and patients can receive effective therapy could result from automated disease prediction. To forecast the presence of CVD and determine the maximum predictive value Based on their Rough sets values, we used a Gradient Boosting model for this study. CVD is then analyzed using a variety of DNN techniques. The following is a list of this work's main contributions:

- Detecting cardiac disease early using a DNN model.
- By employing an appropriate feature selection method, prediction accuracy can be increased. A powerful DNN can help enhance the early diagnosis of CVD.
- This enables prompt action and promotes the identification of essential components to help recovery procedures.
- By utilizing an extensive, cutting-edge dataset on CVD, CVD prediction.
- Providing medical professionals with reliable advice regarding significant advancements in the healthcare sector.

The remainder of this research is structured as follows: The work on DNN and heart disease prediction by other researchers is reported in Section 2; Section 3 outlines the research's methodology, including the dataset utilized for experiments on heart disease and the feature reduction technique. In Section 4, experimental results are presented and the conclusions are compared to previous research. Section 5 brings the analysis to a close.

2. RELATED WORK

These mathematical frameworks take into account different algorithms' training procedures and data observation methods [4]. To validate our strategy's efficacy, we combined the Heart

Database with additional categorization techniques. The preciseness of the proposed method is around 96% better than that of other existing approaches, and a comprehensive analysis across several parameters has been presented. Additional data from different medical facilities will help deep learning research and could be utilized to create neural network-based solutions.

The present research employed data from the publicly accessible University of California Irvine library to diagnose CVD using two reliable machine learning methods: K-nearest neighbor (K-NN) and multi-layer perceptron (MLP) [5]. The capabilities of the models are optimized by removing anomalies and variables with null values. Experiments reveal that the MLP model achieves 82.47% and 86.41% area-under-the-curve percentages, subsequently, which are superior to the K-NN network in terms of detection reliability.Therefore, it was proposed that CVD testing be automated using the proposed MLP model. Other ailments can also be identified using the suggested methods. Additionally, other commonly used information sources can be applied to evaluate the suggested model's efficacy [6].

In order to create efficient models for forecasting for CVD manifestation, a supervised machine learning-based approach is introduced [7], emphasizing the superiority of the SMOTE approach. In-depth examination and comprehension of risk variables are demonstrated to examine their significance and role in the prediction of CVD. These criteria are supplied as input characteristics to the models in order to identify which of the several machine learning techniques is best suited for our objective in a binary classification issue with a uniform category frequency distributions [8]. The reliability, persistence, precision, and area under the curve of a several machine learning models were evaluated utilizing the Synthetic Minority Oversampling Technique or not.

ML-based CVD is an approach In order to forecast CVD with high accuracy and efficiency, diagnosis is recommended. The methodology specifically addresses data imbalance and missing values initially. Then, for feature selection, the Feature Importance approach is applied. Lastly, a combination of KNN classifiers and logistic regression is suggested for a more accurate prediction.The structure is validated on three benchmark data sets [9]: Cleveland, Heart Disease, and Framingham. The resultant accuracies are 96.5%, 97.0%, and 98.1%, respectively. Finally, the comparative study shows that MaLCaDD forecasts are more accurate than the state-of-the-art approaches at the moment (using a smaller set of parameters). As a result, MaLCaDD is very dependable and useful for early coronary disease detection in real-world settings.

Even though there have been a lot of research done to evaluate the risk of coronary artery disease, they have limitations such the need to increase the detection rate and the possibility of becoming stuck in local optima. The QPSO technique was chosen due to its high classification accuracy, low number of parameters, and ease of development and application [10]. Two sets of the Cleveland heart disease records, accessible through the University of California, Irvine repository, were subjected to the suggested model.

Clinicians cannot diagnose CAD based solely on a patient's symptoms since they are neither specific nor sensitive. Heart scanning can help doctors treat patients more successfully and identify CAD earlier. Invasive coronary angiography is the core stone for CAD diagnosis. The left main, left anterior ascending, radial, or right coronary arteries with more than 60% stenosis are suggestive of CAD. Invasive cardiac angiography, however, is costly and may be dangerous. Cardiovascular imaging is less expensive, safer, and can assist doctors in making a non-invasive diagnosis of CAD with confidence. Therefore, imaging by itself may act as a gatekeeper for definitive reperfusion treatment and subsequent invasive coronary angiography [11]. Coronary computerized tomographic angiogram (CCTA), nuclear cardiac perfusion tests, stress electrocardiogram, and echocardiogram are the cornerstones of invasive imaging studies for CAD.

3. METHODS AND MATERIAL

This paper describes the creation of a novel, reliable, efficient, and intelligent predictive framework for early CVD diagnosis using DNN, specifically designed for maximizing early detection and treatment for CVDs by automatically selecting key traits and detecting early-stage coronary artery disease [12].

3.1. Data Pre-processing

To construct and train machine learning algorithms, raw data must be prepared, cleaned, and organized using a data mining technique known as data preprocessing. Data gathered from various sources is typically unorganized and unsuitable for rapid analysis [13]. Outliers, noisy data, and lacking characteristics must therefore be examined and eliminated from the dataset. In this work, we employed cleaning techniques such identifying missing data, looking for outliers, and eliminating them. Finding, identifying, and eliminating outliers prior to using a model for predicting can greatly lower errors and increase precision [14]. No missing data was found when the missing data preparation methods were checked, however after using the Interquartile Range approach, we found a number of outliers, or values that deviated from the mean, and removed them.

3.2. Noise Removal

One method for calculating how much the dataset's data points depart from the mean is to utilize the interquartile range. The IQR technique facilitates the identification of a constantly dispersed anomaly in the data set [15]. Stated otherwise, the higher the IQR, the more distant information units are from the mean, and the data units are closer to the average the lower the IQR. Subtracting the first or lower quantile (Q1) from the third or upper quantile (Q3) yields the IQR. The boxplot format, which splits a point by 27%, can be used to graphically display the IQR [16]. Using this outlier reduction strategy, the dataset is divided into four equal pieces and the quantiles from the first to the third (Q1 and Q3) quantiles in Figure 2.

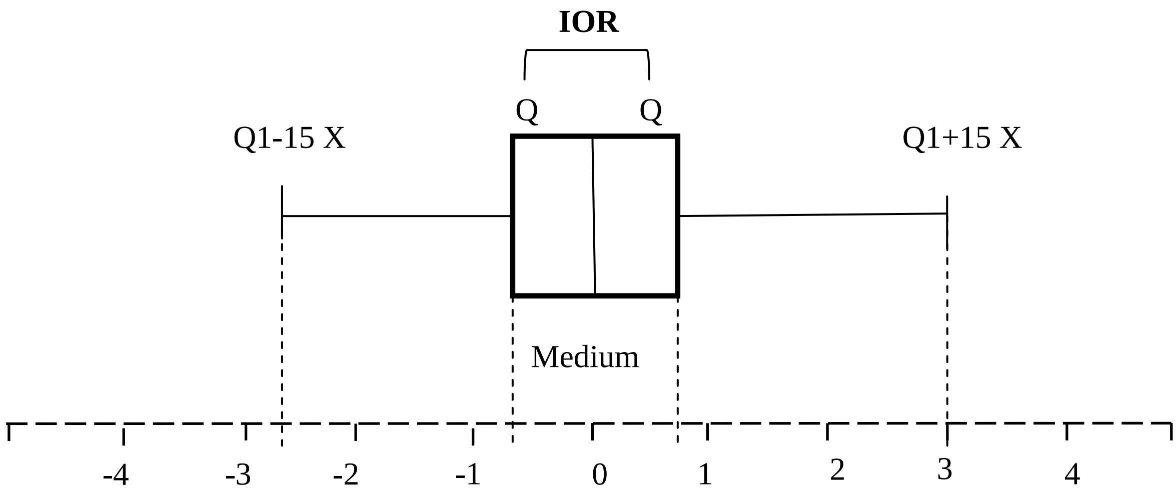

Figure 2. Interquartile Range

3.3. Feature Extraction Using RF with DNN

Since the quality of the features that are extracted has a direct impact on the predictive performance of the model, feature extraction is an essential stage in creating strong deep learning models. RF are frequently used as a feature extraction or selection technique prior to supplying input to a DNN. RF is a decision tree-based ensemble learning technique that rates the significance of features by calculating the relative contribution of each attribute to the reduction of classification error [17, 18]. RF helps remove noisy or redundant characteristics and keeps just the most important variables by employing this importance score. By ensuring that the DNN is trained on a condensed and informative feature set, this preprocessing step increases learning effectiveness and lowers the possibility of overfitting.

RF is a technique for DNN that uses training data sets to build several choice tree structures in order to produce a category model. By choosing an arrangement based on a majority of choices, this method offers exceptional performance when working with large datasets. This approach creates a more efficient ensembles model by combining two feature selection techniques: random selection and bagged. The RF technique reduces training time and the risk of over fitting by using several trees [19]. In order to increase accuracy, it also provides estimates of deficient data and important categorization variables.

The DNN uses these chosen properties as inputs once the most important features have been retrieved using RF. In order to learn intricate, non-linear relationships that shallow models can miss, the DNN then passes these improved features via several hidden layers. The advantages of both approaches are combined in this hybrid approach: While the DNN is excellent at hierarchical representation learning and precise classification, RF helps with dimensionality reduction and noise eradication. In medical diagnostics, for example, RF can eliminate less important indicators while keeping the most important ones intact. The DNN can then use those fine-tuned features to determine whether a patient has a disease.

There are various advantages of combining DNNs with RF-based feature extraction. Because feature importance is ranked, it improves model interpretability, speeds up training by concentrating on key features, and minimizes computing cost by restricting the input space. Furthermore, when compared to employing DNNs alone with raw characteristics, this combination frequently yields superior classification accuracy. In fields like healthcare, cyber security, and finance, where early, precise forecasts are crucial yet datasets are high-dimensional and noisy, such a hybrid pipeline is particularly helpful.

3.4. Early Diagnosis Based Deep Neural Networks (DNNs)

DNNs are capable of automatically learning complex patterns from large amounts of medical data, such as MRI scans, ECG signals, gene expressions, or even electronic health records. By leveraging multiple hidden layers, these models can uncover non-linear relationships and features that may not be immediately visible to human experts, producing a more accurate and faster prediction of potential health risks. Early diagnosis based on DNNs has become a revolutionary approach in modern healthcare, especially in identifying diseases at their earliest stages. Traditional diagnostic methods often rely heavily on manual interpretation of clinical symptoms, medical imaging, or laboratory results, which can sometimes delay the detection of subtle or hidden abnormalities.

The ability of DNNs to extract features and recognize patterns is what makes them effective in early diagnosis. In medical imaging, for example, a DNN can detect minute alterations in tissues that may signal the early start of neurological illnesses, cardiovascular problems, or cancer before they manifest clinically. Similarly, DNNs can identify anomalous patterns in time-series data, like as glucose levels or heart rate variability that could indicate chronic diseases. This capability allows for prompt intervention, lowers diagnostic errors, and gives doctors a decision-support tool. By stopping the progression of the disease, early identification not only enhances patient outcomes but also reduces treatment costs.

All things considered, DNN-based early diagnosis marks a significant change in healthcare toward predictive and preventive measures. These models have the potential to revolutionize standard clinical procedures as they develop further in tandem with big data and computing power. To fully reap their benefits, however, issues like the requirement for sizable annotated datasets, the interpretability of the findings and ethical concerns over patient data must also be resolved.

3.5 Efficiency of the Developed Model

The capacity of the DNN model to produce precise predictions with the least amount of time and resources is a measure of its effectiveness for early diagnosis. The DNN can handle enormous volumes of patient data, including imaging scans, test reports, or real-time biosensor readings, in a matter of seconds, in contrast to traditional diagnostic techniques that could call for invasive procedures or drawn-out manual evaluations. In addition to lessening the workload for medical staff, this quick analysis guarantees that patients receive therapy on time, which is essential for conditions where early intervention greatly improves results. Performance criteria that show how well the model detects actual disease cases while reducing false alarms, such as accuracy, precision, recall, F1-score, and computing speed, are frequently used to assess efficiency.

The model's scalability and generalization represent another important aspect of efficiency. In addition to performing well on training data, a well-designed DNN should be able to correctly diagnose cases that have not yet been observed in a variety of patient populations. For example, the model can produce more accurate predictions in actual clinical situations if it is trained on heterogeneous datasets that include differences in gender, ethnicity, age and disease stage. Furthermore, the model achieves great performance without consuming unnecessary computational resources by refining the architecture and utilizing strategies like transfer learning or dropout regularization. The model is suitable for use in diagnostic centers, hospitals, and even portable medical equipment since it strikes a compromise between processing speed and predicted accuracy.

DNN Based Classification Model

An effective ML technique for classifying incoming data into predetermined groups is a DNN classification model. DNNs are made up of several hidden layers that gradually learn high-level abstractions from raw input, in contrast to shallow models that just extract a small number of features. DNNs are particularly good at handling complicated, non-linear correlations seen in medical data, text, pictures, audio, or sensor signals because of their hierarchical learning process. The model's main objective in classification tasks is to translate input features to matching class labels as accurately and as minimally as possible. A DNN classification model, for instance, might be used in the medical field to determine whether a patient's medical history suggests a high chance of diabetes, cardiovascular disease, or no disease at all.

A DNN classification model is based on a series of layers: input, hidden, and output. Raw data features, like pixel intensities in photos or biometric values in medical datasets, are represented by the input layer. Hidden layers are made up of several interconnected neurons that learn abstract feature representations by using non-linear activation functions (such sigmoid, tanh, or ReLU) and weighted transformations. The sigmoid function for binary classification or the softmax activation function for multi-class classification is commonly used at the output layer.

These routines translate the output of the model into probability values that show how likely each class is. The final forecast is then determined by selecting the class with the highest probability.

A DNN classification model is trained using forward propagation, backpropagation, and optimization. As input data moves through the network during forward propagation, predictions are produced. A loss function that quantifies the error, like cross-entropy loss, is used to compare the model's predictions with the actual class labels. After then, backpropagation computes gradients of the loss in relation to model parameters (weights and biases), which are modified by sophisticated techniques like Adam or RMSProp or optimization algorithms like stochastic gradient descent (SGD). The model improves classification performance by constantly lowering its loss throughout several training epochs.

The automatic feature extraction capability of DNN classification models is one of their main advantages. DNNs are able to directly learn significant features from raw data, in contrast to conventional machine learning techniques that necessitate manual feature engineering. For example, in picture categorization, deeper layers catch intricate forms or even disease-specific signals, while early layers identify basic patterns like edges and textures. DNNs can also capture word semantics, syntactic structures, and contextual meaning for text classification tasks in natural language processing. The model performs better than traditional classifiers like logistic regression or decision trees thanks to its layered feature representation.

Beyond accuracy, performance measures are also used to assess a DNN classification model's effectiveness. Reducing false positives and false negatives is crucial in real-world applications, particularly in security and healthcare. A better grasp of the model's advantages and disadvantages can be gained by examining metrics like precision, recall, F1-score, sensitivity, specificity, and area under the ROC curve (AUC). For instance, in the diagnosis of cancer, high specificity guarantees that healthy patients are not incorrectly classified (reducing false positives), while high sensitivity guarantees that almost all cancer cases are detected (reducing false negatives). DNN models are ideal for crucial classification jobs because of their capacity to balance various metrics.

Nevertheless, there are considerable difficulties in putting DNN classification models into practice. One problem is that in order to attain high accuracy and generalization, big, diverse datasets are required. The model may over fit or perform poorly on unknown data if the training dataset is small or biased. Furthermore, DNNs are computationally demanding, necessitating strong GPUs and training frameworks like PyTorch or TensorFlow. DNNs' black-box nature presents another difficulty since it is hard to understand how the model comes to a certain classification conclusion. This lack of interpretability creates ethical and trust-related issues in delicate domains like law or medicine.

Researchers use a variety of tactics to get over these obstacles. Model stability is increased and overfitting is decreased with the use of regularization strategies including dropout, weight decay, and batch normalization. Transfer learning lessens reliance on large labeled datasets by allowing pre-trained models to be reused on similar tasks. Applications-wise, DNN classification models are extensively employed in a variety of industries. They are used in the medical field for patient risk assessment, medication development, and illness diagnosis. They support credit scoring and fraud detection in the financial industry. DNNs are used in cybersecurity to categorize traffic patterns and spot harmful activity. They also power speech recognition, facial identification, and recommendation systems in commonplace technology. DNN classification models are among the most crucial instruments in contemporary artificial intelligence due to their adaptability.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

In this research, we used four evaluation parameters: accuracy, precision, recall, and F1-score [20]. Model performance estimates were used to compute these measures. Equations provided the method for calculating the performance metric that we utilized to evaluate our classical.

$$Accurracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

For a given total several specimens, accuracy shows how many samples were correctly adjusted.

$$precision = \frac{TP}{TP+FP} \quad (2)$$

For a given several samples, precision shows how many samples were correctly adjusted.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Recall shows how well positive values are predicted to match the actual positive value.

$$F1\ score = \frac{2*Recall*precision}{Recall+precision} \quad (4)$$

I. When a test yields a true positive (TP), it means that the patient indeed has CVD.

II. False positive (FP): When a test indicates that a patient does not have CVD, they actually do.

III. When a test yields a true negative (TN), it indicates that an individual does not have CVD.

IV. False negative (FN): The test indicates that a patient has CVD, although the actual person does not.

4.1. Discussion of Results

Prior to and during the use of feature selection and data preparation methods, the RF classifier's effectiveness as well as that of other classifiers including KNN and LR was assessed on the data. Two statistical measures that were used on Kaggle datasets—the correlation coefficients and the significance of feature selection procedures—formed the basis of our performance metrics. We found that there is no correlation between the target class and the other parameters. This was demonstrated by the different outcomes that were obtained when different hypotheses were applied to the information both before and after using these statistical markers. Our suggested model performs the best across all performance criteria for the dataset under study when compared to other approaches and existing models.

4.2. Results from performance assessments prior to and following feature selection methods

The results and results of the evaluation of diagnosing CVD for all evaluation measures utilized before feature selection approaches were employed are shown in Figure 3. The findings of variables on detecting heart illness using various machine learning algorithms before feature selection procedures show that RF learning has the best accuracy result of 97%, followed by LR, KNN, and DNN with 88%, 87%, and 82%, respectively. DNN, KNN, LR, and RF have precision scores of 82%, 86%, 87%, and 99%, accordingly, before feature selection techniques were introduced.

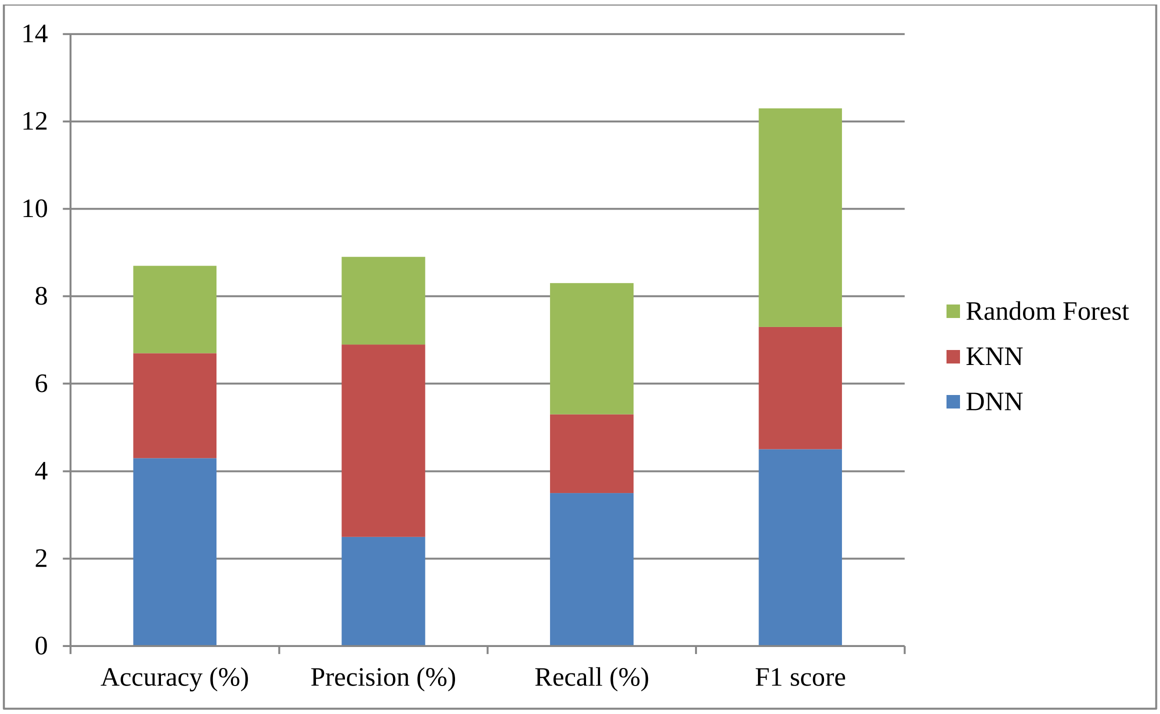

Figure 3. Prior to feature selection, the DNN effectiveness in detecting heart disease is assessed

Figure 4 displays the outcomes of variables on identifying heart disease using various machine learning techniques after feature selection procedures, where RF achieves the maximum accuracy. The respective results for KNN, DNN, and LR were 96%, 88%, and 86%. Following feature selection techniques, DNN, KNN, LR, and RF algorithms have accuracy scores of 87%, 97%, 88%, and 98%, consecutively.

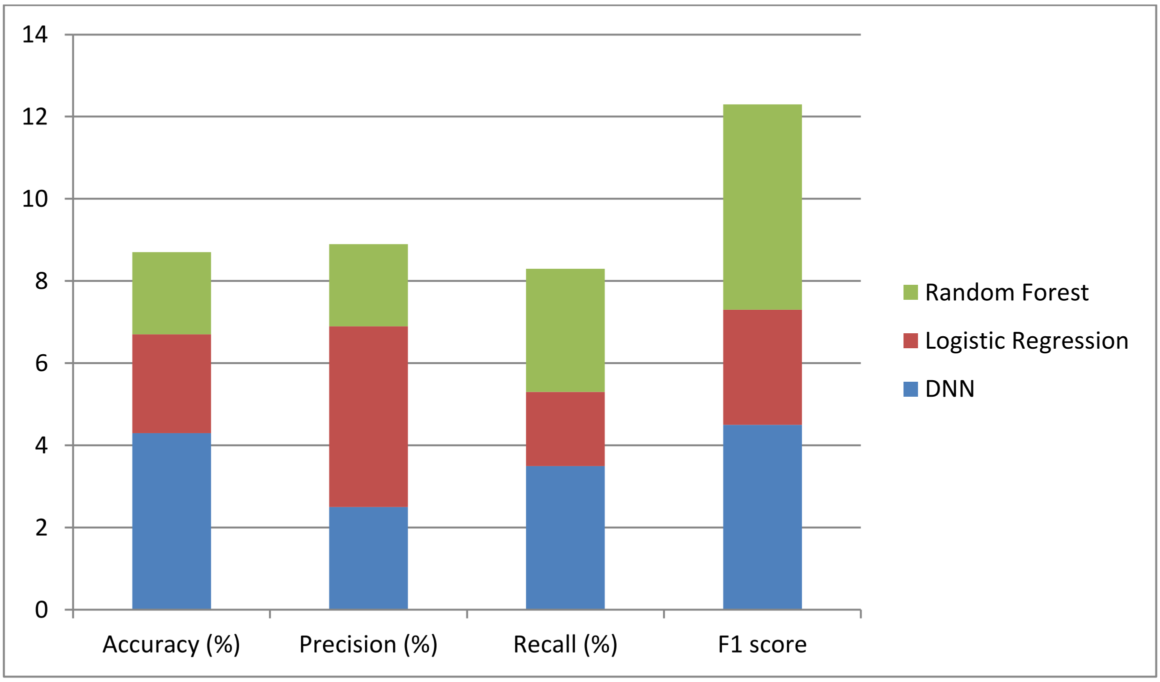

Figure 4. Assessment of the DNN performances in detecting heart disease following feature selection

For each algorithm, accuracy ratings are given when the outcomes of applying the strategies show positive results, especially for our suggested RF model, Figure 5 compares the accuracy results before and following the feature selection strategies on a variety of techniques.

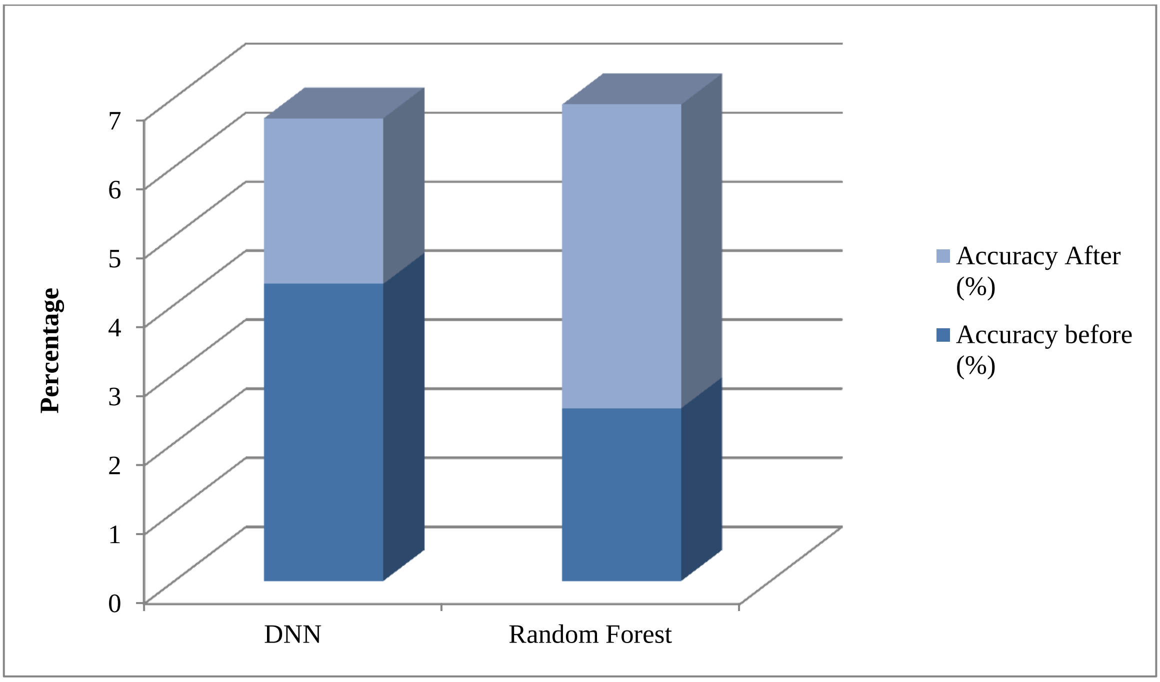

Figure 5. An examination of the results and precision of RF and DNN

To improve prediction, we also employed hyper-parameter tuning strategies like bootstrap or RF for choice and change of random parameters. We used n estimation techniques equal to five in our parameter configurations to regulate the number of trees. Additionally, we set random state to seven, which helped to maximize or average predictions. These shuffling techniques improved performance by balancing the parameters and cutting down on the total training and testing time when used with the RF model.This research clearly improved the precision of the RF Simulation, which will significantly impact people with CVD because, when paired with IoT devices such as smart watches, the simulation will provide current data to monitor people, possibly preserving many lives that might have perished due to a lack of immediate data.

5. CONCLUSION

In this article, we describe the creation of a novel, reliable, efficient, and intelligent predictive DNN framework for early CVD using DNN models, especially intended for maximizing early detection and therapy for CVDs through an automatic assessment of critical features and the identification of early-stage cardiac disease. The recommended DNN models average precision, recall, precision, sensibility, and F1-score are, in that order, 99.98%, 98.78%, 97.86%, and 98.56%. Consequently, DNN model successfully achieved and optimized classification performance with greater percentages of precision and pinpointing in comparison to an excessive number of other state-of-the-art approaches nowadays.

This shows that, when considering variables like F1 score, recall, reliability, and exactness, the proposed DNN model outperforms the other models tested in terms of projected accuracy. In regards to precision, the suggested DNN model routinely outperforms the alternatives. When compared to earlier models, the results of this study show an important leap in forecasting of CVD. With its excellent accuracy rates, the suggested DNN model shows promise as a tool for CVD prevention and early detection.

REFERENCES

[1] Patro, S. P., Padhy, N., &Chiranjevi, D. (2021). Ambient assisted living predictive model for cardiovascular disease prediction using supervised learning. *Evolutionary intelligence*, *14*(2), 941-969.

[2] Nugroho, K. S., Sukmadewa, A. Y., Vidianto, A., &Mahmudy, W. F. (2022). Effective predictive modelling for coronary artery diseases using support vector machine. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *11*(1), 345.

[3] Duraisamy, B., Sunku, R., Selvaraj, K., Pilla, V. V. R., &Sanikala, M. (2024). Heart disease prediction using support vector machine. *Multidisciplinary Science Journal*, *6*.

[4] Subramani, S., Varshney, N., Anand, M. V., Soudagar, M. E. M., Al-Keridis, L. A., Upadhyay, T. K., ...&Rohini, K. (2023). Cardiovascular diseases prediction by machine learning incorporation with deep learning. *Frontiers in medicine*, *10*, 1150933.

[5] Pal, M., Parija, S., Panda, G., Dhama, K., &Mohapatra, R. K. (2022). Risk prediction of cardiovascular disease using machine learning classifiers. *Open Medicine*, *17*(1), 1100-1113.

[6] Saikumar, K., & Rajesh, V. (2024). A machine intelligence technique for predicting cardiovascular disease (CVD) using Radiology Dataset. *International Journal of System Assurance Engineering and Management*, *15*(1), 135-151.

[7] Taylan, O., Alkabaa, A. S., Alqabbaa, H. S., Pamukçu, E., &Leiva, V. (2023). Early prediction in classification of cardiovascular diseases with machine learning, neuro-fuzzy and statistical methods. *Biology*, *12*(1), 117.

[8] Venkatesh, C., Prasad, B. V. V. S., Khan, M., Babu, J. C., &Dasu, M. V. (2024). An automatic diagnostic model for the detection and classification of cardiovascular diseases based on swarm intelligence technique. *Heliyon*, *10*(3).

[9] Rani, P., Kumar, R., Ahmed, N. M. S., & Jain, A. (2021). A decision support system for heart disease prediction based upon machine learning. *Journal of Reliable Intelligent Environments*, *7*(3), 263-275.

[10] Mondal, A., Mondal, B., Chakraborty, A., Kar, A., Biswas, A., &Majumder, A. B. (2024). Heart disease prediction using support vector machine and artificial neural network. In *Artificial Intelligence and Applications* (Vol. 2, No. 1, pp. 45-51).

[11] Owusu, E., Boakye-Sekyerehene, P., Appati, J. K., &Ludu, J. Y. (2021). Computer-Aided Diagnostics of Heart Disease Risk Prediction Using Boosting Support Vector Machine. *Computational intelligence and neuroscience*, *2021*(1), 3152618.

[12] Reddy, S. R., & Murthy, G. V. (2025). Cardiovascular Disease Prediction Using Particle Swarm Optimization and Neural Network Based an Integrated Framework. *SN Computer Science*, *6*(2), 186.

[13] Nandy, S., Adhikari, M., Balasubramanian, V., Menon, V. G., Li, X., &Zakarya, M. (2023). An intelligent heart disease prediction system based on swarm-artificial neural network. *Neural Computing and Applications*, *35*(20), 14723-14737.

[14] Manimurugan, S., Almutairi, S., Aborokbah, M. M., Narmatha, C., Ganesan, S., Chilamkurti, N., ...&Almoamari, H. (2022). Two-stage classification model for the prediction of heart disease using IoMT and artificial intelligence. *Sensors*, *22*(2), 476.

[15] Ekundayo, F., &Nyavor, H. (2024). AI-driven predictive analytics in cardiovascular diseases: Integrating big data and machine learning for early diagnosis and risk prediction. *International Journal of Research Publication and Reviews*, *5*(12), 1240-1256.

[16] Vincent Paul, S. M., Balasubramaniam, S., Panchatcharam, P., Malarvizhi Kumar, P., & Mubarakali, A. (2022). Intelligent framework for prediction of heart disease using deep learning. *Arabian Journal for Science and Engineering*, *47*(2), 2159-2169.

[17] Sekar, J., Aruchamy, P., SulaimaLebbe Abdul, H., Mohammed, A. S., &Khamuruddeen, S. (2022). An efficient clinical support system for heart disease prediction using TANFIS classifier. *Computational Intelligence*, *38*(2), 610-640.

[18] Babu, M. S., &Karthick, V. (2023, November). Improving accuracy in intelligent coronary heart disease diagnosis prediction model using support vector clustering technique compared over bagging classifier algorithm. In *AIP Conference Proceedings* (Vol. 2821, No. 1, p. 020039). AIP Publishing LLC.

[19] Suresh, T., Assegie, T. A., Rajkumar, S., & Kumar, N. K. (2022). A hybrid approach to medical decision-making: diagnosis of heart disease with machine-learning model. *Int J Elec Comp Eng*, *12*(2), 1831-1838.

[20] Chandrika, L., &Madhavi, K. (2021). A hybrid framework for heart disease prediction using machine learning algorithms. In *E3S Web of Conferences* (Vol. 309, p. 01043). EDP Sciences.