Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization

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**ABSTRACT**

Disorders of the heart and blood vessels are named cardiovascular disease. The heart’s proper functionality is of utmost necessity for the survival of life. The death rate due to heart disease, has been increased rapidly. Cardiovascular illness is believed the deadliest cause of death across the globe. From the facts and figures shared by the WHO (World Health Organization) 17.9 Million human lost their lives due to cardiovascular diseases. This research is carried out for the effective diagnosis of heart disease using the heart disease dataset available on the UCI Machine Repository. Heart disease diagnosis with an optimization algorithm can be fruitful in terms of higher accuracy and sensitivity. Finding an acceptable optimal solution among multiple solutions for a specific problem is known as optimization. Different machine learning algorithms have been applied as Support Machine Vector (SVM), K-Nearest Neighbor (KNN), Naïve Bayes (NB), Artificial Neural Network (ANN), Random Forest (RF), and Gradient Descent Optimization (GDO). Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization model produces the optimal results among under consideration classification algorithms. 98.54\% accuracy has been achieved by the GDO based model while performance evaluation it. 99.43\% sensitivity (recall) and 97.76\% precision have also been recorded. From the prediction results of the system, it’s satisfactory to utilize it for cardiovascular disease diagnosis. The proposed system will be helpful for the analysis of cardiovascular disease.

1. Introduction

There are multiple factors that play an integral part in the disorder of cardiovascular disease (CVD). These factors are closely related to the lifestyle of the patients; therefore, for the detection of heart disease, all these factors related to lifestyle and eating habits are needed to be considered. Numerous studies have been conducted to improve health standards. American Health Association (AHA) released its strategic plan for 2020, and it was concluded that only 5 percent of individuals achieved ‘ideal cardiovascular health’ \cite{1}.

For many years, there has been a visible increase in the death rate specifically caused by heart diseases, and misdiagnosis is one of the major reasons for this. However, it may be established that there are inherently two aspects leading to a possible misdiagnosis, i.e., the existence of a sense of ignorance towards the severity of the disease at the part of the patient and attending physicians aren’t well aware of the factors \cite{2}. The increased probability of misdiagnosis is the lack of an expert system \cite{3}.

Heart diseases, also commonly known as cardiovascular diseases, are identified among the most lethal and deadly diseases in the world. As per the report of the World Health Organization, it is estimated that 17.9 million died due to heart diseases in one year (2017). Furthermore, they also make up 31\% of all global death annually. 85\% of death occurred due to heart diseases befall due to strokes and heart attacks.

A heart disease, at its very generic understanding, could be stated as a disorder that specifically affects the heart, and in order to reach the objectives of this research, it is important to consider aspects such as causes of heart diseases, the various complications faced by patients and medical doctors and finally the possible remedies. It becomes significant to highlight that such aspects would essentially be taken into consideration as this research primarily aims to develop an Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization model that would be specifically directed towards building better results in diagnosing heart disease effectively and efficiently.

Heart disease has been considered a men’s disease, and for heart disease, women have been ignored significantly. In 1999, the first...
women-specific clinical recommendations for taking in place preventive measures for cardiovascular disease were published by the American Heart Association (AHA). It brought awareness among women regarding heart disease from 30 % to 54% from 1997 to 2009 [4].

Finding an acceptable optimal solution among multiple solutions for a specific problem is known as optimization. For finding a minimum of a function, an optimization algorithm can be used. For updating parameters in machine learning models, gradient descent is used. Parameters depend on the algorithm; in the case of neural networks, parameters are weights [5].

It is considered that the development of a system based on Gradient Descent Optimization (GDO) would provide a better solution to the currently existing complications faced by medical experts and patients while diagnosing heart disease. Thus, the system would specifically be intended towards essentially decreasing the death rate in correlation with heart diseases as it would increase the rate of successful diagnosis. Therefore, the error on part of the medical experts, i.e., misdiagnosing, would be eliminated based on the neural network system, and a timely prevention strategy could eliminate the disease at its core.

However, in order to develop such a model, this research would be specifically structured based upon a specific dataset that will essentially feature the data of diagnosis of various patients that were previously diagnosed with possible heart disease. Through the identification of the various steps of diagnosis, i.e., validation, testing, etc., this research would, at its core, identify the pattern of the neural network amongst the diagnosed patients. In this research, a new intelligent system is proposed for the diagnosis of heart disease. The proposed intelligent system categorizes heart disease according to its symptoms as Positive and Negative. The proposed system uses some parameters such as age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, ST depression induced by exercise relative to rest, the slope of the peak exercise ST segment, number of major vessels (0–3) colored by fluoroscopy and Thallium, a radioactive tracer injected during a stress test as input.

2. Motivation

With a growing number of deaths due to heart failure, it has become of utmost necessity to establish a model for detecting heart disease reliably and effectively. A big problem facing healthcare institutions (health care centers, hospital clinics) is the availability of reliable facilities at manageable prices. Accuracy, usefulness, and reliability are the main concerns for the existing models. The research's motive is to discover the most effective machine learning technique for diagnosing heart disease with higher accuracy, sensitivity, and precision.

3. Literature review

Cardiovascular disease is among the most severe contributors to death worldwide. Researchers have been producing an improved level of performance with an accuracy of 88.7% by using machine learning. ML techniques have also been used in recent developments in various sectors of the Internet of Things [6].

Diagnosis of heart disease by considering previous data and information, SHDP (Smart Heart Disease Prediction) is designed by Navies Bayesian to predict the risk of heart disease. The data required shall be compiled in a standardized form. To order to assess the likelihood of heart failure in a patient, the characteristics are derived through the clinical profiles, which include: age, BP, cholesterol, sex, blood sugar, etc. The attributes obtained function as data for the Navies Bayesian heart disease predictor classification. The output shows that the SHDP effectively did help to predict risk factors Reference [7].

Data mining can predict future heart attacks. Other predictive models like KNN, Neural Networks, and Cluster Classification are inefficient. ANN, Time Series, and cluster analysis, and affiliation laws can also implement soft computational methods. Studies results indicate that the Decision Tree behaves as well as the Bayesian classification is, is reliable [8].

The use of artificial neural networks (ANN) and Bayesian Network (BN) to classify diabetes and cardiovascular disease is studied. Using the Levenberg-Marquardt learning algorithm (multilayer feed-forward neural network) as an ANN technique is incorporated to conclude the hypothesis of higher acquisition of reliable statistics in classifying diabetes and heart disease diagnosis [9].

Heart disease has been found a major cause of death across India. Early-stage diagnosis of the disease is of greater importance and value. Genetic algorithm, neural networks (NN) classifier, and fuzzy rules are the core of the proposed model. The designed model produced high accuracy in the detection of heart disease [10]. Heart disease prediction using a support vector machine with selected features produced an accuracy of 84% values for C and g was set 10 and 0.0001 respectively, and NB classifier had 83% accuracy [11].

K-Nearest Neighbor classifier has been applied for heart disease prediction with ten prioritized attributes which predicted the disease 71.05% accurately [12]. For heart disease diagnosis, various technologies can be combined for better prediction of the disease. Machine learning classifier SVM has been combined with cloud computing. A cloud-based intelligent system empowered by the SVM model gave 93.33% accuracy [13].

Auto-Prognosis greatly enhanced the performance of cardiovascular risk estimation relative to well-performing systems. This methodology was developed using data of more than 4 lac UK Biobank individuals and 450 parameters for each individual. This technique was enabled to explore new Cardiovascular risk factorsagnostically. A comparison was made between the Auto-Prognosis model and traditional Framingham model to assess therapeutic validity. The Auto-Prognosis model predicted 3357 out of 4801 cardiovascular cases accurately [14].

Random forest-based Cardiovascular diseases prediction model for a 3-year risk evaluation of Heart disease was proposed that produced substantial enhancements over the multivariate-regression-model benchmark and including CART, Naïve Bayes, Bagged Trees, Ada Boost. The study was conducted using the random forest on a large scale with a high probability of cardiovascular disease in eastern China [15].

Medical experts need a comprehensive tool for the diagnosis of cardiac failure based on the details given. There were three main steps involved in the given fuzzy expert system i.e., Fuzzification, Rule Base, and Defuzzification. The system was designed using MATLAB Fuzzy Logic Toolbox, and Mamdani Fuzzy Interface System (MFIS) was used. Accuracy and sensitivity were measured, which were high i.e., 94.50 % and 90.19 %, respectively [16].

The deep neural network learning model was composed by combining two subsystems known as the deep neural network prediction (diagnosis) model and the deep neural network training classification model. In the first phase, a deep neural network training class was applied and then obtained final weights were given to deep neural network diagnosis. A deep neural network model has more hidden layers than a traditional multilayer perceptron neural network classification. Accuracy, sensitivity and specificity were 83.67%, 93.51% and 72.86 % respectively [17].

Machine learning techniques have been extensively researched for heart disease predictions. Data mining algorithms like NB, LR, DT, and Random-Forest have been used on the dataset taken from the UCI machine learning repository. These performance techniques showed that the Random Forest Algorithm produced the highest accuracy for heart disease prediction, which is 90.16% [18].

Cardiovascular disease diagnosis has been considered critical for lifesaving. Cardiovascular disease diagnosis using deep extreme machine learning (DCD-DEML) with back-propagation produced reasonably good accuracy of 92.45% than that of DCD Mamdani Fuzzy Inference System and DCD Artificial Neural Network [19].
Gradient descent is a strategy that aims to optimize several loss functions and it is used to optimize function (linear). Stochastic Gradient Descent has been applied here based on the root-finding feature for cardiovascular diseases. For every iteration in Stochastic Gradient, descent samples are selected randomly with the help of batch which is in fact sample size rather than that of the complete dataset. Selected batches help in calculations of the gradient for each iteration. Diagnosis of cardiovascular disease with GDS produced a reasonably good accuracy of 84.39% [20].

4. Architecture of proposed model

The design of an intelligent system includes emulation of the decision-making computer system that can detect cardiovascular disease using binary classification technique. An intelligent system takes human signs as inputs and tries to identify the disease. A traditional expert system works with the help of if-then-else rules instead of procedural code. However, in work, machine learning algorithms are used to develop an intelligent system instead of if-then-else rules. The intelligent
system generates results after some important phases. Data is taken from the user in the form of a file (.csv), pre-processing is carried out for data refinement i.e., handling missing values and redundant data. After pre-processing data is sent to binary classification algorithms for training and validation of data. Results produced by the GDO, K-NN, NB, ANN, RF, and SVM are compared in terms of accuracies and sensitivities. The architecture of the intelligent system is shown in Figure 1. The intelligent system comprises different phases for the identification of cardiovascular disease.

5. Proposed model

The methodology of intelligent cardiovascular disease prediction empowered with gradient descent optimization is shown in Figure 2. Data is collected by dataset available on the UCI machine repository for the proposed model. The presented model is divided into two phases i.e., the training phase and validation phase. There are four layers in the training phase that are labeled as sensor layer, object layer, pre-processing layer, and application layer. The sensor layer senses the inputs from the dataset like age, sex, chest pain type, thallium, etc. The sensor layer passes these inputs to the object layer via some wireless connection due to which may introduce some noisy values. Object layer passes obtained data to data pre-processing layer where noise present in the received data is handled using average moving, mean, etc. methods. After pre-processing data is sent to the application layer which is further consisted of two sub-layers named as prediction layer and the performance evaluation layer. Gradient descent optimization (GDO) technique is used for the proposed model’s training in this phase.

When training is done, the system is evaluated in terms of accuracy, sensitivity, specificity, and precision. If required training criteria are met then the training phase is completed results are stored at the server for the validation phase system is retrained with GDO to meet the training criteria.

The second phase of the intelligent system is utilized for cardiovascular disease as data for input is taken from the dataset present at the UCI machine learning repository. The trained model uses this input to predict the presence or absence of cardiovascular disease.

Table 1 contains the information related to input and output variables present in the dataset.

5.1. Mathematical model for proposed expert system

The mathematical model describes the working of the proposed model for the prediction of heart disease. The proposed model consists of three layers input layer, hidden layer, and output layer. Each layer contains a fixed number of neurons. An input layer, hidden layer, and output layer contain thirteen, five, and one neuron, respectively. Gradient Descent Optimization (GDO) implementation includes different steps such as initial weight selection for inputs, after that feed forwarding GDO of the accumulations, updating of weights in backpropagation GDO, and bias calculation. Hidden layer neuron work with an activation function like f(x) = sigmoid(x). For the input layer, this function is given in (1), and (2) describes the sigmoid function of the proposed model. The learning factor of the algorithm is represented by \( \lambda \).

Eq. (1) represents the sigmoid function for the input layer.

\[
x_m = B_1 + \sum_{i=1}^l (w_{1m} \times r_i)
\]  

Eq. (2) represents the sigmoid function for the hidden layer.

\[
y_m = \frac{1}{1 + e^{-x_m}}, m = 1, 2, 3, \ldots, n
\]  

Eq. (3) shows the input provided by the output layer

\[
x_p = B_2 + \sum_{m=1}^b (v_{ap} \times y_m)
\]  

Eq. (4) gives the activation function for the output layer

\[
y_p = \frac{1}{1 + e^{-x_p}}, p = 1, 2, 3, \ldots, r
\]  

Eq. (5) shows an Error in back-propagation

\[
Error = \frac{1}{2} \sum_p (r_p - y_p)^2
\]

The desired output of the system is described as \( r_p \). However, the actual output reported is \( y_p \).

The rate of change in weight is given in (6)

\[
\Delta w \propto -\frac{\partial Error}{\partial w}
\]

Application of Chain Rule in (6) is shown in (7)

\[
\Delta v_{ap} = -\frac{\partial Error}{\partial v_{ap}} \times \frac{\partial y_p}{\partial x_p} \times \frac{\partial x_p}{\partial v_{ap}}
\]
\[ \Delta v_{in,p} = (t_p - y_p) y_p (1 - y_p) x_m \]

If we put values in (7), the result can be written as (8) which provides the changed weight

\[ \Delta v_{in} = \varepsilon v_m \]

(8)

Where,

\[ \varepsilon = (t_p - y_p) y_p (1 - y_p) \]

\[ \Delta w_{in} = - \varepsilon \frac{\partial \text{error}}{\partial y_p} \frac{\partial y_p}{\partial x_p} \frac{\partial x_p}{\partial v_m} \frac{\partial v_m}{\partial y_m} \]

\[ \Delta w_{in} = - \varepsilon \frac{\partial \text{error}}{\partial y_p} \frac{\partial y_p}{\partial x_p} \frac{\partial x_p}{\partial v_m} \frac{\partial v_m}{\partial y_m} \]

\[ \Delta w_{in} = - \varepsilon \left( \sum_p \left( t_p - y_p \right) y_p (1 - y_p) v_{m,p} \right) x_m (1 - y_m) \]

\[ \Delta w_{in} = - \varepsilon \left( \sum_p \left( t_p - y_p \right) y_p (1 - y_p) v_{m,p} \right) x_m \]

(9)

Where,

\[ \Delta w_{in} = - \varepsilon v_m \]

Such As,

\[ \varepsilon_m = \left[ \sum_p \left( t_p - y_p \right) y_p (1 - y_p) v_{m,p} \right] x_m (1 - y_m) \]

Eq. (10) represents weight updating between the hidden layer and output layer, \( \nabla v_{in,p} \) represents the gradient descent with respect to the parameters \( v_{m,p} \)

\[ v_{m,p} = v_{m,p} + \lambda \nabla v_{n,p} \]

(10)

Eq. (11) represents weight updating between the input layer and the hidden layer, \( \nabla v_{m,p} \) represents the gradient descent with respect to the parameters \( w_{in} \)

\[ w_{in} = w_{in} + \lambda \nabla w_{in} \]

\[ \lambda \text{ is the learning rate by which we find the step size to obtain the minimum (local).} \]

6. Data set evaluation

The dataset used in this work is obtained from the UCI repository. Training, testing, and validation of Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization Model are performed on Cleveland data set for detection of heart disease. The dataset is available online for educational and learning purposes. Data set details are shown in Table 1. This data set consists of 14 characteristics which consist of human characteristics and biochemical properties. Dataset consists of 1025 patients record. There are 499 healthy samples and 526 diseased samples. The dataset contains records of 713 male and 312 female samples.

7. Experimental results

A new model “Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization” is proposed for cardiovascular disease diagnosis with better accuracy and the same dataset is used for different machine learning algorithms like ANN, RF, KNN, SVM, and NB. By experiments it’s found that the proposed model predicted the heart disease with higher sensitivity, specificity, precision, and accuracy.

The results consist of performance analysis of different machine learning algorithms including SVM, NB, KNN, RF, and their comparison with the Proposed Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization model. Moreover, performance evaluation is performed using the measures of classification accuracy that included counting of TruePositive and FalsePositive factor and creating a comparison graph for them. Moreover, ROC analysis is performed to know about results and real-time facts. The confusion matrix is given in Table 2.

Accuracy can be defined as under

\[ \text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \]

(12)

Sensitivity or recall can be calculated through the following equation

\[ \text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \]

(13)

Specificity can be calculated through the following equation:

\[ \text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \]

(14)

PPV and NPV of an algorithm can be calculated by the following equations

\[ \text{Positive Predictive Value} = \frac{\text{TP}}{\text{TP} + \text{FP}} \]

(15)

\[ \text{Negative Predictive Value} = \frac{\text{TN}}{\text{TN} + \text{FN}} \]

(16)
Performance evaluation of Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization model with the different train-test ratio is shown in Table 3.

When k-fold cross-validation is applied with setting the value of k as 3, 5, and 10, the gradient descent optimization model’s average accuracy is presented in Table 4.

Accuracy, sensitivity, specificity for Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization, NB, SVM, K-NN, RF, and ANN are calculated. Table 5 displays a comparison of the performance of Proposed Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization with NB, SVM, K-NN, RF, and ANN.

It is observed that the classification module worked with maximum accuracy and precision value with Gradient Descent Optimization (GDO) based model. GDO reached a maximum accuracy of 98.54% with automatic selection of features for binary classification. ANN reached the second maxima of accuracy with 95.31 percent accurate classification.

Naive Bayes produces 83% accuracy which is considered pretty reasonable but not up to the mark. SVM is reportedly found with reasonable accuracy on the UCI data set. SVM merely hit 75 percent accuracy which is low when compared with other algorithms like ANN and K-NN.

Random Forest produces 92.48% accuracy. Moreover, it is observed that the automatic selection of features resulted in better accuracy for the proposed model (GDO). Figure 3 shows a graphical comparison among machine learning approaches.

### 7.1. Sensitivity and specificity of proposed model

Medical diagnostic systems are evaluated with sensitivity and specificity abilities. The ability to identify true positives is defined as the sensitivity of the algorithm. Moreover, the specificity is decided as the ability to decide the true negatives correctly. True negatives and true positives are observed for all the classification algorithms, which are discussed earlier. The proposed model has achieved a clearly higher sensitivity (99.43%) and specificity (99.6%).

### 7.2. ROC analysis

ROC points describe the sensitivity of the algorithm about a specific decision threshold. An algorithm with 100% specificity and sensitivity makes a curve on the upper left corner of the graph. The more the ROC curve is towards the left top corner, the more accurate algorithm obtained. The results are plotted on the basis of TP and FP values of all algorithms [21].

ROC graphs are plotted between the sensitivity and specificity of the algorithm. While the sensitivity of the algorithm is represented on the y-axis, the specificity of the algorithm is displayed on the x-axis. Generally, an AUC score of 0.5 is considered as no good because it did not describe a good ability of the algorithm to diagnose the disease. Moreover, an AUC score of 0.7–0.8 is considered acceptable for its diagnosis to be nearly accurate. However, an AUC score of 0.9 and above describes that the algorithm has excellent accuracy of disease diagnosis. On the other hand,

### Table 4. Simulation results produced by the Proposed Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization model with K-Fold cross-validation.

| Value of K | Accuracy (%) |
|------------|--------------|
| 3          | 97.56        |
| 5          | 97.01        |
| 10         | 97.73        |

### Table 5. Simulation results of Proposed Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization, NB, SVM, K-NN, RF, and ANN classifiers.

| Algorithm                          | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|------------------------------------|--------------|-----------------|-----------------|
| Support Vector Machine             | 75           | 75              | 78              |
| K-Nearest Neighbor                 | 66.73        | 68              | 64              |
| Naive Bayes                        | 83           | 78              | 87              |
| ANN                                | 95.31        | 95.35           | 95.28           |
| Random Forest                      | 92.48        | 91.17           | 93.87           |
| Intelligent CVD Prediction         | 98.54        | 99.43           | 97.6            |

Figure 3. Simulation results produced by SVM, K-NN, NB, ANN, RF, and Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization model.
an AUC score of above 0.9 is considered to be near real for its better accuracy predictions. The proposed model's implementation with GDO achieved an AUC score of 0.9854, which shows its ability for better heart disease diagnosis. ROC curves produced using NB, K-NN, GDO, SVM, RF, and ANN are given in Figure 4.

### 7.3. Mean square error (MSE) analysis

A neural network works with a basic example of learning in an iterative model. MSE function defines its learning performance and affects the results also. Error reduction is necessary for the efficiency of the system. Mean square error is calculated as a difference between the desired output and actual output. Table 5 shows the mean square error values corresponding to the number of epochs for training, testing, and validation phases. It is observed that a linear minimization of MSE is seen with the increasing number of training iterations. At the end of the training proposed model, after 173 training epochs, the minimum mean square error is reduced to 0.0644. The testing phase ended after 173 testing epochs, the mean square error is reduced up to 0.07071. And best validation performance is also achieved at epoch 167.

From Table 6, it can be established that the actual and predicted values are very close to each other which shows that the proposed model is a better performer.

### 7.4. Comparative study

The proposed model has been compared with recently published research models in terms of performance. It’s been established that the proposed model has produced much better accuracy than previous research models. Table 7 contains comparative results from various models.

### 8. Research contributions

The proposed model helps in detecting heart disease with higher accuracy, precision, sensitivity and specificity. The proposed Expert System is believed to be easy to use. Research provides awareness and

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**Table 6. Values of mean square error (MSE), root mean square error (RMSE) and absolute mean error (AME) corresponding to no. of epochs for training, testing, and validation.**

| No. of Epochs | 0   | 20  | 40  | 60  | 80  | 100 | 120 | 140 | 160 | 173 |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| **Training Phase** |     |     |     |     |     |     |     |     |     |     |
| MSE           | 1.669 | 0.2839 | 0.1782 | 0.13 | 0.1073 | 0.0948 | 0.0822 | 0.072 | 0.0671 | 0.0644 |
| RMSE          | 1.291 | 0.5328 | 0.4221 | 0.3605 | 0.3275 | 0.3078 | 0.2867 | 0.2683 | 0.2537 | 0.2537 |
| MAE           | 0.951 | 0.3901 | 0.3367 | 0.3021 | 0.2812 | 0.1912 | 0.1412 | 0.1712 | 0.1812 | 0.1202 |
| **Testing Phase** |     |     |     |     |     |     |     |     |     |     |
| MSE           | 1.765 | 0.3039 | 0.1782 | 0.1242 | 0.1352 | 0.1244 | 0.0972 | 0.0791 | 0.0731 | 0.0707 |
| RMSE          | 1.328 | 0.5512 | 0.4229 | 0.3663 | 0.3594 | 0.3527 | 0.3117 | 0.2812 | 0.2685 | 0.2658 |
| MAE           | 0.932 | 0.3421 | 0.3017 | 0.2811 | 0.2514 | 0.2312 | 0.1822 | 0.1613 | 0.1711 | 0.1313 |
| **Validation Phase** |     |     |     |     |     |     |     |     |     |     |
| MSE           | 1.839 | 0.3318 | 0.2641 | 0.142 | 0.1268 | 0.1185 | 0.0972 | 0.0803 | 0.0731 | 0.0707 |
| RMSE          | 1.356 | 0.5760 | 0.5139 | 0.3778 | 0.3698 | 0.3584 | 0.3274 | 0.2833 | 0.2711 | 0.2677 |
| MAE           | 0.984 | 0.4501 | 0.4311 | 0.3242 | 0.2931 | 0.1731 | 0.1316 | 0.1680 | 0.1532 | 0.1307 |

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**Figure 4.** Six ROC curves i.e. (a), (b), (c), (d), (e), and (f) show receiver operating characteristic (ROC) curves produced by Naïve Bayes (NB), K-Nearest Neighbor (KNN), Gradient Decent Optimization (GDO), Random Forest (RF), Artificial Neural Network (ANN) and Support Vector Machine (SVM), respectively.
sensitivity of heart disease. A comparative study demonstrates the effectiveness of the Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization Model. Overall, it is proved that the proposed research improves the accuracy, sensitivity, specificity, and precision of classification with high AUC output when compared with other techniques.

9. Conclusion and future work

Analysis of cardiovascular disease is one the most frequent field for modern-day research; it is because of the severity of the cardiovascular disease. Facts and figures published by WHO show that about 17.9 million people lost their lives in the year 2017 just because of cardiovascular diseases. Different approaches have been used for the analysis of heart disease, but the major concern has been of the accuracy of prediction/detection. This paper has shown great improvements in performance for cardiovascular disease detection. The accuracy, precision, sensitivity, and specificity of the proposed system are visibly higher than most of the existing approaches that make this research more impactful. Comparative studies have also been discussed in this research paper. 98.54 %, 99.43 %, 97.6 %, and 97.76 % accuracy, sensitivity, specificity, and precision have been recorded, respectively.

This research is conducted with limited data of about 1025 instances. In the future, large-size datasets with a greater number of attributes or fused datasets that may be obtained by combining two different datasets can be used to enhance the diagnosis procedure using deep extreme machine learning.

Declarations

Author contribution statement

M. S. Nawaz: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

B. Shoaib: Conceived and designed the experiments; Performed the experiments; Wrote the paper.

M. A. Ashraf: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Table 7. Comparison of the proposed model with literature models.

| Model                                                      | Accuracy (%) |
|------------------------------------------------------------|--------------|
| Cloud-based Intelligent System Empowered by the SVM Model (2020) | 93.33       |
| Diagnosis Cardiovascular Disease-Deep Extreme Machine Learning (2020) | 92.45       |
| Random Forest Based Model (2020)                           | 90.16        |
| Fuzzy Expert System Kasbe and Pippals (2018)               | 94.50        |
| Deep Neural Network Based System by Miao and H. (2018)     | 83.67        |
| Intelligent CVD Prediction Empowered with GDO              | 98.54        |
| Intelligent CVD Prediction Empowered with GDO (3-Fold CV)  | 97.56        |
| Intelligent CVD Prediction Empowered with GDO (5-Fold CV)  | 97.01        |
| Intelligent CVD Prediction Empowered with GDO (10-Fold CV) | 97.73        |

Data availability statement

Data associated with this study has been deposited at UC Irvine Machine Learning Repository.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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Data associated with this study has been deposited at UC Irvine Machine Learning Repository.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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