Next-Gen Heart Disease Prediction: A Gradient Boosting Approach with L1-Regularized Neural Networks

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***Abstract*—Heart diseases, also known as diseases caused by cardiovascular complexities, cover a range of heart and blood vessels affecting condition, emerging as a notable concern in global health. Timely detection of any cardiovascular disease is of immense significance to effective treatment and prevention. This paper introduces a new method to diagnose and predict cardiac disease using gradient-boosting classifier with L1-regularized neural networks as a base estimator. The proposed method can effectively handle small datasets and resist overfitting, a common challenge in traditional machine-learning methods. Using a neural network as the base estimator of a gradient-boosting Classifier allows the model to capture non-linear relationships between risk factors and improve prediction accuracy. Besides, L1 regularization, in particular, can effectively promote sparsity in the neural network weights, which can be considered as helpful to identify the most important predictors of heart disease. Five publicly accessible cardiac disease datasets are used to evaluate the suggested methodology. Experimental results demonstrating better performance of the proposed strategy than conventional machine learning approaches, achieving 97.11% accuracy, 95.51% precision, 98.84% recall, and 97.14% F1-score. The suggested approach can deliver precise forecasts, and is robust to noise and outliers, making it a valuable technique for clinical diagnosis and decision-making.**

***Index Terms*—Heart Disease, Gradient Boosting Classifier, L1 Regularization, Neural Network, Machine learning**

I. Introduction

Cardiovascular or heart-disease forecasting is a vital area of research aimed at decreasing the high rates of morbidity and death connected to these conditions which explains the essentiality of early detection. Some machine learning techniques like SVM [1], Random Forest [2], and Decision Tree [3] have shown promise in predicting heart disease, allowing for better patient outcomes. Ensemble learning methods, such as Gradient Boost, AdaBoost, XGBoost classifier, etc have been successfully applied in various domains to improve prediction accuracy by combining multiple base models. Gradient Boost [4] combines several weak learners with powerful ones and is widely considered as an appreciated ensemble learning technique. The base estimator in Gradient Boost is trained iteratively, with each iteration assigning greater weight to the incorrectly classified samples from earlier iterations. Strong non-linear models, such as neural networks, are capable of capturing intricate correlations between input variables. Risk variables (including age, blood pressure, cholesterol levels, etc.) may have non-linear connections at the time of heart disease prediction. It automatically extracts most relevant features from input data, eliminating the need for manual feature engineering. When it comes to predicting heart disease, there may be many potential risk factors, and it may not be immediately obvious which ones are most important.Models can identify key indicators for heart-disease prediction more effectively by using a neural network as base estimator. L1 regularization [5] stands out as a powerful technique for feature selection in high-dimensional and small datasets, which can help eliminate irrelevant features and reduce overfitting. Neural networks [6] have also been extensively used for heart disease prediction, showing excellent performance in various studies. However, to date, no research has examined the usage of a gradient-boosting classifier consisting of neural networks with L1 regularization for heart disease prediction.

Our paper introduces a novel proposed method for cardiac disease anticipation using a gradient-boosting classifier with L1-regularized neural networks as base estimators. The method intends to tackle the difficulties of overfitting and high dimensionality while providing accurate and robust predictions. The Key contributions provided by this research are as follows:

- A method using a new combination of Gradient Boosting Classifier with L1-regularized neural networks as base estimators.
- Reducing computational complexity by eliminating extensive feature engineering and addressing overfitting.
- Benchmarking performance of our proposed model concerning other traditional methods as well as previous research where our proposed model outperforms previous research.
- Sequential error optimization in each iteration of the based estimator, eventually ensuring high performance of the model.
- Usage of a combination of large publicly accessible data and ensuring more transparency and generalization in the research.

II. Related Work

In machine learning, predicting illness of heart has drawn significant attention with numerous approaches proposed focusing on accurate prediction. Traditional approaches, like Support Vector Machines (SVM), Decision Trees (DT), and k-nearest Neighbors (KNN), were initially implemented to predict heart disease(Singh and Kumar et al [7]). However, issues like overfitting and limited scalability remained as significant challenges. Das et al. [8] addressed this problem by applying L1 and L2 regularization in their stacked SVM model. Burse and Wadhvani [9] compared various regularization techniques to address overfitting and found L1/L2 logistic regularization producing the sparsest result. Karthikeyan et al. [5] proposed an efficient heart disease prediction system utilizing an L1-norm-based regularized Support Vector Machine (SVM). However, extensive feature engineering increased the overall computational complexity of the models. Theerthagiri [10] addressed this issue and further optimized their model by recursively eliminating irrelevant features with gradient boosting. Iftee et al. [11] leverage autoencoder as an unsupervised learning method for proficient dimensionality reduction. Li et al. [12] integrated multiple feature selection techniques such as lasso, MRMR, FCMIM, into an e-healthcare system, improving prediction accuracy to 92.37%. Nevertheless, the models are still limited by scalability issues and computational complexities. Kavitha et al. [3] came up with a hybrid approach combining Decision Trees and Random Forests, achieving 88.7% accuracy. Similarly, Latha and Jeeva [13] implemented ensemble techniques like majority voting and bagging, which enhanced classifier performance. Anuradha et al. [14] used feature selection methods like XGBoost and CatBoost within the ensemble model. Nazri et al. [15] suggested a model to predict heart disease using several ML classifiers with soft voting. Tama et al. [16] developed a two-tier ensemble classifier using Random Forest, GBM, and XGBoost, integrating majority voting and bagging techniques resulting in an increased accuracy of 95.2%. Although ensemble approaches showed promise, reliance on manual feature engineering remained an obstacle to optimized performance. Consequently, it set the stage for more advanced deep learning and hybrid strategies. Miao et al. [17] built a DNN for coronary heart disease diagnosis, achieving 83.67% accuracy. Sajja and Kalluri [18] proposed a CNN model for a similar purpose, yielding better results on the UCI dataset (94.78%).

However, the model's dataset-specific tuning limited its generalizability. Experimenting with hybrid approaches combining deep learning and ensemble methods emerged as a real game changer in heart disease prediction research. Mohan et al. [2] developed a Hybrid Random Forest with a Linear Model (HRFLM) and reached a high accuracy using all features without feature selection restrictions. Bharti et al. [19] proposed a hybrid approach which integrates techniques of both machine learning (ML) and deep learning (DL) achieving 94.2% accuracy. Hassan et al. [20] combined pre-trained DNNs to extract the features, PCA to reduce dimensionality, and Logistic Regression for classification, achieving up to 93.33% accuracy avoiding extensive tuning. Yazid et al. [6] improved ANN accuracy to 90.9% using systematic tuning but at a high computational cost. Xu et al. [1] enhanced generalization with S-LSTSVM, but its complex tuning limits practical application efficiency. We have found that Cleveland and UCI Cleveland datasets are predominantly used in previous research in heart disease predictions.

III. Methodology

This section describes the detailed methodology used in this study predicting heart-disease with the usage of Gradient Boosting Classifier with L1-regularized neural networks as base estimators.

A. Datasets

The research utilizes a collection of datasets, integrating five datasets (Cleveland, Hungarian, Switzerland, Long Beach VA, and Stalog (Heart) with 303, 294, 123, 200, and 270 observations respectively) related to heart disease producing a total of 918 observations after eliminating duplicates from the initial 1190. The common features of the combined data are shown in Table

TABLE I
Features Information

Features	**Description**
Age	patient's Age [years]
Gender	patient's gender [M: Male, F: Female]
Pain in Chest	kind of chest discomfort
Bps while in rest	Measurement of pressure in blood at rest [mm Hg]
Cholesterol	level of bloodstream cholesterol [mm/dl]
Fasting GL	fasting glucose levels
ECG_in_rest	electrocardiogram readings during rest
CR_max	reached the highest cardiac rate
Angina_after_exercise	Angina caused by exercise [Y: Yes, N: No]
Ca	the quantity of major vessels as a color range (0-3)
Oldpeak	evaluation of depression using numbers
Angle_ST	ST segment angle at peak workout
Disease_of_Heart	presence (1) or absence (0) of disease in heart

B. Data Preprocessing

In the preprocessing phase for the input data of heart disease diagnosis, the initial step involves categorizing numeric features such as 'Age' and 'Resting bps' through binning such as creating distinct age groups ('child', 'young', 'mature', 'old') from numeric age values. Subsequently, data cleaning is executed to eliminate noise, addressing issues like negative 'cholesterol' values and abnormal 'Max CR' values (below 40 or above 190). Addressing missing data is a significant step, accomplished through the application of Multivariate Imputation by Chained Equations (MICE) and K-Nearest Neighbors (KNN) imputation methods. Outliers are treated with quadratic interpolation, contributing to a more robust and reliable dataset. Class imbalance, if detected, is mitigated by employing the Synthetic Minority Over-sampling Technique (SMOTE) for upsampling. Feature encoding utilizes one-hot encoding, ensuring categorical variables are appropriately represented. The data is finally normalized utilizing standard scaler, eventually enhancing performance of subsequent machine-learning models. All the flows of preprocessing steps are shown in Figure 1.

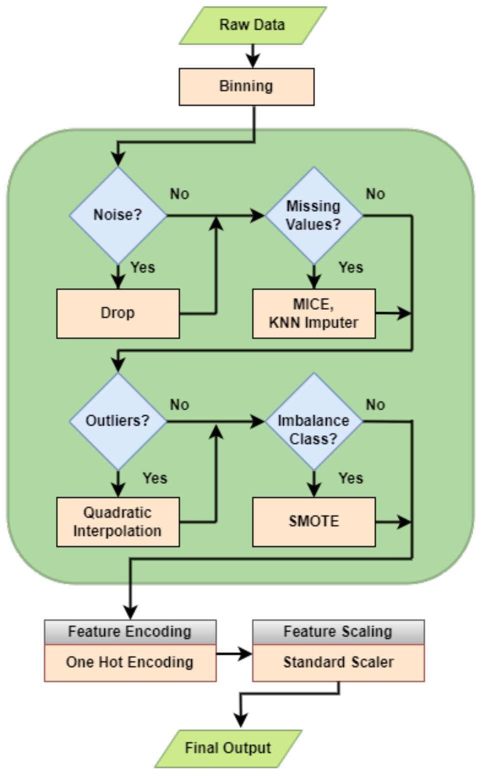


Fig. 1. Preprocessing Steps are used before model training

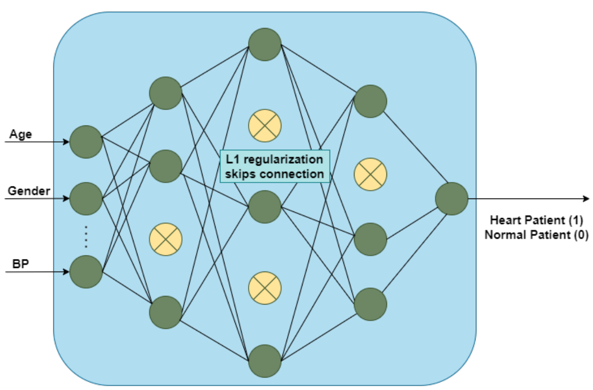


Fig. 2. Proposed weak classifier (L1 regularized Neural Network) for the Gradient Boosting algorithm.

C. model build up

1) Base Estimator: A neural network with one hidden layer was used as the base estimator in the Gradient Boosting Classifier algorithm. At the first layer of the neural network consists of 13 neurons to feed 13 input features, Three hidden layers with 256, 512, and 64 neurons each made up the neural network architecture used in this research. Table II

TABLE II
MODEL SUMMARY OF THE WEAK CLASSIFIER.

Layers	Output Shape	Parameters
Input	1×13	–
Dense-1	1×256	3,584
Dense-2	1×512	1,31,584
Dense-3	$1\times1{,}024$	5,25,312
Dense-4	1×512	5,24,800
Dense-5	1×64	32,832
Output	1	65
Total Parameters		1,218,177

TABLE III
ALL HYPERPARAMETERS USED IN PROPOSED METHOD

Hyperparameters	Values
Number of Trees (Boosting Iterations)	100
Count of layers hidden	5
Neurons per Hidden Layer	256, 512, 1024, 512, 64
Activation Functions	Relu, Sigmoid
L1 Regularization Parameter (λ)	0.001
Optimizer	Adam
Batch Size	32
Number of Epochs	100

provides the output shapes and parameters of the proposed base estimator neural network and Figure 2 shows the structure of it. All of the neurons in the network were activated using the rectified linear unit (ReLU). To determine the likelihood of cardiac disease, the output layer contained a sigmoid activation function. The L1 regularization technique was used in each of the layers of a neural network to select the most relevant neurons to predict heart disease. The L1 regularization technique aims to shrink the coefficients of the less important neurons to zero, resulting in a sparse model with only the most informative features. The optimal regularization parameter (lambda) was determined using 5-fold cross-validation.

2) Gradient Boosting Algorithm: In the proposed classifier model, the Gradient Boosting Classifier, an ensemble machine learning technique combines the predictive power of multiple weak classifiers to create a strong predictive model. Here, it uses the L1-regularized neural network as a base estimator, where each of them corrects the errors or adjusts the weights made by the previous ones. During training, the model calculates the class probabilities based on the weighted votes of these trees. Initially, all data points have equal weights, but with each iteration, the weights are adjusted to give more importance to the misclassified data points of the heart disease dataset. This strategy effectively identifies classes by learning from the mistakes of previous neural network estimators and continuously improving its heart disease classification accuracy.

Table III shows the hyperparameters used by the proposed model.

IV. RESULT AND DISCUSSION

For training and evaluation, A training set made up of 80% of that combined dataset and a testing set made up of 20%.

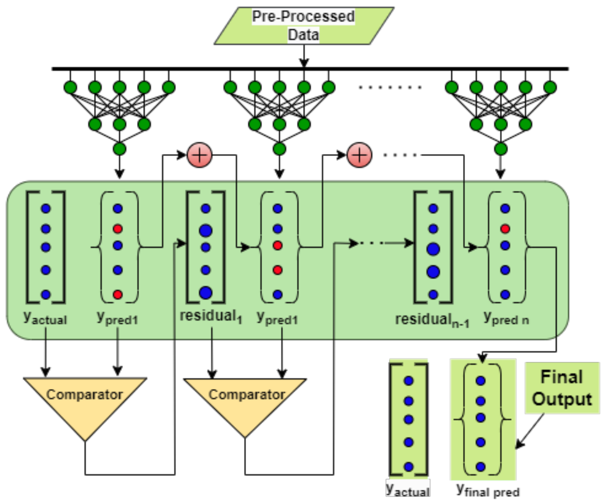


Fig. 3. Working Procedure of the Gradient Boosting algorithm, where N no of weak classifiers are utilized to create a final strong classifier for the proposed system.

Algorithm 1 Gradient Boosting Classifier with Neural Network Base Learner

Initialize F as a zero vector of length n_{samples} {Initial predictions}

for $t := 1$ *to* $n_{estimators}$ **do**

(i). Calculate pseudo_residuals $= y - y_{\text{pred}}$ where $y_{\text{pred}} = \frac{1}{1+e^{-F}}$

(ii). Fit a neural network:

nn $\leftarrow$ NeuralNetwork(hidden_layers, learning_rate)

nn.fit(X, pseudo_residuals)

(iii). Perform forward propagation in the neural network:

$$Z^{(l)} = W^{(l)} A^{(l-1)} + b^{(l)}$$
$$A^{(l)} = \text{ReLU}(Z^{(l)})$$

(iv). Perform backward propagation to compute gradients:
Compute layer activation gradients:

$$\delta^{(l)} = \nabla^{(l)} \odot \text{ReLU}'(Z^{(l)})$$

Calculate weight gradients with L1 regularization:

$$\nabla_W^{(l)} = \frac{1}{m} \delta^{(l)} A^{(l-1)T} + \frac{\lambda}{m} \text{sign}(W^{(l)})$$

Compute bias gradients:

$$\nabla_b^{(l)} = \frac{1}{m} \sum_{i=1}^{m} \delta_{(i)}^{(l)}$$

Propagate gradients to the previous layer:

$$\nabla^{(l-1)} = W^{(l)T} \delta^{(l)}$$

(v). Update the predictions with a fraction of the neural network's predictions:

$$F \leftarrow F + \text{learning\_rate} \times \text{nn.predict}(X)$$

(vi). Append 'nn' to the list of estimators.

TABLE IV
PERFORMANCE EVALUATION OF THE PROPOSED METHOD AGAINST OTHER EXISTING TECHNIQUES.

Methods	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
Logistic Regression	88.58	86.23	94.00	89.95
KNN	86.41	81.65	94.68	87.68
Decision Tree	86.95	91.74	86.95	89.28
SVM	91.30	87.15	97.93	92.23
Random Forest	91.84	88.07	97.95	92.75
Only Gradient Boost	94.50	95.66	92.06	93.82
CatBoost	95.50	96.11	94.21	95.15
Only Neural Network	95.39	93.82	94.11	93.96
Proposed model	**97.11**	**95.51**	**98.84**	**97.14**

TABLE V
PERFORMANCE REVIEW ON CLEVELAND DATASET PROPOSED METHOD VS AGAINST OTHER EXISTING WORKS

Methods	Accuracy (%)
Hybrid approach [13]	85.48%
KNN [7]	87.00%
SLSTSVM [1]	87.82%
HRFLM [2]	88.40%
Decision Tree + Random Forest [3]	88.70%
Parameter Turned ANN [6]	90.09%
FCMIM-SVM [12]	92.37%
SMOTE + Soft Voting [15]	92.42%
Neural network + PCA [20]	93.33%
C-BiLSTM [21]	94.78%
Ours	**97.11%**

The following metrics were used to rate the model's evaluation:
Cardiac$_{\text{correct}}$(TP): Total number of data points that were accurately categorized as heart diseases, **Cardiac$_{\text{incorrect}}$(FN)**: Total number of data points that were inaccurately categorized as heart diseases, **Normal$_{\text{incorrect}}$(FP)**: Number of data inaccurately classified as 'No Diseases', **Normal$_{\text{incorrect}}$(FP)**: Number of data accurately classified as 'No Diseases', **Total$_{\text{sample}}$**: Total number of data accurately classified

$$Total_{\text{correct}} = Cardiac_{\text{correct}}(TP) + Normal_{\text{correct}}(TN) \quad (1)$$

$$Total_{\text{incorrect}} = Normal_{\text{incorrect}}(FP) + Cardiac_{\text{incorrect}}(FN) \quad (2)$$

$$Total_{\text{sample}} = Total_{\text{correct}} + Total_{\text{incorrect}} \quad (3)$$

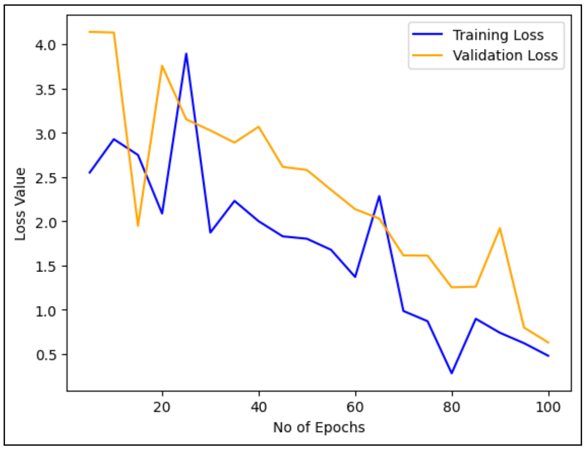
$$Accuracy = \frac{Cardiac_{\text{correct}}(TP) + Normal_{\text{correct}}(TN)}{Total_{\text{sample}}} \quad (4)$$

$$Precision = \frac{Cardiac_{\text{correct}}(TP)}{Cardiac_{\text{correct}}(TP) + Normal_{\text{incorrect}}(FP)} \quad (5)$$

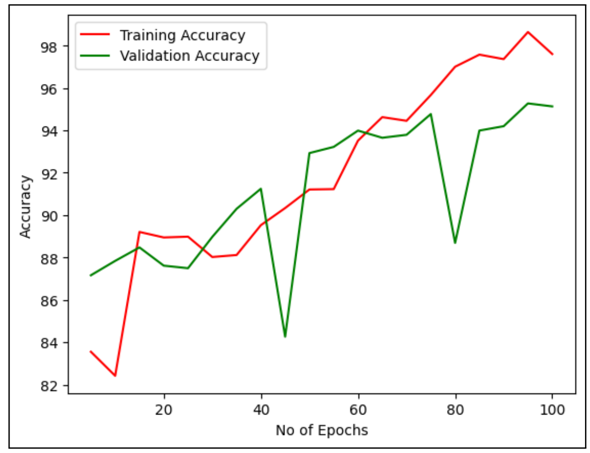
$$Recall = \frac{Cardiac_{\text{correct}}(TP)}{Cardiac_{\text{correct}}(TP) + Cardiac_{\text{incorrect}}(FN)} \quad (6)$$

$$F1 - Score = \frac{2 * (Precission * Recall)}{Precission + Recall} \quad (7)$$

In table IV, the model proposed here is compared with several existing algorithms such as SVM, Logistic Regression, KNN, Decision Tree, Random Forest, Gradient Boost and Neural Network, etc. (table IV shows all of them). It should be noted that this analysis is done with the combined dataset

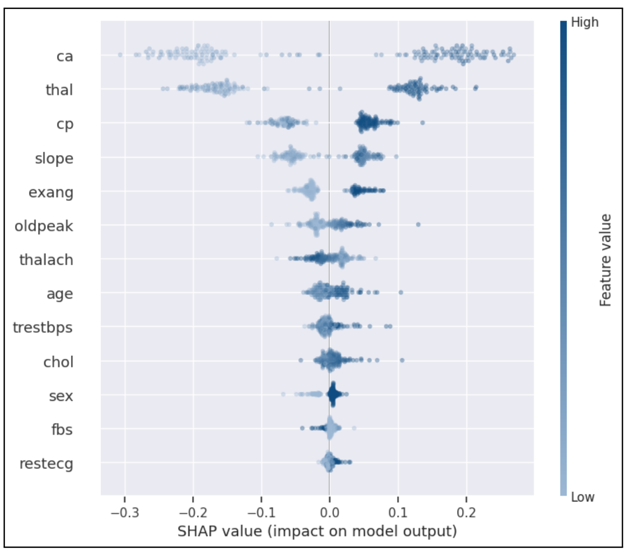


(a) Loss curve of Gradient Boost

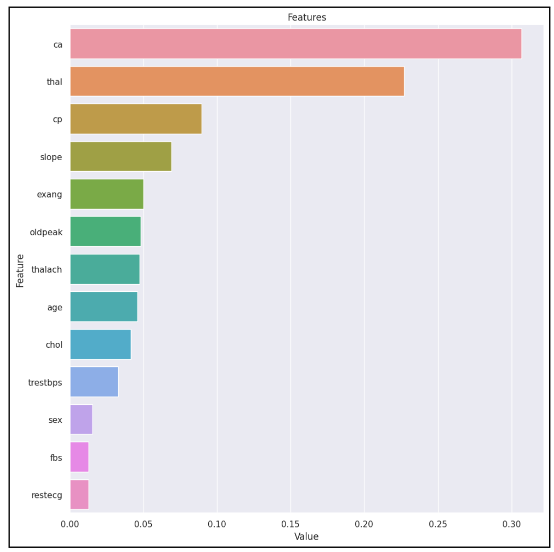


(b) Accuracy curve of Gradient Boost

Fig. 4. The loss and accuracy curve of training and validation data of a base estimator in Cleveland dataset



(a) SHAP Value of the Features



(b) Feature Importance by the proposed Model

Fig. 5. Feature Importance and Model Interpretability by SHAP Value

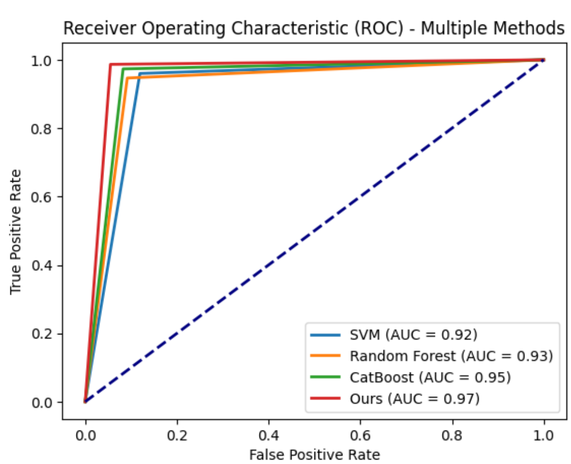


Fig. 6. Receiver Operating Characteristics Curve (ROC) for the proposed model.

upon which we trained our model. The results showed that the proposed Gradient Boosting classifier used a neural network with L1 regularization as the base estimator and reached higher precision, with average 97.11% accuracy on the testing set. Even more, the precision was high, demonstrating that a substantial percentage of the patients could be correctly identified by the classifier with heart disease while minimizing false positives. The high recall value achieved by the proposed model is a good concern in medical disease diagnosis as the false negatives are very harmful to patients. Table V compares the suggested model to other existing works that are displayed. Comparing the suggested model to other previous attempts, there was a noticeable improvement in accuracy and performance.It should be noted that here in this case the Cleveland dataset has been used as the standard baseline to evaluate the improvements concerning previous methods, as it has been extensively studied and offers a point of comparison across different previous research's proposed models. The superior result of 97.11% accuracy clearly indicates the effectiveness of our model, ultimately contributing to and improving heart disease prediction research. The loss curve in Figure 4 of a base estimator monitors the evolution of the loss function of the base estimator during training, aiding in fine-tuning and optimization. Here, it also shows an accuracy curve in there which is used to understand how the model's performance changes with different hyperparameter settings or the number of boosting iterations. Furthermore, a feature importance analysis and model interpretability by SHAP (SHapley Additive exPlanations) analysis are shown in Figure 5 was conducted to recognize the most important features of heart disease and indicated the model's explainability. The results showed that the color range (0-3) for the quantity of major vessels was the most important predictor along with the highest shap value. Overall, the results demonstrate how effective it was to use the proposed model to predict heart disease, as these can provide precise and interpretable predictions of heart disease risk based on readily available patient characteristics.The AUC-ROC was 0.97 shown in Figure 6, indicating high discrimination between the patients who have heart disease and those who do not. The classifier's effectiveness was compared to other classification methods such as SVM, random forest, catboost, etc. The F1 score was high, indicating a balance between precision and recall, and outperformed all other algorithms.

V. Conclusion

In this paper, a new heart-disease prediction method is proposed using a gradient-boosting classifier with L1 regularized neural networks as base estimators. This method was used to address overfitting and high dimensional data issues, by leveraging a comprehensive dataset integrating five more heart disease datasets. The combination of Gradient Boosting and L1-regularized neural networks optimized errors, leading to robust and accurate predictions yielding an accuracy of 97.11 percent. Additionally, the SHAP analysis of this model reveals how various factors significantly influence the prediction of heart disease, enhancing its interpretive power. The proposed method outperforms traditional machine learning methods, with an AUC-ROC of 0.97, demonstrating excellent ability in distinguishing individuals with and without heart disease. This approach can contribute significantly to aid practitioners in the early diagnosis of heart-disease, leading to better patient outcomes and effective healthcare interventions.

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