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Enhanced accuracy for heart disease prediction using artificial neural network

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ABSTRACT

Making an accurate and timely diagnosis of cardiac disease is critical for preventing and treating heart failure. The accuracy of results produced by traditional machine learning (ML) algorithms is satisfactory. On the other hand, deep learning algorithms result in higher prediction accuracy. In this study, we used an artificial neural network (ANN) model to construct a deep learning diagnosis system for heart disease prediction. The developed ANN prediction model achieved 93.44% accuracy, which is 7.5% higher than a traditional ML model support vector machine (SVM). Additionally, using a simpler neural network reduced the time taken for training and classification to less than a minute.

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1. INTRODUCTION

The workload on a person has increased dramatically in recent years. Due to this unavoidable situation, the person is likely to get heart disease [1]. According to World Heart Federation (WHF) data, worldwide, heart disease kills millions of people a year [2]. Heart disease (HD) is caused when the blood flows to the brain, heart, lungs, and other vital organs is reduced. Defective heart valves can also result in heart failure (HF). Furthermore, angina pectoris, stroke, congestive heart failure (CHF), and dilated cardiomyopathy are linked to heart disease. Therefore, it is essential to monitor cardiovascular disease (CVD) biomarkers and identify a person's risk of heart failure [3], [4]. Humans have developed in machines and health care since ancient times. Medicine and health care have improved significantly since the introduction of machines and AI [5]-[7]. As technology advances, healthcare facilities must now store massive amounts of data in databases, making data interpretation harder. By using several longitudinal research results, the prediction models for heart disease are constructed [8].

Machine-learning algorithms (ML) can solve many challenges in medical centers management and data analysis. These tools and approaches help analyze and interpret large datasets. Many factors contribute to heart diseases, including age, weight, height, gender, cholesterol, ECG results, blood pressure, chest pain, smoking, obesity, and eating habits [9]. The traditional approaches for heart disease risk diagnosis rely on a physician's study of a patient's medical history, physical examination report, and relevant symptoms, leading to inaccuracies and delays in diagnosis [10], [11]. Early identification of heart disease can reduce the disease progression. Thus, detection of cardiac disease at an early stage is critical to lower mortality and increasing survival rates [12], [13].

Early heart disease detection is challenging, so many computer-aided methods have been developed to overcome this issue. One of the most used computer-aided methods is machine learning [14], such as support vector machine, k-nearest neighbor, decision tree, and fuzzy logic. However, with huge healthcare data, deep learning methods like artificial neural networks (ANN) and deep neural networks (DNN) are currently gaining popularity [15]. Deep learning (DL) algorithms which are part of ML can combine information from several sources and manage large amounts of data, enhancing prediction ability [16].

Many studies have proposed medical decision support systems based on deep learning algorithms [1]. Palaniappan *et al*. [17] suggested a diagnostic heart disease system using Naive Bayes, decision trees, and ANN. The ANN predictive model's prediction accuracy was 85.68%. Heart disease diagnosis using an ANN ensemble model was obtained with 89.01% accuracy by Das *et al*. [18]. Olaniyi *et al*. [19] developed an ANN-based intelligent system to diagnose cardiac problems that were 85% accurate. Samuel *et al*. [20] used ANN and fuzzy AHP to identify heart disease. Their proposed classification approach was accurate to 91.10%. Miao *et al*. [12] proposed a model based on a DNN to predict coronary artery disease (CAD) and achieved an accuracy of 83.67%. ANN was used by Haq *et al*. [21] to diagnose cardiac problems with an accuracy of 86%. Das *et al*. [1] used the ANN model to predict cardiac disease with 92% accuracy. Priyanga [15] suggested a clustered deep neural network (C-DNN) model for heart disease detection. The proposed model outperformed DNN, SVM, KNN, and ELM with an accuracy of 83.6%. Mienye *et al*. [22] proposed an enhanced sparse autoencoder based ANN for heart disease prediction. Traditional machine learning approaches were outperformed by the researchers' proposed model, which achieved an accuracy of 90%.

In this research, an ANN model is developed and optimized by fine-tuning its hyperparameters to improve diagnostic accuracy and predict whether patients have cardiac disease. The performance of the proposed ANN model is then evaluated in terms of accuracy, precision, recall, f1-score, and area under the curve (AUC). This study's main contributions are as shown in:

- To develop a heart disease diagnosis system using ANN for enhanced prediction accuracy.
- To optimize ANN model hyperparameters, such as hidden layer width, learning rate, and activation function by using random and grid search method.
- To validate the results yielded by the proposed model using a 10-folds cross-validation.
- To study how a neural network's depth affects prediction accuracy on a small dataset.
- To evaluate the accuracy of the suggested heart disease diagnosis model by comparing it to the traditional ML model support vector machine (SVM) using several performance measures.

2. METHOD

In the sections that follow, a detailed description of the methods that was used for this work is provided. In section 2.1, the details of the dataset that was used are explained. Section 2.2 outlines the data preparation technique. In section 2.3, the artificial neural network design for predicting heart disease is explained in greater detail.

2.1. Heart disease dataset

For this study, we utilized the Cleveland dataset obtained from the machine learning repository at the University of California, Irvine (UCI) [23]. This dataset comprises 76 raw attributes, but only a subgroup of 13 features is mostly used in research for the prediction of heart disease [24]. The 13 attributes include age, gender, type of chest pain, blood pressure, cholesterol level, maximum heart rate, fasting blood sugar, exercise-induced angina, resting ECG, ST depression, ST slope, thalassemia, number of significant vessels colored by fluoroscopy. The presence or absence of cardiac disease is determined by a final target attribute with binary values of 0 and 1. Detailed information on the dataset's characteristics can be found in Table 1. The data used in the work are publicly available at the UCI machine learning repository. The code of our model is available at heart disease prediction using ANN UCI_dataset Kaggle.

2.2. Data pre-processing

Considering the used dataset, no missing values were found. However, some features had uneven data distribution, which will lead to wrong results in model training if not treated well. Therefore, the data is standardized by subtracting the mean and dividing by the standard deviation. A data point (x_i) is converted as stated in (1).

$$x_{std} = \frac{x_i - mean}{standard\ deviation} \quad (1)$$

Table 1. Attributes description of Cleveland datasets

Name	Type	Description
age	numeric	Age in years
sex	categorial	0 = Female or 1 = male
cp	categorial	Type of Chest pain (1: typical angina, 2: atypical angina, 3: non anginal pain, 4: asymptomatic)
trestbps	numeric	Resting blood pressure (mm hg)
chol	numeric	Serum cholesterol (mg/dl)
fbs	categorial	Fasting blood sugar >120 mg/dl (0: no, 1: yes)
restecg	categorial	Resting ECG results (0: normal, 1: ST-T wave abnormality, 2: left ventricular hypertrophy)
thalach	numeric	Maximum heart rate
exang	categorial	Exercise-induced angina (1: yes, 0: no)
oldpeak	numeric	St depression induced by exercise
slope	categorial	Slope of peak exercise ST segment (1: upsloping, 2: flat, 3: downsloping)
ca	categorial	No. of vessels coloured by fluoroscopy
thal	categorial	Thalium stress test result (3: normal, 6: fixed, 7: reversible defect)
num	categorial	Heart disease status (1: yes, 0 = no)

2.3. Artificial neural network architecture

ANNs are supervised learning algorithms that mathematically represent biological brain networks [21]. An artificial neural network mimics the structure and function of the human brain. An artificial neural network is a deep learning algorithm [1]. DNN was developed from an artificial neural network. The only difference between ANN and DNN is the number of hidden layers; DNN has more than one hidden layer, whereas ANN has only one [25]. ANN consists of three layers: input layer, hidden layer, and output layer [25]. As shown in Figure 1, inputs are passed to the first layer, and the last layer provides output.

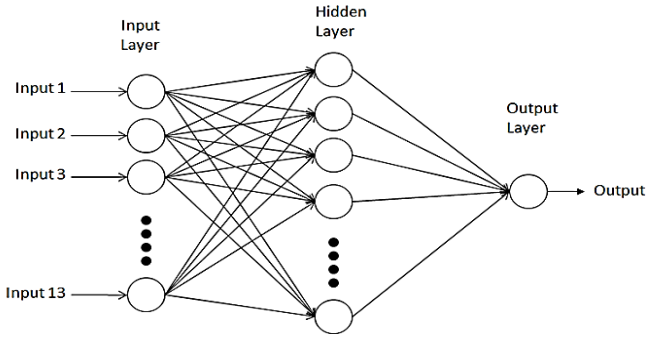


Figure 1. Typical ANN structure [26]

Each layer comprises nodes known as artificial neurons that model the biological neurons. Weights are assigned to the connections between neurons [1]. ANN is trained with a backpropagation network that modifies its weights [19]. Weights are modified based on the difference between predicted and actual outcome [21]. Finally, weights' changes are sent from the sink back to the source to be tested by the feedforward network. The optimal goal of this process is to minimize error, which means producing outputs that are as close to the target as possible [19]. The basic unit in ANN is the artificial neuron.

Each neuron calculates its output by summing up the values of all neurons in the previous layer to which it is connected. It uses an activation function that accepts the weighted inputs and produces a number (usually between 1 and -1) based on a pre-defined threshold set by the function's type [1], [25]. Each neuron's function is depicted in Figure 2. In this study, we developed an ANN model to determine if a person has a cardiac disease or not. The model consisted of two layers. There were 30 units in the input layer, which was also the first hidden layer. Through this input layer, a patient's heart-related attributes were fed into the network and multiplied by their respective weights. Next, nodes in the hidden layer compute the weighted sum and add a bias (b_i) as described in (2) to analyze incoming data (x_i). To indicate the weighted connection between nodes, w_{ij} is used.

$$N_j = b_i + \sum_i^m x_i w_{ij} \quad (2)$$

After that, the ELU activation function [27] was used to transfer N_j, as presented in (3):

$$y = \begin{cases} x \; when \; x \geq 0 \\ \alpha(e^x - 1) \; when \; x < 0 \end{cases} \quad (3)$$

where α is an adjustable parameter that controls the saturation point of the ELU's negative part. The output layer had one node which applied a sigmoid activation to produce the final output. A detailed description of our model is shown in Table 2.

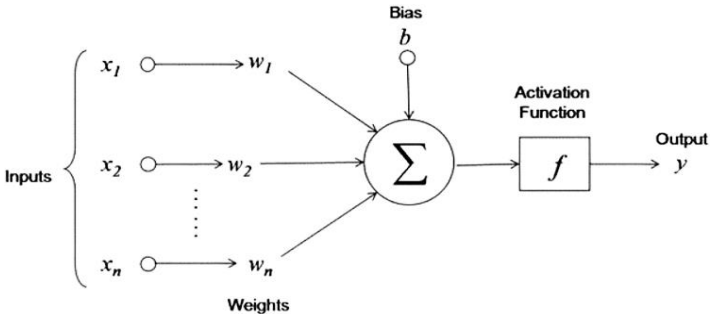


Figure 2. Neuron components [25]

Table 2. Architecture details of proposed ANN model

Layers (Type)	Units	Output Size	Activation	Kernel	Params #
Inputs (Dense)	30	(None, 30)	elu	he_normal	420
Output (Dense)	1	(None, 1)	sigmoid	he_normal	31
Total params: 451, trainable params: 451, non-trainable params: 0					

To begin the network training, connection weights in our network were randomly initialized. Afterward, the neural network processed the input data and generated the output value. Network output was then compared to the desired output, and error was calculated using binary cross-entropy loss, as shown in (4).

$$L_{BCE} = -\frac{1}{n}\sum_{i=1}^{n}(y_i \times log(\hat{y}_i)) + (1 - y_i) \times log(1 - \hat{y}_i) \quad (4)$$

Where L_{BCE} is the binary cross-entropy, n is the number of samples, y and $\hat{y}$ represent the actual and predicted output. While training, the calculated error was propagated back to the network, and weights were adjusted accordingly as shown in (5).

$$\Delta w_{ij} = -\eta \frac{\partial Error}{\partial w_{ij}} \quad (5)$$

Where Δw_{ij} is the weight change, and η is the learning rate, which is a constant that indicates the relative weight change. After all the weights were updated based on the training errors, the output value was recalculated. This process was repeated until the network had converged with the minimum possible error.

To improve the performance of a neural network model, its hyperparameters must be configured appropriately [25]. Hyperparameters are model parameters that are not trainable but manually set values during model creation. Therefore, we used an optimization technique to find the best combination of hyperparameters before building our model. We used random and grid search methods to optimize the number of neurons in the hidden layer, learning rate, and activation function. Using the optimization technique, the achieved optimal hyperparameter configuration is shown in Table 3. Furthermore, to tune the model's hyperparameters and improve its performance, we used the 10-fold cross-validation scheme [28] in combination with search. First, we ran a hyperparameter search to generate a variety of hyperparameter value combinations. Then, one combination at a time, we built a model. The model was then trained and evaluated using 10-fold cross-validation, and the average accuracy was stored. Then we took a different set of hyperparameter values and repeated the same procedure. After considering all the possible combinations, we chose the best combination of hyperparameters that resulted in the best performance as the optimal combination for building our model. Figure 3 depicts a detailed process. Manual adjustments have been made to the ANN model's other hyperparameters, as follows: 30 batches, which speeds up the model's learning process, 250 epochs of training.

Table 3. Hyperparameter tuning best configuration

Hyperparameter	Value
No. of layers	1
No. of neurons	30
Activation function	elu
Learning rate	0.001

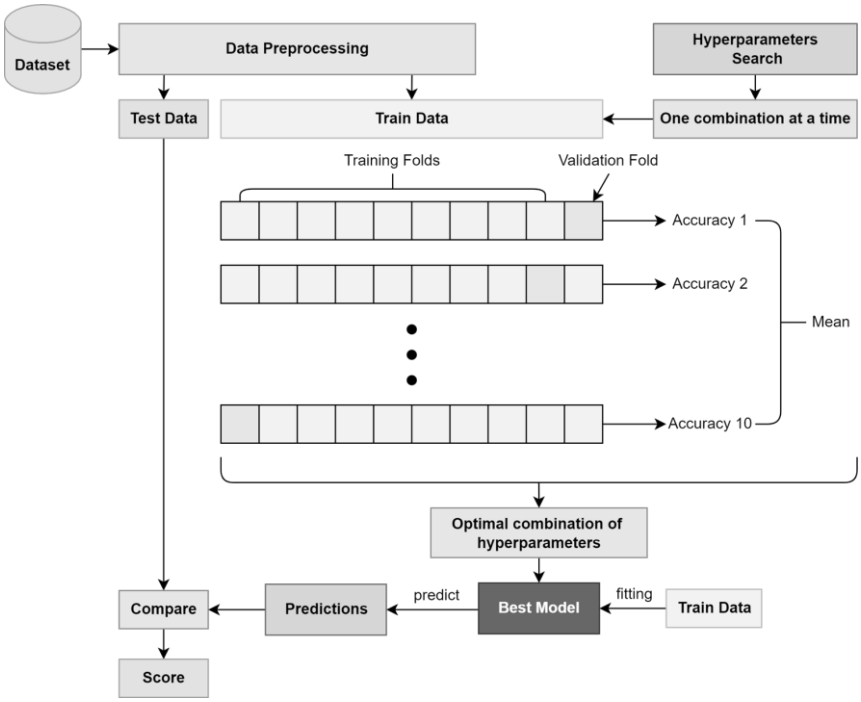


Figure 3. 10-fold cross-validation with hyperparameters tuning

3. RESULTS AND DISCUSSION

A total of 303 samples were collected in the Cleveland dataset. First, we partition the data set into 242 training and 61 testing samples in an 8:2 ratio. Then, we further partitioned the training set using an 8:2 ratio into training and validation sets. Training data is used to train the model, validation data is used to validate model performance, and testing data is used to evaluate the performance. The performance of the proposed ANN model was evaluated on the following metrics: accuracy, precision, recall, f1-score, and area under the curve (AUC). After implementing our proposed ANN model, we got an accuracy of 93.44%, precision of 93.35%, recall of 93.30%, f1-score of 93.35%, and AUC of 0.95.

Any learning algorithm's goal is to find a good fit between an underfit and an overfit model. This means that the training and validation accuracies should be stable and have a slight difference between them. The accuracy plot for train and validation data over epochs is shown in Figure 4. It is evident from the plot the effect of the overfitting problem. Furthermore, we compared our proposed model with the ML model based on SVM, which achieved an accuracy of 86.88%, precision of 87.75%, recall of 86.40%, f1-score of 86.44%, and AUC of 0.93 as depicted in Figure 5 and Figure 6.

The proposed ANN model is evaluated in greater detail in comparison to the SVM model by making use of the confusion matrix metric, which can be seen in Figure 7. The resulting confusion matrix of the ANN model is presented in Figure 7(a). The figure shows that the proposed model can correctly detect 32 patients and classify 25 out of 27 healthy persons. The resulting confusion matrix of the SVM model is presented in Figure 7(b). It shows that 32 patients were detected correctly, and 21 of 27 healthy people were accurately classified. We further evaluated the proposed ANN model with a DNN model to show network depth's effect on model accuracy when having a small dataset. The DNN model that we used consisted of 16 neurons in the input layer, 1 neuron in the output layer, and 2 hidden layers with 32 neurons for each. The model achieved an accuracy of 87%, precision of 88%, recall of 86%, and f1-score of 86%. This shows that even when a DNN is fine-tuned (i.e., not made that deep), ANNs with one hidden layer outperform DNNs. The proposed method results are detailed in Table 4.

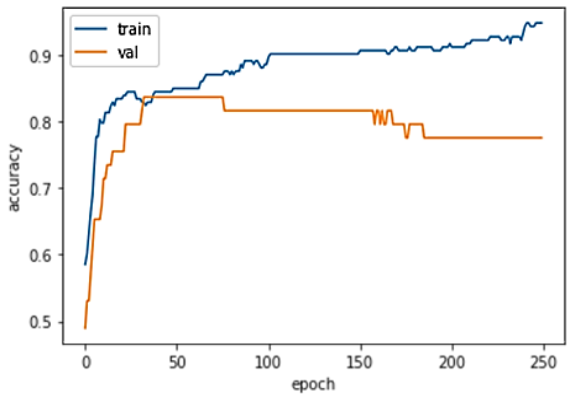


Figure 4. ANN model accuracy with epochs

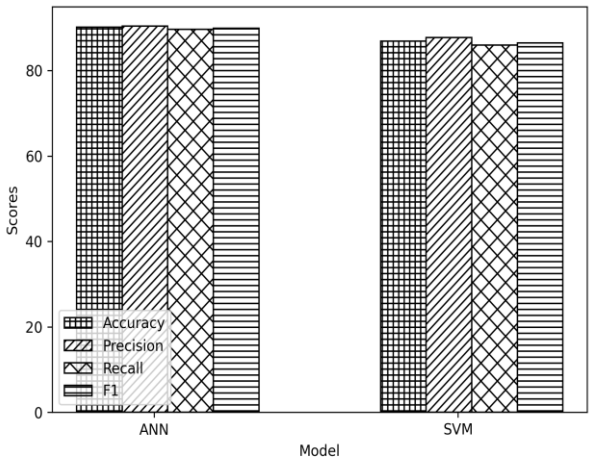


Figure 5. Comparison of ANN and SVM

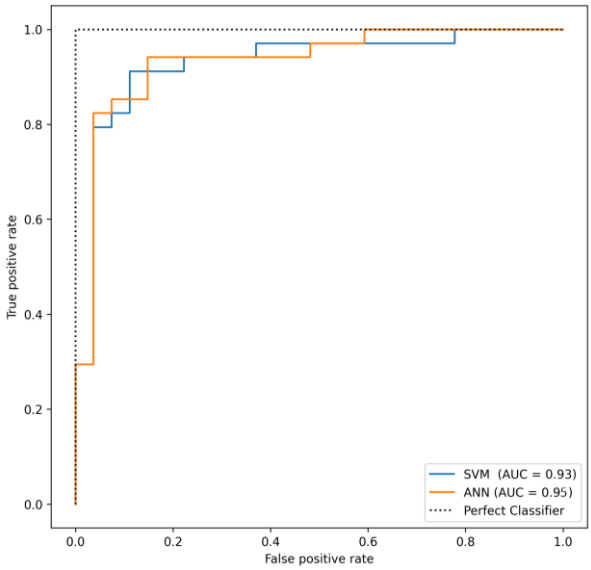
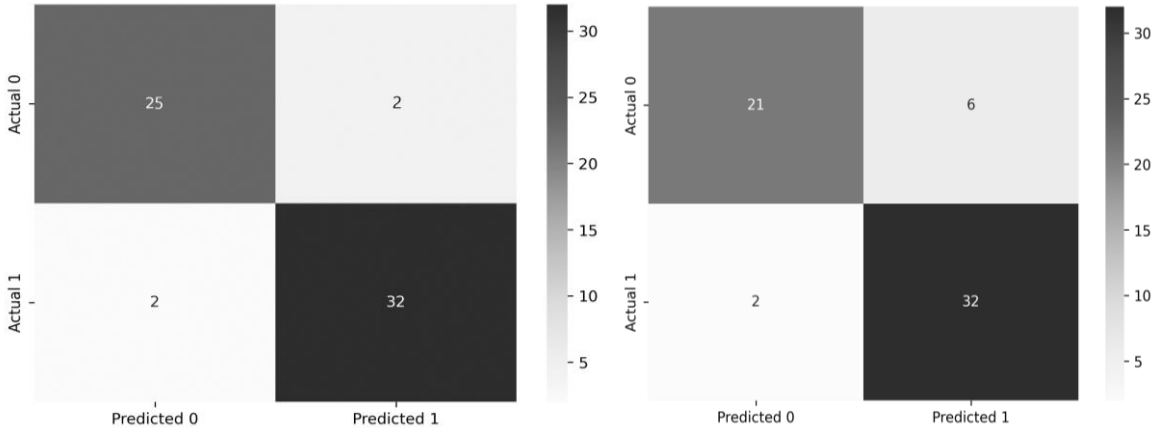


Figure 6. AUC measures of ANN and SVM

Table 4. Comparison of Performance metrics for the ANN model

Method	Accuracy	Precision	Recall	F1-Score
SVM	86.88%	87.75%	86.40%	86.44%
DNN	87%	88%	86%	86%
Proposed	93.44%	93.35%	93.30%	93.35%



(a) (b)

Figure 7. Confusion matrix of (a) ANN and (b) SVM

Moreover, the proposed model results are compared to other state-of-art is detailed in Table 5. All previous techniques have already used ANNs or DNNs either in their current form, or they have been improved or hybridized with other methods. Three previous state of art methods [1], [17], [19] used simple ANN consisting of three layers: input, hidden and output units. They achieved 92%, 85.68%, and 85% accuracy rates, respectively. A prior state of the art method [21] used feature selection techniques to evaluate the ANN classifier's performance on a set of important features and obtained an accuracy of 86%. Prior approaches [12], [15] developed enhanced DNN and cluster based DNN models to improve accuracy and speed of training respectively. Their scores were 83.67% and 83.6%, accordingly. One prior study [18] suggested neural networks ensemble and achieved 89.01% accuracy. Another previous study [22] offered an optimized sparse autoencoder based ANN and attained a 90% accuracy rate. It was reported in [20] that they had attained a 91.10% accuracy rate with a hybrid decision support system (ANN and Fuzzy AHP). Our suggested model gives better accuracy to predict heart diseases. It achieves an accuracy of 93.44% which outperforms the previous state-of-the-art methods for predicting cardiovascular diseases.

Table 5. Comparative analysis of proposed model with other state-of-the-art techniques

Method	Accuracy	Precision
Mohammed *et al.* [15]	C-DNN	83.6%
Miaoa and Miaoa [12]	DNN	83.67%
Olaniyi *et al.* [19]	ANN	85%
Palaniappan and Awang [17]	ANN	85.68%
Haq *et al.* [21]	ANN	86%
Das *et al.* [18]	Neural networks ensemble	89.01%
Mienye *et al.* [22]	ANN	90%
Samuel *et al.* [20]	ANN and Fuzzy AHP	91.10%
Das *et al.* [1]	ANN	92%
Proposed	Enhanced-ANN	93.44%

Notes: C-DNN: Cluster Based Deep Neural Network; Fuzzy AHP: fuzzy analytic hierarchy process.

4. CONCLUSION

The goal of this research is to increase diagnostic accuracy and predict whether patients have cardiac disease. To achieve this goal, an artificial neural network (ANN) model is developed and optimized by performing fine-tuning on its hyperparameters including (i.e number of hidden layers, number of neurons in each layer, the learning rate, and the activation function). After that 10-fold cross-validation approach is adopted to estimate performance of a variety of hyperparameter value combinations and chose the best

combination. Finally, the performance of the ANN model that was proposed is assessed using a number of metrics, including accuracy, precision, recall, f1-score, and area under the curve (AUC). The results demonstrate improved accuracy that is greater than 93%. This improvement is 7.5% higher than a traditional ML model (i.e support vector machine model). In addition, the amount of time needed for training and classification has been significantly decreased due to our simple one layer ANN architecture. This result indicates that our proposed model is superior to existing methods that are considered to be state-of-the-art when it comes to predicting heart disease.

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