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Original Article

Coronary Artery Disease Detection Using Pre-Trained ResNet and VGG-16

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Abstract - *Coronary Artery Disease (CAD) affects coronary arteries, responsible for supplying oxygen and vital nutrients to the heart muscle. This is because of the development of atherosclerotic plaques on the walls of coronary arteries. The early detection of coronary atherosclerosis is a challenging task and can increase the financial burden on patients. In this research, an ensemble neural network is developed for the detection and classification of coronary artery disease. The ensemble neural network has integrated two models, VGG-16 and ResNet 50. The datasets used in the research are the coronary artery disease dataset, which has images and the MIT-BIH Arrhythmia dataset. The min-max normalization approach is employed in the pre-processing stage and an ensemble neural network is utilized for both the detection and classification of coronary artery diseases. The proposed ensemble neural network attained an accuracy of 99.45%, precision of 98.82%, recall of 98.85%, and f1-score of 98.80%, comparatively higher than conventional methods like Convolutional Neural Network (CNN), ResNet and VGG-16.*

Keywords - *Coronary Artery Diseases, Ensemble neural network, MIT-BIH arrhythmia database, ResNet 50, VGG-16.*

1. Introduction

Atherosclerosis, also known as Coronary Artery Disease (CAD), stands as a prominent cause of death and disability worldwide, contributing to nearly 8 million fatalities annually. The symptoms and outcomes of CAD are determined by the location and stability of lesions, as well as collateral circulation and myocardial responsiveness [1, 2]. Acute phase proteins are involved in the body's immune response, which is critical for the early detection of cardiovascular illnesses of atherosclerotic etiology. This acute-phase protein can be observed in its rise in inflammatory diseases [3]. Early detection of coronary atherosclerosis is quite challenging due to the high amount of risks in the invasive procedures and also increases the financial burden on patients. Some studies have attempted to utilize alternative imaging technologies, like magnetic resonance angiography, to improve the detection of coronary atherosclerotic plaque in patients using contrast-enhanced images [4, 5]. On the other hand, scientists closely monitor the development of non-invasive predictors for CAD based on contemporary CTA technologies. The development of new studies and the improvement of CAD diagnosis methods have been facilitated by artificial intelligence [6, 7].

The data capacity of hospital databases has been steadily growing in recent years as a result of the growing computer information systems and usage of digital medical equipment [8]. These excellent sources of medical knowledge are particularly beneficial for identifying diseases and doing medical research [9, 10]. Machine Learning (ML) and Deep Learning (DL) algorithms can efficiently integrate medical electronic data, including analysis and evaluation of visualized imaging data, allowing for the creation of an intelligent diagnostic method for coronary heart disease or advancement of present imaging diagnostic techniques [11, 12]. The term "machine learning" refers to a wide range of methods that use interaction analysis to solve challenging large data challenges. In the medical industry, machine learning concentrates on developing automated clinical decision tools to assist doctors in making predictions that are more accurate than those made using traditional statistics. These machine-learning techniques are successfully applied in various medical research projects [13-15].

The previous coronary artery disease detection methods had huge execution costs and training time for generating a result and required valuable features to find a key image pattern. The present methods have difficulty in resolving the problems of overfitting and underfitting. The VGG-16 and ResNet 50 are ensembled using Softmax voting. Generally, voting combines various base models and provides the optimum outcomes. Through leveraging the data captured by these techniques on common image features, good performance and quick convergence are attained. The ensemble neural network detects and classifies coronary artery diseases as normal or abnormal.

The major contributions of this research are:

- The pre-processing stage utilizes the min-max normalization on the coronary artery diseases dataset to remove noise and normalize the dataset.
- A hybrid VGG16 and ResNet have been developed to detect and classify coronary artery diseases, which accurately detect the disease and are classified into two classes: normal and abnormal.

This research paper is described as follows: relative research is in Section 2. The proposed method for the detection and classification of CAD is detailed in Section 3. The performance and comparison of the proposed method are given in Section 4, and the conclusion is in Section 5.

2. Literature Review

Akanksha Pathak et al. [16] suggested a CAD detection model using CAD and PCG signals with transfer learning from VGG16. Using a deep embedding from pre-trained CNN, a novel Multiple Kernel Learning was proposed to detect CAD. The suggested approach has attained better accuracy at an epoch level by using an SVM classifier. However, the suggested method did not perform feature selection for selecting more relevant features. The future work focuses on implementing the suggested method of ECG and PCG for CAD diagnosis. The overall analysis [16] introduced the CAD detection method with Multiple Kernel Learning, and the SVM classifier attained high accuracy.

Maria Trigka et al. [17] developed the Synthetic Minority Oversampling Technique (SMOTE) to evaluate the performance of various ML algorithms with the use or non-use of SMOTE in predicting CAD. The suggested stacking ensemble model after SMOTE has achieved better prediction accuracy due to its ability to generate new synthetic samples that avoid overfitting. The future work of this research aims to extend the suggested ML framework by using DL methods. In the examination of [17], the SMOTE was developed for assessing the effect on different ML approaches, with the stacking ensemble method representing enhanced accuracy through mitigating the overfitting.

Adel A. Ahmed et al. [18] developed a deep learning architecture, 1D-CNN, to address the limitations of conventional ECG in CAD prediction. The cardiac arrhythmias from ECG signals of the MIT-BIH dataset were classified using 1D CNN. Even though 1D CNN has lower computational complexity and is easier to train, the suggested approach has a limitation of unbalanced testing data, which severely impacts generalization. The suggested approach needs large datasets to train the suggested DL model, enhance the generalization ability, and handle variability. The overall analysis of [18] enhanced the CAD prediction from the ECG signals, addressed traditional techniques' drawbacks, and mitigated the high computation time and easy training.

Saroj Kumar Pandey et al. [19] developed a Wavelet transform-based CNN model for detecting the arrhythmia heartbeats from ECG signals in the MIT-BIH dataset. A wavelet self-adaptive thresholding technique was utilized to de-noise signals, followed by feature extraction and signal classification using 12-layer CNN. This approach has achieved better prediction accuracy but requires a huge amount of trained information for fast network training. This approach's generalization ability was also low, which needs to be improved for real-time applications. The analysis of [19] attained high prediction accuracy, that demands extended training data for quick network training and has restricted generalization and improvements in real-time application.

George Konstantonis et al. [20] introduced a novel Machine Learning (ML) algorithm for detecting cardiovascular disease in individuals at medium to high cardiovascular risk. The introduced ML based algorithm has two distinct time points for CVD at-risk satisfaction of RA patients. There are three ML algorithms utilized Linear Discriminant Analysis (LDA), Random Forest (RF) and Support Vector Machine (SVM) for the detection of cardiovascular risk with and without RA. The proposed method was efficient and strong, while the carotid ultrasound image-based phenotypes were merged with conventional and laboratory phenotypes, which depend on biomarkers. The introduced method has a high computational cost. The overall examination of [20] effectively combined the carotid ultrasound phenotypes with traditional and laboratory biomarkers.

Yu Jiang et al. [21] implemented an unsupervised machine learning algorithm that depends on clinical factors for coronary artery atherosclerosis detection in type 2 diabetes mellitus. The segment plaque type of coronary artery and stenosis, Segment Involvement Score (SIS) and Segment Stenosis Score (SSS) are estimated and measured. The implemented method identifies T2DM patients along heterogeneous clinical indicators and finds various kinds of coronary plaque sets and coronary stenosis degrees. The training time and cost of the model were high. The analysis of [21] effectively identified T2DM patients with diverse clinical indicators and different coronary plaque types.

Xiaoteng Feng et al. [22] evaluated the LASSO technique to find key genes for constructing a diagnostic method. The analysis of ssGSEA was utilized to examine the variant immune cell infiltration. The cardiovascular detection method was developed to find the correlation between screened genes and the severe process of cardiovascular detection. The presented technique has better detection accuracy. The model required a large amount of data for the training. The overall analysis of [22] correlated the screened genes with the severity of cardiovascular disease and attained high detection accuracy.

Abdul Rahaman Wahab and Ashit Kumar Dutta [23] introduced a deep learning-based detection of coronary artery disease method utilizing computer tomography images. The introduced method has three stages for CAD detection. In the first stage, the image quality is enhanced by utilizing a fuzzy function. The second stage utilized the AO algorithm for hyperparameter optimization of the UNet++ model, and the third stage was performance evaluation of the introduced method. The method has less execution time and training costs. The method failed to overcome the overfitting and underfitting problems. The overall analysis of [23] enhanced the image by utilizing the fuzzy function of the hyperparameter optimization of the UNet++ method with the AO algorithm.

Liang-Hung Wang et al. [24] suggested the Three-Heartbeat Multi-Lead (THML) in that every fragment has 3 full processes of heartbeat in multi leads of ECG. Four arrhythmia classification methods were developed depending on One-Dimensional (1D-CNN) integration with priority technique, a combined voting technique for optimizing the merged effect of classification. The suggested method has strong parallelism and adaptability. The examination of [24] merged with the priority and voting methods for optimizing the classification results and has good adaptability and parallelism.

Yared Daniel Daydulo et al. [25] presented the automated DL method for correctly classifying ECG signals into three classes such as Cardiac Arrhythmia (ARR), Congestive Heart Failure (CHF) and Normal Sinus Rhythm (NSR). The data were pre-processed and segmented for DL algorithm training. The pre-trained techniques, such as AlexNet and ResNet 50, were configured to attain optimum classification outcomes. The presented method attained less training loss. The analysis of [25] is configured to attain the optimum classification outcomes and determines less training loss.

The existing approach needs large datasets to train the suggested DL model, enhance the generalization ability, and handle variability. This approach's generalization ability is also low, which needs to be improved for real-time applications. Some methods failed to overcome the overfitting and underfitting problems.

3. Proposed Methodology

In the proposed methodology, the ensemble neural network (VGG 16 – ResNet 50) is proposed for the effective detection and classification of coronary artery diseases. Two datasets used in this research are the coronary artery diseases dataset, which has images, and the MIT-BIH Arrhythmia dataset, which has ECG signals. The min-max normalization technique-based pre-processing and ensemble VGG-16 and ResNet are employed to detect and classify coronary artery diseases. The process of the proposed approach is represented in Figure 1.

3.1. Pre-Processing

Pre-processing is a step to increasing image quality. The significant preprocessing techniques considered in this research are resizing, cropping, background removal, and normalization of images using min-max normalization.

3.1.1. Background Removal, Cropping, Resizing

A resizing process is used for dataset images to obtain the resized images in 64×64 dimensions. In the removal of the background process, all RGB image is transformed into blue image channels through modifying scores of green and red to zero. Next, the blue image channel is modified to a grayscale image through employing mean scores of blue, red, and green elements. The image cropping increases visual image quality.

3.1.2. Min-Max Normalization

The min-max normalization is performed before images are fed into the segmentation process, and the mathematical expression in Equation (1),

$$f(x,y) = \frac{f(x,y)-Z_{min}}{Z_{max}-Z_{min}} \tag{1}$$

In the above Equation (1), f is the brain image, x and y represents pixel position in the image, Z_{min} and Z_{max} represents minimum and maximum pixel values, respectively.

The intensity normalization scales the intensity values in the range [0 1] and resizes images to 227×227 before being given into the segmentation process. Figure 2 represents dataset images after preprocessing and normalization using min-max normalization.

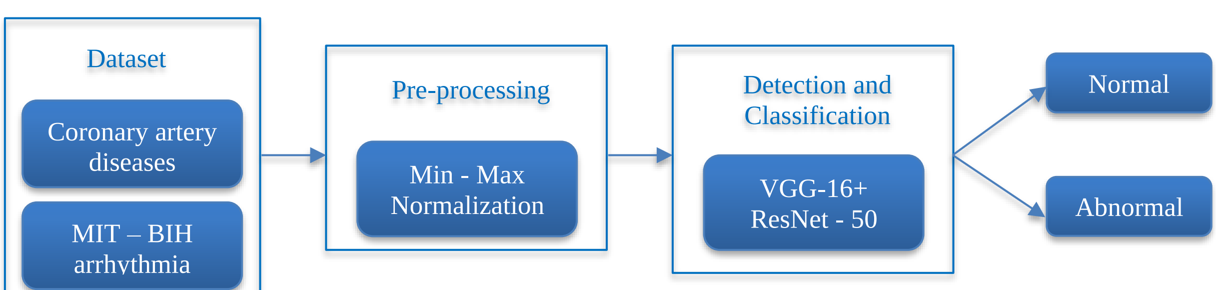

Fig. 1 The overall process of the proposed methodology

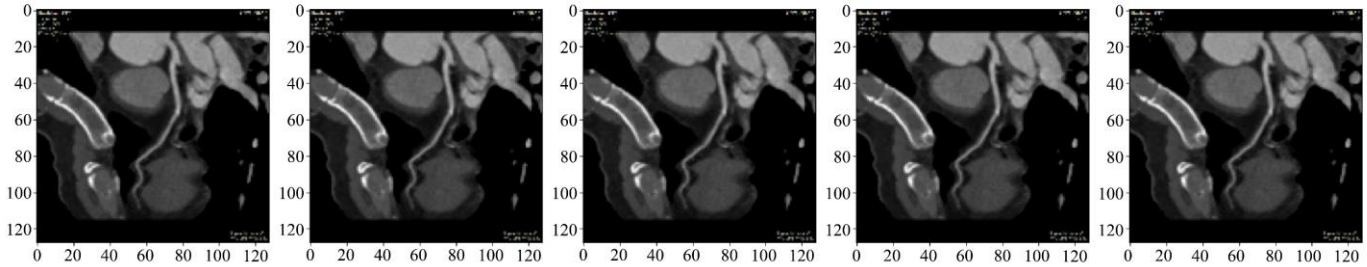

Fig. 2 Dataset images after preprocessing and normalization

Figure 2 represents dataset images after preprocessing and normalization using min-max normalization. The preprocessed dataset images are given as input to an ensemble neural network for effective detection and classification.

3.2. Detection

In this section, coronary artery diseases are detected and classified by combining VGG - 16 and ResNet – 50 models. The process of detection and classification by VGG – 16 and ResNet – 50 is explained as follows:

3.2.1. VGG – 16

VGG–16 model is a convolutional neural network with 16 layers. The structure and process of VGG–16 model are represented in Figure 3. The model contains convolution, max pooling, ReLU, and SoftMax layers.

Every layer represents various levels of importance for the image utilized in CNN architecture. Actual pixel value depends on three color channels Red, Green and Blue for detection and classification of CAD.

The layers used in the VGG-16 model are convolutional, max pooling, rectified linear unit, and softmax layers. The progression of these layers is described below.

Convolution Layer

The convolution layer is a major element in CNN and manages an issue of object. The critical layers utilize a group of source input images and filters, which can develop $2D$ animation cards.

The CNN allows the model to record image function because of weight distribution, which lowers the integral cost. In the detection of coronary artery diseases, the model has 13 convolutional layers, a 3×3 filter, and the data size is $[7 \times 7 \times 512]$.

Max Pooling Layer

The CNN pooling layer is utilized for image feature extraction. The major general form of the pooling layer utilizes steps 2×2 filter for choosing 25% activation of the activation map of the convolutional layer. Utilizing a pooling layer minimizes object size and execution parameters in the network, which manages overfitting and maximizes the network process.

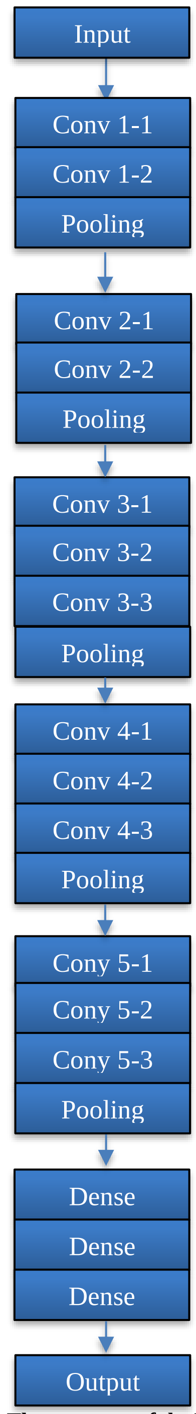

Fig. 3 The structure of the VGG-16 model

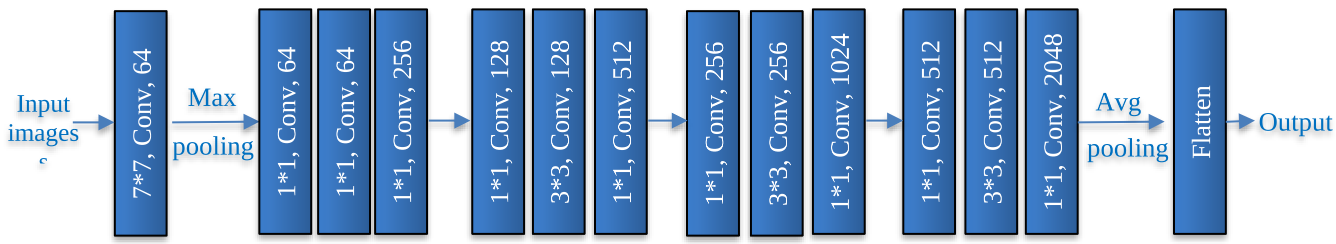

Fig. 4 The structure of the ResNet 50 model

Rectified Linear Unit (ReLU)

ReLU is a kind of activation function which measures the addition of input values and determines if needed. ReLU needs fewer computer resources when compared with other activation functions. This activation function gives zero outcomes for negative inputs. The NNs are trained by a method of vanishing gradient, which has backpropagation stages and is a chain rule to modify weights to minimize losses followed by every epoch. The gradient linearly decreases when the number of layers maximizes. This can minimize the first slice gradient value and protect the slices from being trained correctly. The gradient is zero due to network activation and depth pushing the values to zero, known as the vanishing gradient problem. The model utilizes the ReLU activation function for speed convergence. The mathematical formula for rectified linear units is given as Equation (2).

$$f(x) = \max(x, 0) \tag{2}$$

In the above Equation (2), the $f(x)$ is the result of the ReLU activation function, the x represents the input value, and the $\max(x, 0)$ represents the ReLU function outputs the maximum of x and 0.

SoftMax

The softMax layer converts fully connected layer output to a single whole probability and returns a vector with probable result classes and related possibilities. The major aim of this function is to make unnormalized results of K units FC layer to the probability distribution, and these factors are summed up in a single probability distribution. It is initially utilized to include $0s$ and $1s$ into neural network results and represents the certainty probability. The mathematical formula for softmax is given as Equation (3).

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{c-1}^{C} e^{z_i}} \tag{3}$$

In the above Equation (3), the e^{z_i} represents the exponential function employed to ith element, and the C is the total number of classes in the vector.

3.2.2. ResNet 50

ResNet 50 or Residual networks contains 50 layers and similar maps related to VGG-16, and ResNet forecasted delta for the final prediction from one layer to another. ResNet 50 provides a different technique that enables gradient flow and resolves the vanishing gradient problem. Figure 4 represents the structure of ResNet 50.

The ResNet 50 included 3 blocks: identity, convolutional and residual. These blocks are explained in the following section.

Identity Block

It is a primary phase in ResNet 50, and it is used in ResNet architecture that includes the same stages when input activation comprises the same output dimension from the activation function.

Convolutional Block

It contains layers similar to VGG-16, which contains a normalization layer to normalise all images. In Resnet 50 architecture, skip connection uses a gradient which is directly backpropagated into primary layers. Its block is divided into 5 phases, and every phase contains several combinations and blocks.

Residual Block

The residual block is powerful when compared to VGG 16, and its size is a minimum of cost size. The Resnet 50 uses a 1×1 wrapper to reduce channel depth and reconstruct the 10-layer bottleneck block to alter the rest phases of each 2-layer to reduce execution load.

It has 50 layers of neural residual, and its architecture employs residual networks. It uses Skip Connection that skips normalize when every layer achieves architecture performance. Figure 5 represents a pictorial representation of the residual block of ResNet 50.

The skip connection is a direct connection that skips a few model layers. Input X is increased through layer weights and bias updating without skipping connection. The $F\ (X)$ is an activation function, and its result is represented as Equation (4).

$$F(w * x + b) = \big(F(X)\big) \tag{4}$$

The numerical expression for output with skip connection is denoted in Equation (5).

$$F(X) + x \tag{5}$$

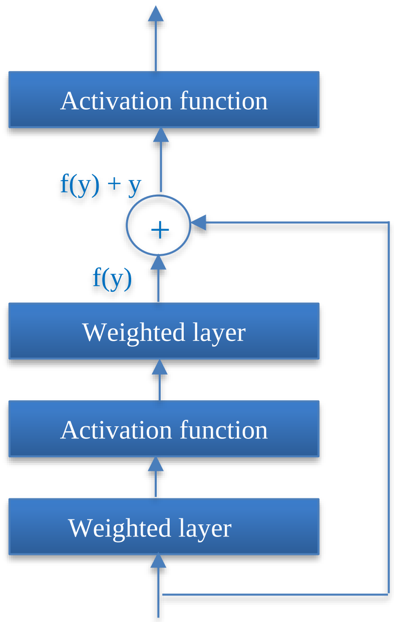

Fig. 5 ResNet 50 residual block

The score of X is efficient for the output layer if the input and output size are the same, whether it updates the convolutional block to alter its input size and same output. The fine-tuning uses the learned representation from the pre-trained techniques VGG-16 and ResNet-50. Through leveraging the data captured through theses techniques on common image features for good performance and quick convergence is attained. In this process, some pre-trained techniques were chosen when allowing others to train. The developed algorithm has 21 layers in VGG-16 and 143 layers in ResNet-50. This chosen freezing supports for retaining learned representation in previous layers that are much transferable and generic, allowing the following layers to adopt. This technique balanced the knowledge of pre-trained techniques and tailored it for classification. The VGG-16 and ResNet 50 are ensembled using Softmax voting. Generally, voting combines various base models and provides the optimum outcomes. The ensemble neural network detects and classifies coronary artery diseases as normal or abnormal. The proposed ensemble neural network (VGG-16 + ResNet 50) accurately detected coronary artery diseases and effectively classified whether they were normal or abnormal. The algorithm for ensemble VGG-16 and ResNet 50 is given below.

Input: Pre-processed image
Output: Detected class of image
Initialize the VGG 16 and ResNet 50 parameters
Create the architecture of pre-trained VGG-16
Create the architecture of pre-trained ResNet-50
Develop the proposed ensemble architecture
Choose the coronary dataset
Split the dataset
Assign 80% of data for training
Assign class label data to each image for training of ensemble architecture
Assign 20% of data for testing and validation
Process the suggested stage 1 for training
for $\forall I_i \in Z_n T$ **do**
use the Adam optimizer for performing the supervised training of ensemble architecture
Choose input image
Resize it to 224×224
Give to trained ensemble architecture for class label prediction
Return the classified class label

4. Performance Analysis

The performance of the developed algorithm is simulated through a Python environment with system requirements: RAM: 16GB, processor: Intel core i5, and Operating System: Windows 10. The performance of the developed VGG-16 – Resnet 50 is tested by performance metrics like Accuracy, Precision, Recall and F1 - score. The numerical formulae of performance metrics are described in equations (6) – (9),

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{Total\ Instances} \tag{6}$$

$$Precision = \frac{True\ Positive}{(Predicted\ Instances = True)} \tag{7}$$

$$Recall = \frac{True\ Positive}{Actual\ number\ of\ Instances\ as\ True} \tag{8}$$

$$F1\ Measure = \frac{2 * Precision * Recall}{Precision + Recall} \tag{9}$$

Where FP - False Positive, TP - True Positive, TN - True Negative, and FN - False Negative.

4.1. Dataset

The datasets considered in the research are the Coronary Artery Diseases Dataset [24], which has image data and the MIT-BIH Arrhythmia Database [25] which has ECG data. The detailed description and explanation of the datasets are given as follows.

4.1.1. Coronary Artery Diseases Dataset

The Coronary Artery Diseases dataset is an image dataset collected by colleagues at the University of Jordan Science and Technology that contains normal and abnormal medical images. An algorithm is utilized to trace the vessel blood at the lab. The dataset contains two folders, which are labeled class and the sizes of images are not fixed. The dataset has 78 abnormal images and 127 normal images. Table 1 represents the description of the coronary artery disease dataset. Figures 6 and 7 represent the sample images taken from the coronary artery disease dataset.

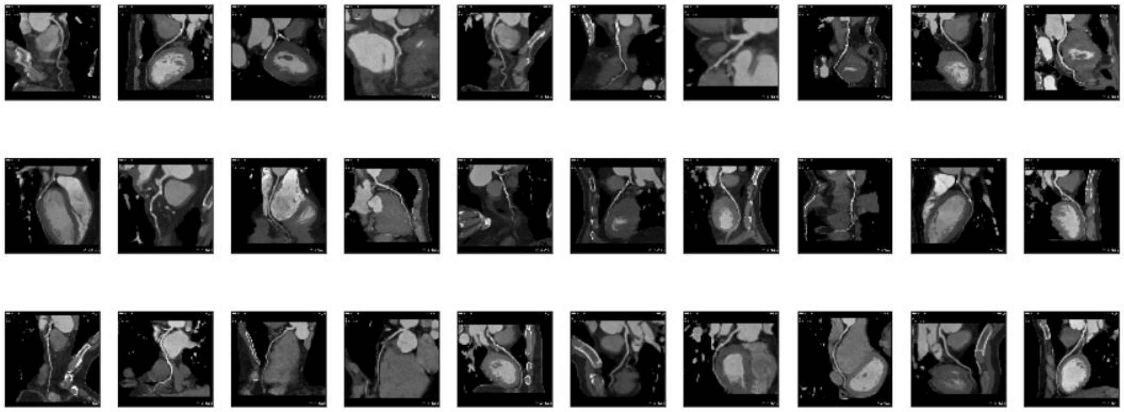

Fig. 6 Sample images of abnormal coronary artery diseases

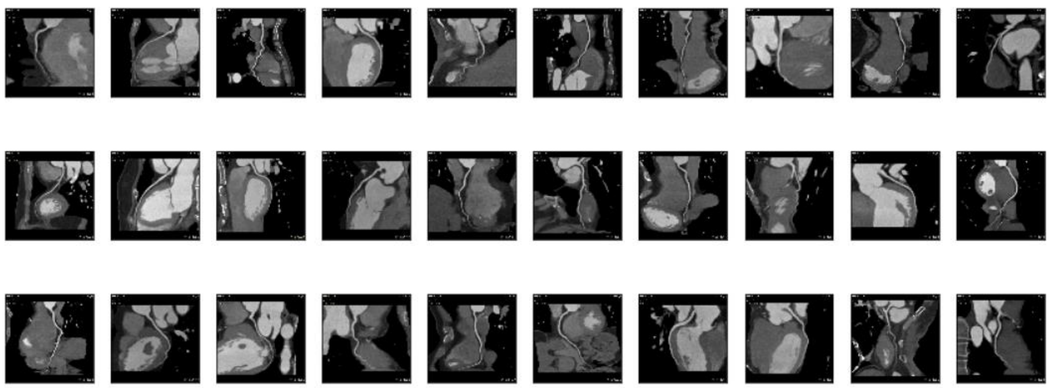

Fig. 7 Sample images of normal coronary artery diseases

Table 1. Data description of coronary artery diseases dataset

Coronary Artery Diseases Dataset	
Classes	**Images**
Abnormal	78
Normal	127

Table 2. Data Description of MIT-BIH Arrhythmia Database

Types of Heartbeat	Total
Normal Rhythm (NOR)	74,607
Left Bundle Branch Block (LBBB)	8069
Atrial Premature Contraction (APC)	2514
Premature Ventricular Contraction (PVC)	7127
Right Bundle Branch Block (RBBB)	7250

4.1.2. MIT-BIH Arrhythmia Database

This database is given by MIT and commented on by different experts based on worldwide standards. The researchers majorly utilized this dataset to classify arrhythmic heartbeats. This database has 48 30-minute recordings of ECG signal samples at $360\ Hz$. An electrocardiogram contains 2 leads, and every beat in the MIT-BIH database is explained in their class. Various abnormal heartbeats are utilized including a right and left block of bundle branch, ventricular and atrial premature contraction are kinds of heart blocks which occurs. In the research, every block size in the data sample is 360 due to the ECG signals sampling rate in the dataset is 360 Hz. Table 2. represents the description of the MIT-BIH Arrhythmia database.

4.2. Quantitative and Qualitative Analysis

The performance of the developed ensemble neural network is assessed with a K value of 10 and various epochs of 10 and 20. Figures 8 and 9 represent the classified result images of coronary artery diseases. Figure 8 represents classified abnormal images of coronary artery diseases, and Figure 9 represents classified normal images of coronary artery diseases.

Table 3 and Figure 10 signify the performance of the proposed model with K values 10 and 20 epochs. The proposed ensemble neural network is evaluated with other existing techniques like Artificial Neural Network (ANN), Convolutional Neural Network (CNN), ResNet, and VGG 16 models. The developed algorithm attained a precision of 98.55%, accuracy of 99.35%, F1 score of 98.58%, and recall of 98.60% with 20 epochs, which is better than various previous algorithms.

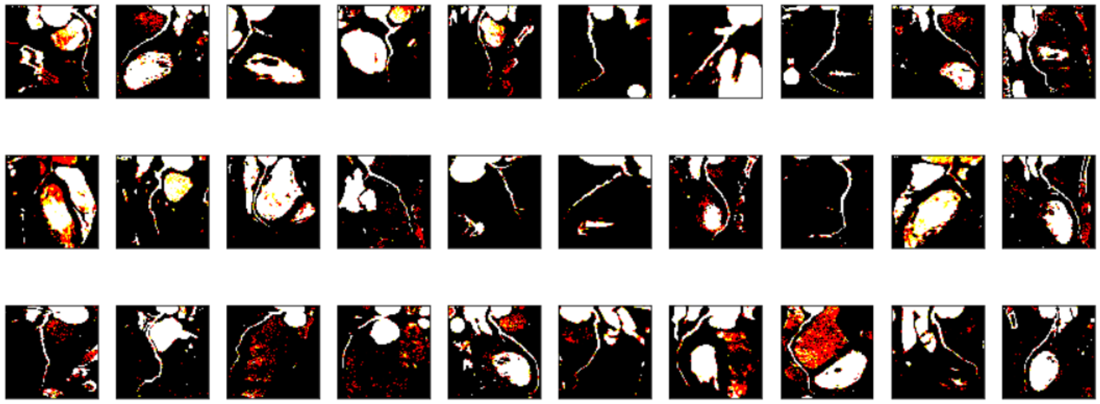

Fig. 8 Classified abnormal images of coronary artery diseases

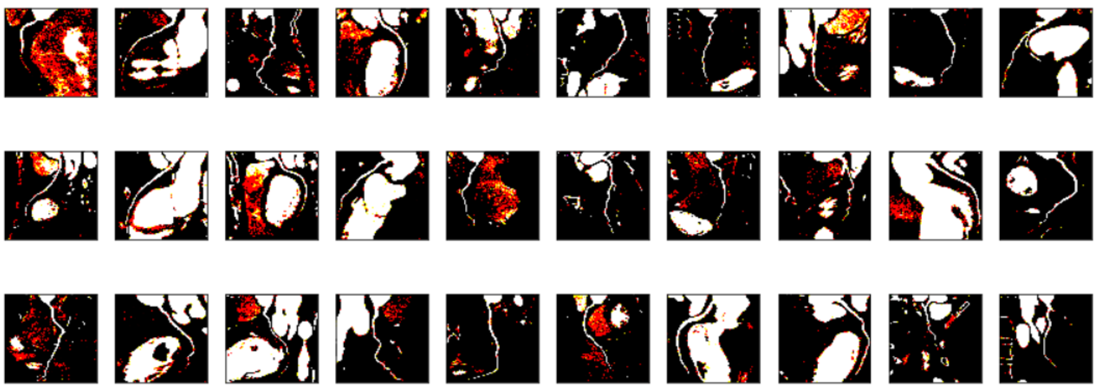

Fig. 9 Classified normal images of coronary artery diseases

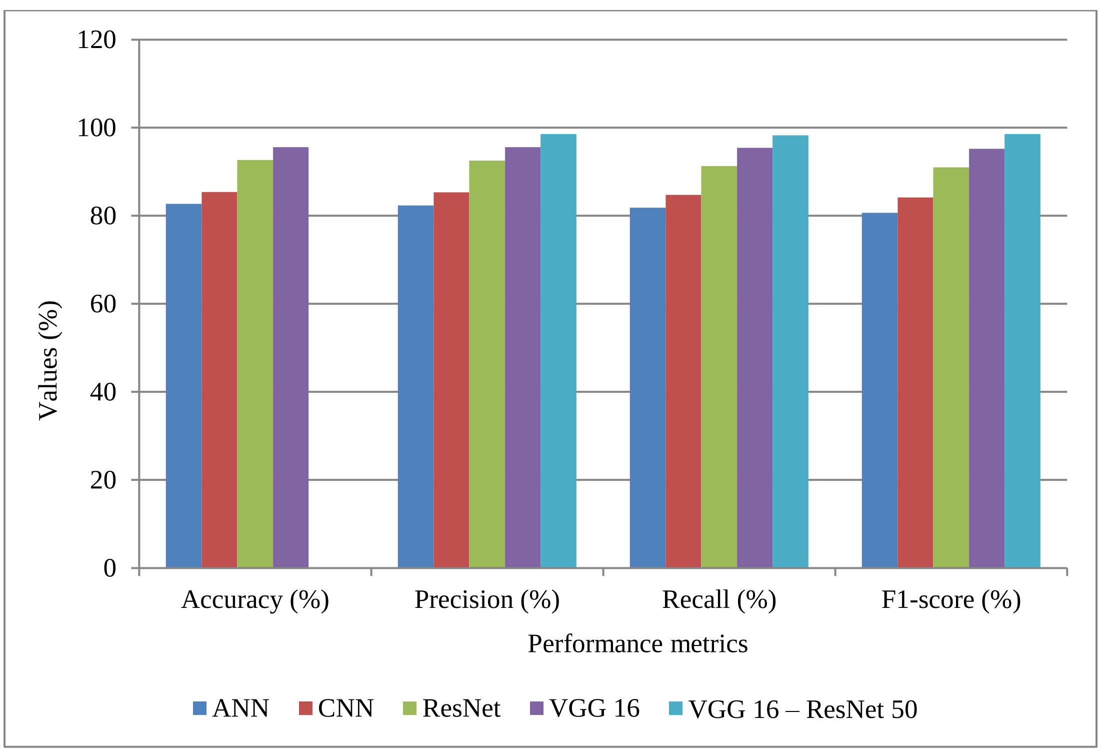

Fig. 10 Performance of proposed model with K=10 and 20 epochs in coronary artery disease dataset

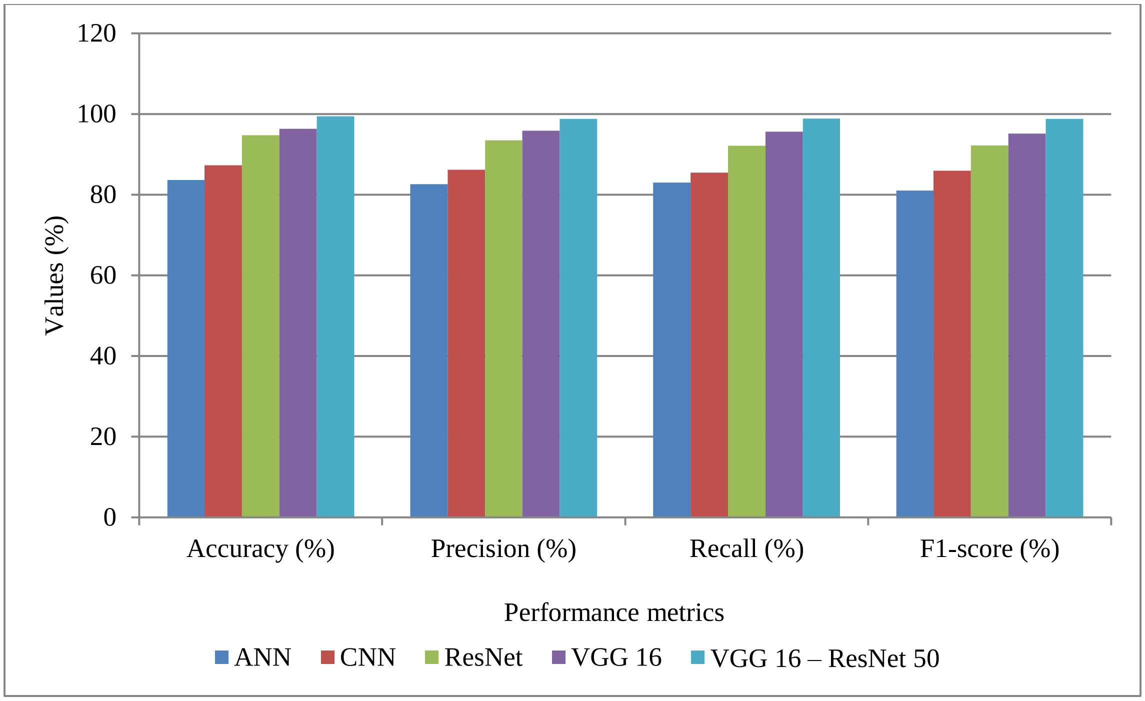

Fig. 11 Performance of proposed method with K=10 and 30 epochs in coronary artery disease dataset

Table 3. Performance of proposed method with K=10 and 30 epochs in coronary artery disease dataset

Models	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
ANN	83.62	82.64	82.97	81.00
CNN	87.27	86.17	85.49	85.97
ResNet	94.71	93.46	92.10	92.23
VGG 16	96.34	95.88	95.60	95.17
VGG 16 – ResNet 50	99.45	98.82	98.85	98.80

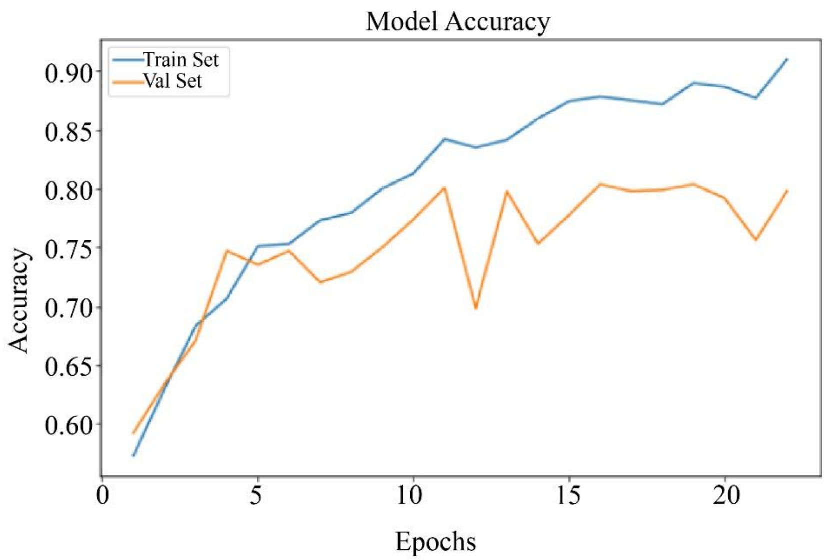

Fig. 12 Accuracy vs epochs in coronary artery disease dataset

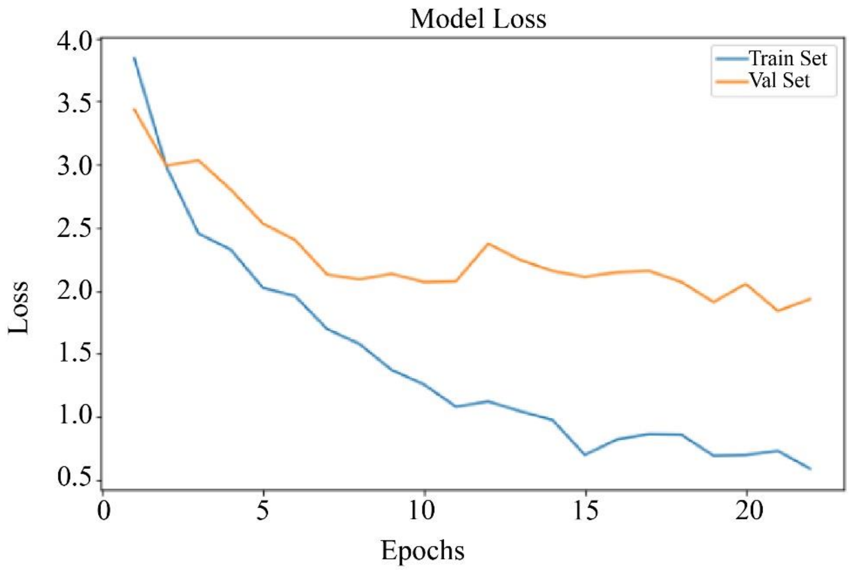

Fig. 13 Loss vs epochs in coronary artery disease dataset

Table 3 and Figure 11 signify the performance of the proposed method with K values 10 and 30 epochs. The proposed ensemble neural network is assessed using existing techniques like ANN, CNN, ResNet, and VGG 16 models. The developed technique reached a precision of 98.82%, accuracy of 99.45%, F1 score of 98.80% and recall of 98.85% with 30 epochs, which is better than various existing algorithms.

Figures 12 and 13 represent the accuracy and loss graph of the proposed method with 20 epochs, respectively. The accuracy and loss of the algorithm are taken for the training and validation set. The accuracy of the training set is higher than the validation set, and there is less loss in the training set.

4.3. Comparative Analysis

The comparative analysis of the developed algorithm is discussed in Table 4. The existing methods [16], [18], [19], [23], [24], and [25] are utilized for comparison with the proposed approach in the MIT-BIH Arrhythmia dataset. The proposed ensemble neural network achieved an accuracy of 99.45%, which is higher than previous algorithms [18] and [19], which attained an accuracy of 99.00% and 99.40%, respectively.

Table 4. Comparative analysis of the proposed method

Author	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Akanksha Pathak et al. [16]	MIT-BIH Arrhythmia database	89.25	-	-	-
Adel A. Ahmed et al. [18]		99.00	99.00	94.00	-
Saroj Kumar Pandey et al. [19]		99.40	98.78	98.78	98.74
Abdul Rahaman Wahab and Ashit Kumar Dutta [23]		99.40	98.50	98.65	98.60
Liang-Hung Wang [24]		94.4	NA	NA	NA
Yared Daniel Daydulo [25]		99.2	NA	NA	99.2
Proposed VGG-16 and ResNet 50		99.45	98.82	98.85	98.80

4.4. Discussion

The VGG-16 and ResNet 50 method results are compared with different classifiers like ANN, CNN, ResNet and VGG-16 with coronary artery disease dataset. Moreover, its performance is compared with existing like methods [16], [18], [19], [23], [24] and [25] with the MIT-BIH Arrhythmia dataset. This section gives a discussion about the proposed algorithms and their result comparison. The previous coronary artery disease detection methods had huge execution costs and training time for generating results, and they required valuable features to find a key pattern of image [18]. The present methods are critical in resolving the problems of overfitting and underfitting [19]. The ResNet 50 model resolves the gradient issue with high accuracy. Moreover, residual networks are more suitable for image detection and classification. The VGG16 network provides accurate results in training datasets and shows improved performance. The transfer learning model solves the issues of overfitting and underfitting. By ensemble models, the issues of gradient vanishing and overfitting are resolved, and the model provides high accuracy with less execution costs and training time. The proposed method shows effective performance when compared to existing methods like [16], [18], [19], [23], [24] and [25] in terms of accuracy.

5. Conclusion

The early detection of coronary atherosclerosis is a challenging task and increases the financial burden on patients. In this research, an ensemble neural network is proposed to detect and classify coronary artery disease. The ensemble neural network has integrated two models, VGG-16 and Resnet 50.

The imaging dataset is named CAD, and the ECG signals dataset is named MIT-BIH Arrhythmia database and is used for research. The min-max normalization method is applied for the pre-processing stage, and an ensemble neural network is utilized to detect and classify coronary artery diseases.

The model attained a high precision of 98.82%, accuracy of 99.45%, f1-score of 98.80%, and recall of 98.85% compared to conventional techniques. The proposed ensemble neural network provides accurate detection and classification with less execution time and training cost. In the future, the segmentation process will be involved in coronary artery disease detection, which will reduce the complexity of the classification process.

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