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Bioinspired Optimization with Deep Learning Driven Cardiovascular Diseases on Retinal Fundus Images

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Abstract: ***Earlier diagnosis of cardiovascular diseases (CVDs) is important for timely intervention and improved survival rates. Retinal fundus images are developed as a precious diagnostic resource owing to their non-invasive nature and capability to reveal vascular abnormalities representative of CVDs. This study designs an automated Cardiovascular diseases using Seagull Optimization Algorithm with Deep Learning (ACVD-SOADL) method on retinal fundus images. This study introduces a wide-ranging approach for CVD diagnosis by leveraging DL approaches, particularly employing MobileNet as a feature extractor, Back propagation Neural Network (BPNN) for classification, and Seagull Optimization Algorithm (SOA) for parameter tuning. MobileNet, a lightweight DL model, is utilized for extracting meaningful features from these images. SOA is an innovative optimizer algorithm stimulated by the foraging behavior of seagulls, which can be employed to fine-tune the model's hyperparameters, improving its performance. The dataset exploited in this study includes a various types of retinal fundus images, allowing generalizable and robust training method. The BPNN classification method is trained to differentiate among normal and CVD-affected retinal images depends on the extracted features. By employing an iterative process, SOA enhances the hyper parameters of the BPNN, confirming that the model attains its highest potential accuracy. For demonstrating the improvised performance of the ACVD-SOADL approach, an extensive simulated value could be accomplished and the comparison analysis assured the excellence of the ACVD-SOADL model.***

Keywords: Fundus images, Deep learning, Cardiovascular diseases, Seagull optimization algorithm, Artificial intelligence

1. Introduction

Cardiovascular diseases (CVDs) are one of the leading reasons of death worldwide [1]. The people more than 17.9 million were died from CVDs in 2019 according to the report of the World Health Organization [2]. This demonstrates 32 percent of all global deaths. In 2015, according to the report, 15.2 million deaths were made by ischemic heart disease and stroke as well as 85.1 percent of the total deaths was caused by CVDs [3]. Many CVDs can be prohibited by addressing high-risk factors like smoking status, blood pressure, gender, chronological age, body mass index (BMI) and metabolic like cholesterol and glucose levels. Identifying CVDs before is very important for effective clinical treatment [4]. So Deep Learning (DL) techniques can be combined into the diagnostic procedure. This research paper is mainly focused on measuring the influences of this automatic analysis of CVDs from retinal images [5].

The retina is known as the “window” to imagine and evaluate CV health. It is mainly considered to share the same physiological function and anatomic structure with cardiac vasculature [6]. The past researchers have designated relations between different retinal features and then the high risk of increasing CVD that ranges from retinal vascular geometry (i.e. branching angle, fractal dimension, vessel calibre and tortuosity), retinal pathologies (arteriovenous nicking, microaneurysm and cotton wool spots) and retinal vascular network patterns [7]. Moreover, it is highly concentrated on exact measurements that may direct some implicit data and underrate the retina potential as a complete to inform CV health [8]. DL is a branch of Artificial Intelligence (AI) models that mainly focuses on employing Artificial Neural Networks (ANN) with many computational networks to train and remove difficult analytical features from high-dimensional data as well as medical images [9]. The current research has proposed DL approaches which are capable of generating precise diagnoses for CV diseases that are mainly needy on morphology like diabetic retinopathy [10]. This method provides improved performance from AI than humans.

This study designs an automated Cardiovascular diseases using Seagull Optimization Algorithm with Deep Learning (ACVD-SOADL) method on retinal fundus images. MobileNet, a lightweight DL model, is utilized for extracting meaningful features from these images. SOA is an innovative optimizer algorithm stimulated by the foraging behavior of seagulls, which can be employed to fine-tune the model's hyperparameters, improving its performance. The BPNN classification method is trained to differentiate among normal and CVD-affected retinal images depends on the extracted features. By employing an iterative process, SOA enhances the hyperparameters of the BPNN, confirming that the model attains its highest potential accuracy. For demonstrating the improvised performance of the ACVD-SOADL approach, extensive simulated values could be accomplished and the comparison analysis assured the excellence of the ACVD-SOADL model.

2. Related Works

Huang et al. [11] projected a graph neural network (GNN) technique for forecasting the CAD-RADS as a proxy. The CCTA scans have been stratified by CAD-RADS scores by proficient researchers, and the vascular biomarkers could be removed in their fundus images. Correlation analyses of CAD-RADS scores are executed along with that quantitative vascular biomarkers, retinal disorders, and patient individualities. Lastly, a GNN method has been developed for process of forecasting the CAD-RADS score. Chang et al. [12] devised a DL method that forecasted atherosclerosis by employing retinal fundus images and for confirming its medical impact by performing a retrospective cohort analysis. The DL algorithm could be trained for predicting carotid artery atherosclerosis which is called the DL funduscopic atherosclerosis score (DL-FAS). This developed research is examined by employing HPC-SNUH databases.

In [13], to design and validate a DL approach for predicting 10-year ICVD risk employing retinal fundus images. This analysis initially labelled fundus images with natural logarithms of ICVD risk evaluated by an earlier confirmed 10-year Chinese ICVD risk predicted method. This method employing CNN has been established for forecasting the evaluated 10-year ICVD risk with the help of fundus images. This approach was validated by employing both internal database. Rajan [14] endures major important factors for determining CVD is utilizing retinal vessels. The captured retinal images are filtered followed by segmented. Its outcomes were employed for vein and arteries classification via the SVM. By identifying the optic disc and optic cup assessment, cup-to-disc ratio (CDR) has been measured. The existence of CVD is identified and their parameters could be measured by using artificial neural networks (ANN). In [15], a new algorithm could forecast CVD. The feature extraction has been attained utilizing Enhanced GLCM technique. Subsequently, the important features could be chosen by employing the ICA method. Risk aspects for heart diseases rate could be identified in the microvasculature of ERNN-categorized retinal fundus image employing MATLAB. By employing the UCI-ML repository, the input images are captured that dependent upon Cleveland database.

3. The Proposed Model

In this study, we have developed an innovativeACVD-SOADL method for CVD classification on retinal fundus images. The ACVD-SOADL algorithm is aimedto detect and classify CVD in retinal fundus images. Then, a sequence of processes such asBPNN classification, SOAparameter tuning, andMobileNet feature extractor. Fig. 1 represents the workflow ofACVD-SOADL approach.

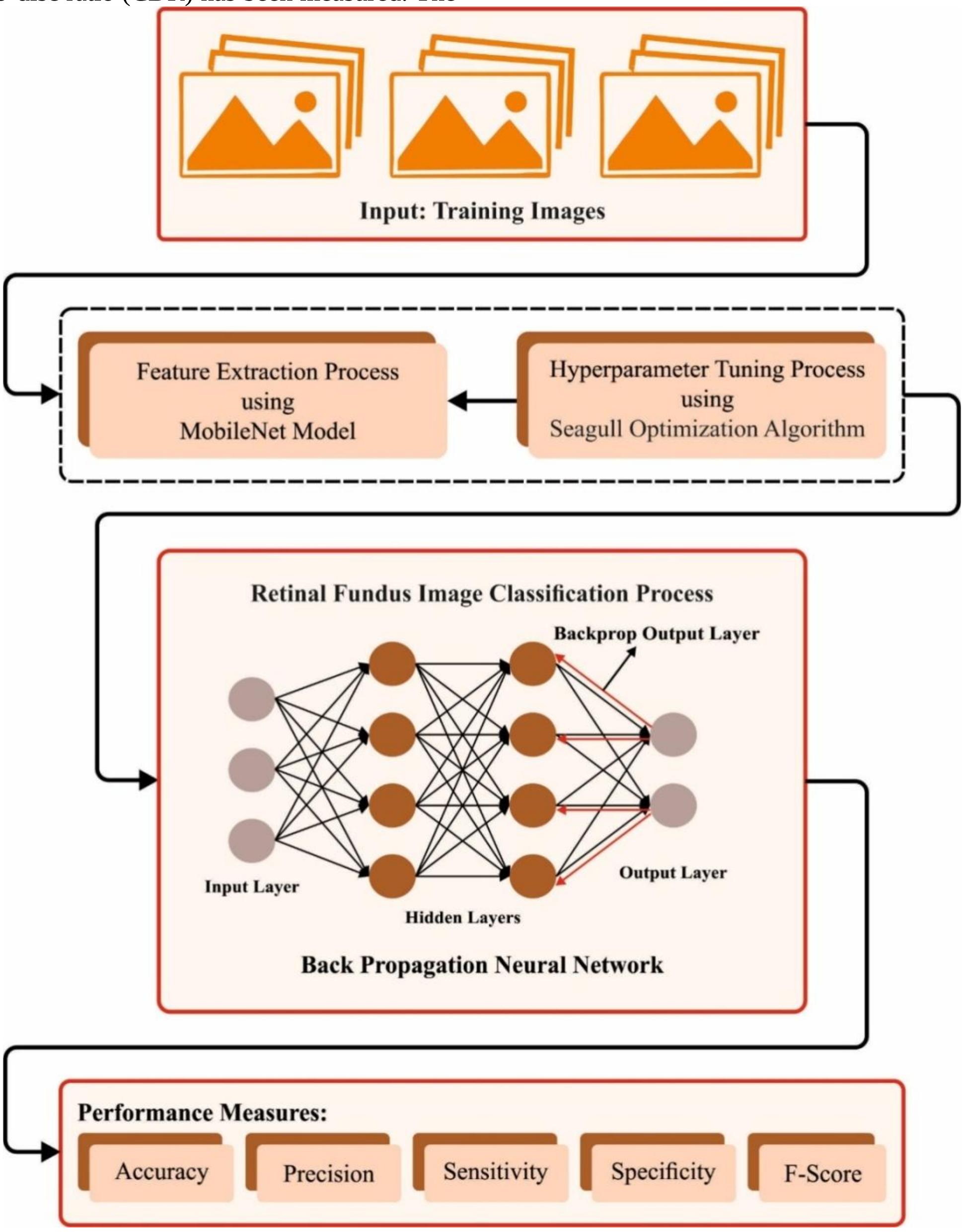

Fig. 1. Workflow of ACVD-SOADL algorithm

3.1 Feature extraction

The ACVD-SOADL method employs MobileNet architecture for developing feature vectors. MobileNet is a branch of CNN developed with a main focus on efficient and lightweight DL algorithms for mobile and embedded applications [16]. It deals with the challenge of deploying DNN on resource-constraint devices like edge devices and smartphones, where memory and computation resources are limited. The key innovation in MobileNet is depthwise separable convolution. MobileNet uses a two-step process rather than classical convolution layers, which apply a complete set of filters to all input channels. Firstly, it employs a depthwise convolution, which convolves all the input channels separately with its set of filters. Next, it exploits pointwise convolution, otherwise called 1x1 convolutions, to combine the output of depthwise convolution. This technique considerably decreases the computational cost and number of parameters while retaining good accuracy for the image classification task. MobileNet model comes in different versions namely MobileNetV1, MobileNetV2, and MobileNetV3, with its optimizations and improvements. This model has been widely adopted for real-time image recognition and object detection tasks on mobile devices, making them a common choice for the edge computing application.

3.2. Hyperparameter Tuning

In this study, the SOAmethodology is implemented for hyperparameter tuning process. Seagulls (scientifically called as Larus minutus) are amongst the birds of the coastal locations that live on [17]. Generally, seagulls live in swarm. Then,the ability is their behavior in migration. Migration is the evaluation of seagulls to the northwards in the spring and south in the fall or from coast to coast to survive winter situations or change from the ground to the heights and to attain the numerous food sources that offer sufficient easements.

Migration (exploration)

Migration behavior simulates the seagulls swarm changing toward the locations. To perform, a 3 cases must be satisfied:

(A) Collisions Avoidance: To prevent the collision between neighbor seagulls, a functionhas been determined by additional variable A to update the novel position of the measured seagull (search agent):

$$\vec{P}_N = A \times \vec{P}_c(i)\,, \quad i = 0,1,2,\dots,\mathrm{Max}\ (i) \tag{1}$$

where, $\vec{P}_N$ defines the position that avoids from colliding with the other search agent, $\vec{P}_c(i)$ is the location of the candidate in the existin ground (i), and Aindicate the motion behavior of the search agent in the search space and mathematical equation shownin given below:

$$A = f_c - \left(i \times \left(\frac{f_c}{Max(i)}\right)\right) \tag{2}$$

where, i denotes the iteration, f_c describes the frequency control of variable A in the limit $[0, f_c]$.

(B) applying the other neighbor's knowledge: Followed by collision avoidance produces the neighbors, the candidates attempt to progress in the direction of the best neighbor (best solution).

$$\vec{d}_e = B \times \left(\vec{P}_b(i) - \vec{P}_c(i)\right) \tag{3}$$

where, $\vec{d}_e$ represent the candidate positions $\vec{P}_c(i)$ to the best fit candidate $\vec{P}_b(i)$. The coefficient B denotes a random value to be create trade-off among exploration and exploitation. B is attained as given below:

$$B = 2 \times A^2 \times R \tag{4}$$

where, Rrepresents a random value among0 and 1.

(C) Change toward the search agent (best solution): lastly, search agents update their position depends on the best solution with this given equation:

$$\vec{D}_e = \left|\vec{P}_N + \vec{d}_e\right| \tag{5}$$

where, $\vec{D}_e$ indicate the variance among the best cost and seagulls.

Attacking (exploitation)

In migration, seagulls are constantly modified the attack's speed and angle. The place can be retained in the air employing their wings and weight.Through the attack procedure, seagulls change spiral in the air at$y$, and z planes as modelled in the following equation:

$$\hat{x} = r \times cos(t) \tag{6}$$

$$\hat{y} = r \times sin(t) \tag{7}$$

$$\hat{Z} = r \times t \tag{8}$$

where, $t$is a random value in the interval 0 and 2πthen$r$defines the radius of the spiral turns lastly, this is expressed as follows:

$$r = \alpha \times e^{\beta t} \tag{9}$$

where,α and β describe the shape of the spiral, then e represents the natural logarithm base. The new position of seagulls can be updated by the next equation:

$$\vec{P}_c(i) = \left(\vec{D}_e \times \hat{x} \times \hat{y} \times \hat{Z}\right) + \vec{P}_B(i) \tag{10}$$

where, $\vec{P}_c(i)$ describes the best outcomes.

3.3. BPNN based classification

In the CVD classification method, the BPNN architecture has been employed in this study. BPNN referred to as neural network, are a class of artificial neural networks(ANNs) used for supervised learning tasks, especially in the fields of pattern recognition, classification, and regression [18]. They are stimulated by the functioning and structure of biological neurons in the human brain. A BPNN comprises layers of interconnected artificial neurons, organized into input layer, multiple hidden layers, and output layer. Each connection between neurons has a weight, and each neuron employs an activation function to the weighted sum of its inputs, which propagates the data forward through the network. The primary innovation in BPNN is the backpropagation model that enables the network to adjust and learn its weights to minimalize the difference between predicted and actual output during training. During the training stage, BPNN iteratively adjusts the weights using gradient descent optimization approaches. This technique includes calculating the gradient of error with respect to the weight and then

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update the weight in the opposite direction of gradient, efficiently minimalizing the error. Backpropagation enables BPNN to learn complex relationship in data, which makes them well-suited for tasks including natural language processing, predictive modeling, and image recognition.

4. Performance validation

The proposedACVD-SOADLsystem is tested employing the DR database from Kaggle repository [19]. The database holds 35126 samples with five class labels as described in Table 1.

Table 1: Details of DR dataset

Label	Class	No. of Instances
DR-0	No DR	25810
DR-1	Mild DR	2443
DR-2	Moderate DR	5292
DR-3	Severe DR	873
DR-4	Proliferative DR	708
Total Number of Instances		35126

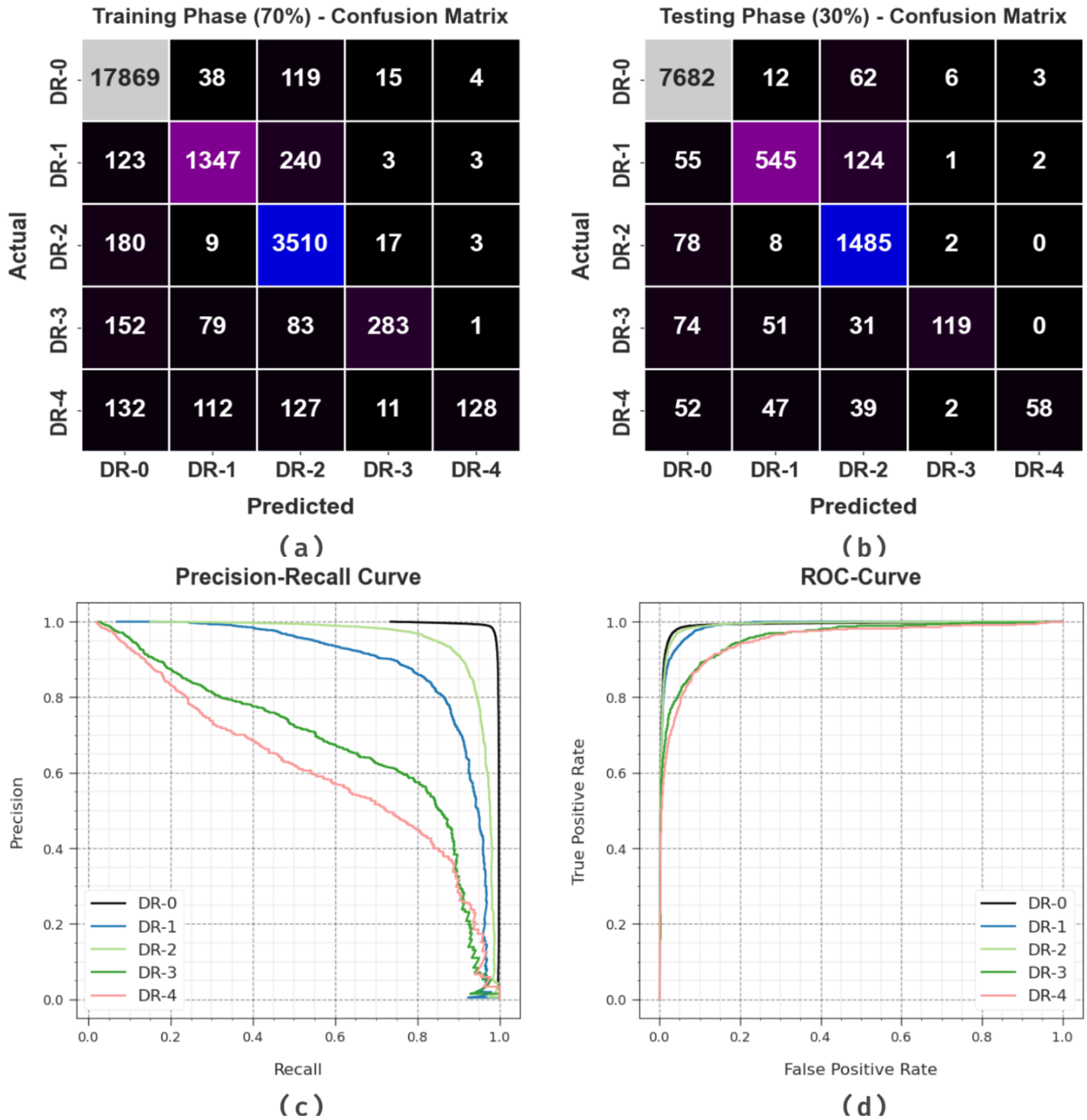

Figure 2: Classifier performance (a-b) Confusion matrices, (c) PR curve, (d) ROC

Fig. 2shows the classifier analysis of the ACVD-SOADL method on the test database. Figs. 2a-2b represents the confusion matrices given by the ACVD-SOADL system at 70:30 of the TR phase/TS phase. The figure denoted that the ACVD-SOADL model has properly identified and categorized all 5 class labels. Additionally, Fig. 2c represents the PR analysis of the ACVD-SOADL approach. The figure described that the ACVD-SOADL methodology is attained excellent PR performance with five classes. Then, Fig. 2d exhibits the ROC study of the ACVD-SOADL technique. The figure revealed that the ACVD-SOADL algorithm leads to efficient outcomes with higher ROC values with each class.

Table 2 depicts the DR classification result of ACVD-SOADL algorithm with 70:30 of TR phase/TS phase. The outcome implies that the ACVD-SOADL approach effectively detects all 5 classes. With 70% of TR phase, the ACVD-SOADL approach gains average $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 97.64%, 89.19%, 68.86%, 97.40%, and 74.01%. Likewise, based on 30% of TS phase, the ACVD-SOADL method achieves average $accu_y$, $prec_n$,

$sens_y$, $spec_y$, and F_{score} of 97.54%, 89.57%, 68.17%, 97.29%, and 73.81% respectively.

Table 2: DR classifier outcome of ACVD-SOADL approach with 70:30 of TR phase/TS phase

Class	Accuracy	Precision	Sensitivity	Specificity	F-Score
Training Phase (70%)					
DR-0	96.90	96.82	99.02	91.03	97.91
DR-1	97.53	84.98	78.50	98.96	81.61
DR-2	96.84	86.05	94.38	97.27	90.02
DR-3	98.53	86.02	47.32	99.81	61.06
DR-4	98.40	92.09	25.10	99.95	39.45
Average	97.64	89.19	68.86	97.40	74.01
Testing Phase (30%)					
DR-0	96.75	96.74	98.93	90.66	97.82
DR-1	97.15	82.20	74.97	98.80	78.42
DR-2	96.74	85.30	94.41	97.14	89.62
DR-3	98.42	91.54	43.27	99.89	58.77
DR-4	98.62	92.06	29.29	99.95	44.44
Average	97.54	89.57	68.17	97.29	73.81

Table 3 and Fig. 3 depicts the comparative outcome of ACVD-SOADL approach with other methods in terms of $accu_y$. The simulation value inferred that the ACVD-SOADL algorithm achieve effectual outcomes. Based on $accu_y$, the ACVD-SOADL approach has outperformed higher value with $accu_y$ of 97.64%, but the AlexNet, VGG-16, ResNet-50, ResNet-101, and Inception V3 approaches have exhibited lower values with $accu_y$ of 88.81%, 95.98%, 92.95%, 93.88%, and 95.10% respectively.

Table 3: $Accu_y$ outcome of ACVD-SOADL approach with other methods

Methods	Accuracy
AlexNet Model	88.81
VGG-16 Model	95.98
ResNet-50 Model	92.95
ResNet-101 Model	93.88
Inception V3 Model	95.10
ACVD-SOADL	97.64

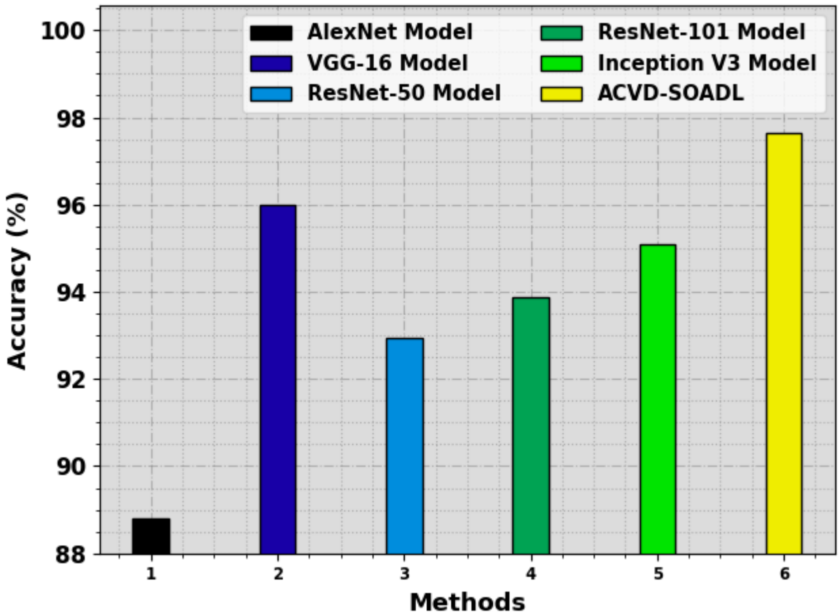

Figure 3: $Accu_y$ outcome of ACVD-SOADL approach with other methods

Table 4: Details of CVD dataset

Class	No. of Samples
CVD_Positive	200
CVD_Negative	200
Total Samples	400

Table 4 depicts the details of CVD dataset. The dataset contains 400 samples with two class labels.

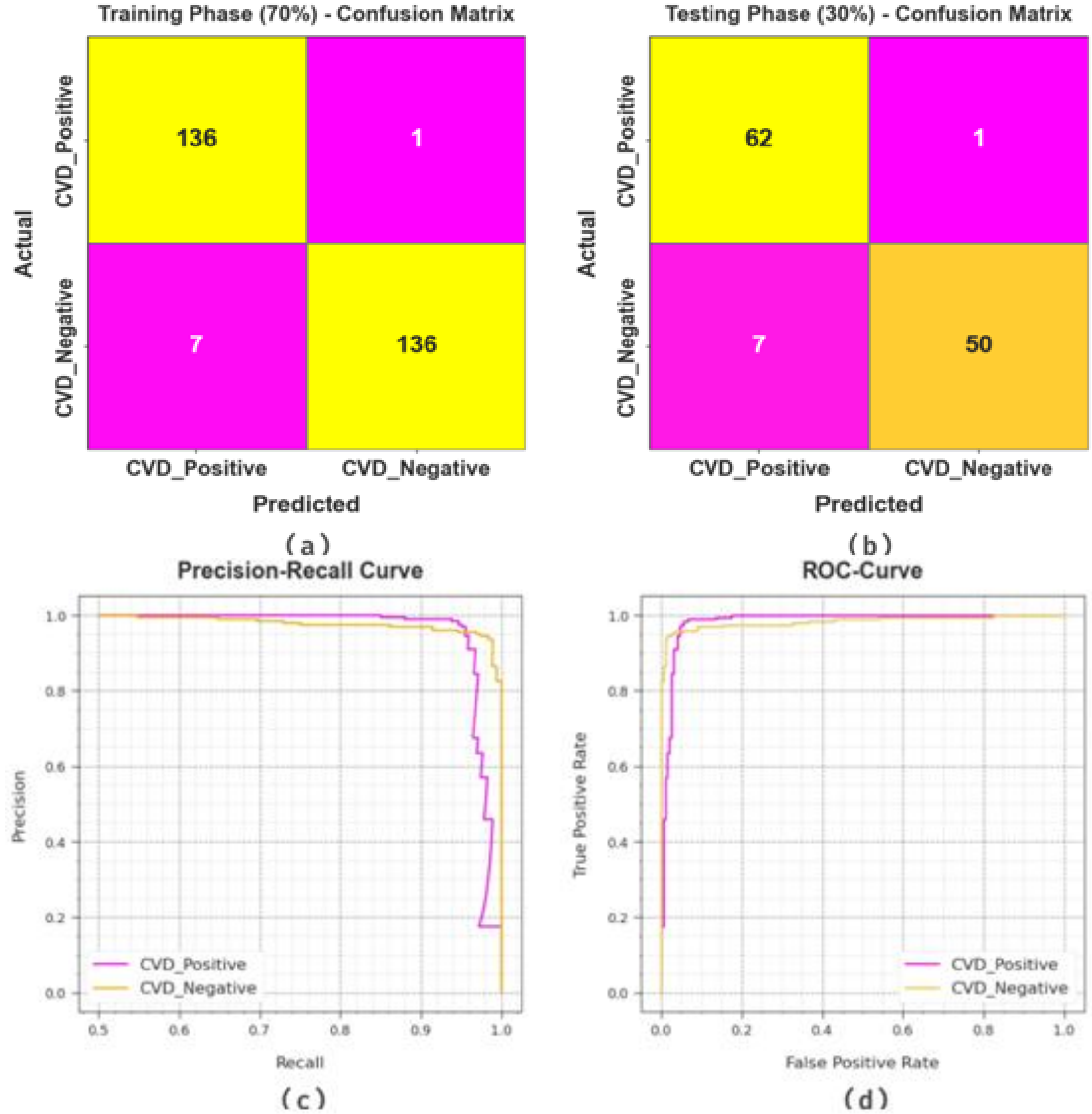

Figure 4: Classifier performance (a-b) Confusion matrices, (c) PR curve, (d) ROC

Fig. 4 represents the classifier outcome of the ACVD-SOADL method with test database. Figs. 4a-4b shows the confusion matrices offered by the ACVD-SOADL system at 70:30 of TR phase/TS phase. The figure indicated that the ACVD-SOADL technique has precisely identified and categorized all 2 classes. Also, Fig. 4c exhibits the PR analysis of the ACVD-SOADL approach. The figure described that the ACVD-SOADL algorithm has gained higher PR performance with each class. Besides, Fig. 4d demonstrates the ROC analysis of the ACVD-SOADL model. The figure exhibited that the ACVD-SOADL methodology can be the effective outcomes with better ROC values with each class.

Table 5 described the CVD classification analysis of ACVD-SOADL method at 70:30 of TR phase/TS phase. The simulated outcome implies that the ACVD-SOADL technique proficiently detects each class. According to 70% of TR phase, the ACVD-SOADL approach gains average $accu_y$, $prec_n$, $sens_y$, $spec_y$, and AUC_{score} of 97.19%, 97.19%, 97.19%, 97.19%, and 97.19%. Likewise, on 30% of TS phase, the ACVD-SOADL methodology attains average $accu_y$, $prec_n$, $sens_y$, $spec_y$, and AUC_{score} of **93.07**%, **93.07**%, **93.07**%, **93.07**%, and **93.07**% correspondingly.

Table 5: CVD classifier outcome of ACVD-SOADL approach with 70:30 of TR phase/TS phase

Class	Accuracy	Precision	Sensitivity	Specificity	AUC Score
Training Phase (70%)					
CVD_Positive	99.27	95.10	99.27	95.10	97.19
CVD_Negative	95.10	99.27	95.10	99.27	97.19
Average	97.19	97.19	97.19	97.19	97.19
Testing Phase (30%)					
CVD_Positive	98.41	89.86	98.41	87.72	93.07
CVD_Negative	87.72	98.04	87.72	98.41	93.07
Average	93.07	93.95	93.07	93.07	93.07

Table 6 and Fig. 5illustrates the comparison analysis of ACVD-SOADL technique with other methods with regard to $accu_y$ [20, 21]. The simulated values inferred that the ACVD-SOADL model accomplish efficacious outcomes. Additionally, with$accu_y$, the ACVD-SOADL technique has exceeded greater value with $accu_y$ of 97.19%, while the Inception-ResNet-V2, U-Net-VGG19, Inception V3, and CNN-ResNet50 algorithms are represented less values with $accu_y$ of 97%, 96%, 91%, and 80% correspondingly.

Table 6: $Accu_y$ outcome of ACVD-SOADL approach with other methods

Architectures	Accuracy (%)
ACVD-SOADL	97.19
Inception-ResNet-V2	97.00
U-Net-VGG19	96.00
InceptionV3	91.00
CNN-ResNet50	80.00

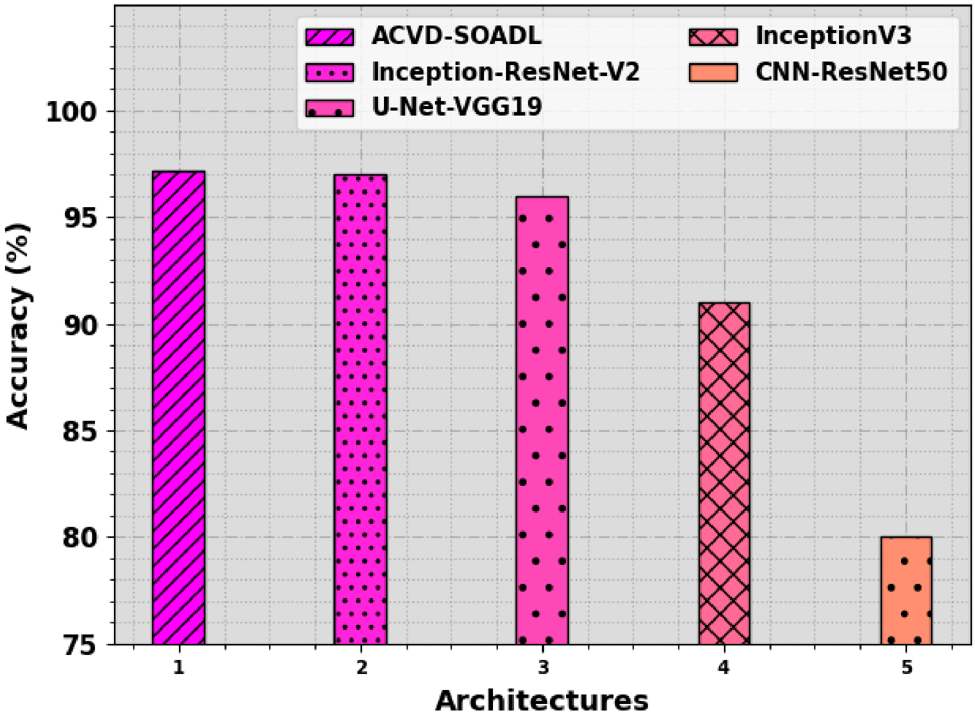

Figure 5: $Accu_y$ outcome of ACVD-SOADL approach with other methods

5. Conclusion

This study designs an ACVD-SOADL method on retinal fundus images. This study introduces a wide-ranging approach for CVD diagnosis by leveraging DL approaches, particularly employing MobileNet as a feature extractor, BPNN for classification, and SOA for parameter tuning. MobileNet, a lightweight DL model, is utilized for extracting meaningful features from these images. SOA is an innovative optimizer algorithm stimulated by the foraging behavior of seagulls, which can be employed to fine-tune the model's hyperparameters, improving its performance. By employing an iterative process, SOA enhances the hyperparameters of the BPNN, confirming that the model attains its highest potential accuracy. For demonstrating the improvised performance of the ACVD-SOADL approach, an extensive simulated value could be accomplished and the comparison analysis assured the excellence of the ACVD-SOADL model.

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