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Original Research Article

WOANet: Whale optimized deep neural network for the classification of COVID-19 from radiography images

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ABSTRACT

Coronavirus Diseases (COVID-19) is a new disease that will be declared a global pandemic in 2020. It is characterized by a constellation of traits like fever, dry cough, dyspnea, fatigue, chest pain, etc. Clinical findings have shown that the human chest Computed Tomography (CT) images can diagnose lung infection in most COVID-19 patients. Visual changes in CT scan due to COVID-19 is subjective and evaluated by radiologists for diagnosis purpose. Deep Learning (DL) can provide an automatic diagnosis tool to relieve radiologists' burden for quantitative analysis of CT scan images in patients. However, DL techniques face different training problems like mode collapse and instability. Deciding on training hyper-parameters to adjust the weight and biases of DL by a given CT image dataset is crucial for achieving the best accuracy. This paper combines the backpropagation algorithm and Whale Optimization Algorithm (WOA) to optimize such DL networks. Experimental results for the diagnosis of COVID-19 patients from a comprehensive COVID-CT scan dataset show the best performance compared to other recent methods. The proposed network architecture results were validated with the existing pre-trained network to prove the efficiency of the network.

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1. Introduction

Coronavirus Disease (COVID-19) is an infectious disease, and this outbreak has changed every individual's lifestyle. Still, the COVID-19 pandemic is going on even in May 2021. In

mid of April 2021, COVID-19 phase-2 is getting started, and many cases have been reported like a country India [1]. Studies suggest pangolins can be the intermediate host from bat to humans for COVID-19. In the present scenario, COVID-19 infected patients are a vital source of infection [2]. Addition-

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ally, respiratory droplets and contact from the infected person is the leading cause of the spread [3,4]. Recent studies presented that the virus in tears, as well as conjunctiva secretion of the infected patient, may be the source of COVID-19 transmission [5,6]. Therefore, to protect against the spread of infection Personal Protective Equipment (PPE) kit, gloves, full face shield, face mask N-95, and eye protection are necessary while being in contact with infected persons [7].

One of the main challenges in COVID-19 for specialists is to diagnose an infected person as symptoms of this infection are regular flu and cough. The spread of the virus can be slowed down or stopped only by isolating and quarantining the infected person. Therefore, accurate identification of the infection with less time is essential to control this virus [8]. Currently, Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR)[9] is used as a diagnostic test for COVID-19. The specificity of the RT-PCR analysis is 100%, which means no false-positive case. However, the sensitivity that is related to the actual positive case is only 64% for the RT-PCR test[10]. Another limitation of using RT-PCR kits is the availability in a few hospitals and intended for use only by trained clinical personnel, and the RT-PCR kit cost is also very high[11].

Imaging modalities are very much helpful for the diagnosis of COVID-19. Computer Tomography (CT) scan images play an essential role in diagnosing the infected person of COVID-19 [12]. Therefore, a CT scan can be considered during the COVID-19 pandemic for early diagnosis purposes. Based on the recent studies, CT images are more accessible than other medical imaging modalities for accurate and fast detection of COVID-19[13]. The advantage of using CT-scan is their availability in many hospitals and their cost-effectiveness. Further to speed up the screening using CT scan images[14]. Fig. 1 shows CT scan images of the COVID-19 infected person and the normal person. Fig. 1. (a) shows the bilateral areas of ground-glass opacities (arrows) in a peripheral distribution, and Fig. 1(b) shows the normal CT scan image without ground-glass opacities.

Deep Learning (DL) networks can be employed to automatic diagnosis with more sensitivity with less time required. This approach also assists radiologists in speeding up the diagnosis process with less effort and high accuracy. Selection of hyperparameters of DL network is one of the important

tasks while training the network, which can help improve classification accuracy. The manual selection of hyperparameters of the DL network is a time-consuming task, so an automated hyperparameters selection is required to get optimum performance. Hence this paper has been proposed to optimize the hyperparameters of the DL network using the Whale Optimization Algorithm (WOA)[15]. Therefore we have named this architecture as WOANet.

In terms of novelty, WOA is firstly used as a seminal attempt to optimize the hyperparameters of the DL network according to the CT images. Secondly, the proposed method is tuned to avoid overfitting issues while training the network.

The contribution of this paper is as per the following:

1. An optimized DL network has been proposed to extract the features from input images to classify COVID-19 and Non-COVID-19 persons.
2. Hyperparameters of the WOANet are optimized using the WOA algorithm to find the more accurate results in classifying COVID-19 and Non-COVID-19 CT images.

The remainder of the paper is organized as follows:

Section 2 presents the related works of recent DL models for diagnosing the COVID-19. Section 3 presents the background of WOA. Section 4 describes the proposed WOANet architecture for classifying normal and COVID-19 cases. Section 5 discusses the experiments, performance, and comparative analysis of this study. Lastly, Section 6 illustrates the conclusions and further works.

2. Related works

CT images are accessible and affordable ways for accurate diagnosis of COVID-19. However, automatic diagnosis using them is a challenging classification problem in Machine Learning. The literature shows that DL models perform accurately in medical image classification. This section illustrates the recent COVID-19 diagnosis methods using the DL model through CT images.

Shah et al.[16] proposed a deep architecture are called CTnet-10 for an accurate diagnosis of COVID-19 using CT

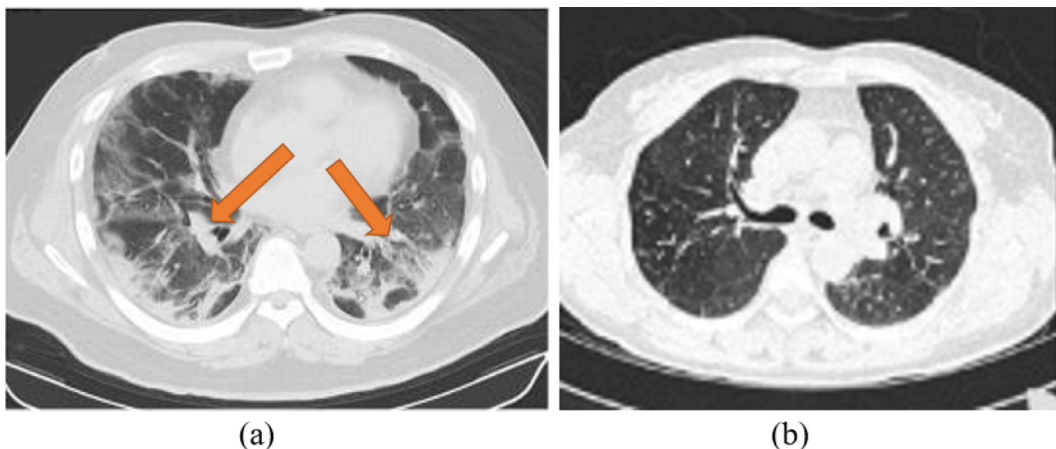


Fig. 1 – CT image: (a) COVID-19; (b) Non-COVID-19 [https://github.com/UCSD-AI4H/COVID-CT].

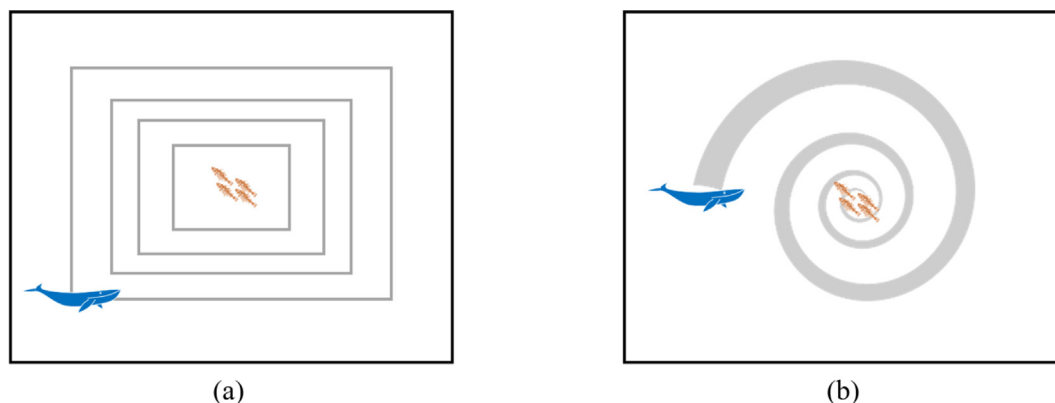


Fig. 2 – Mathematical models for: (a) prey encircling; (b) bubble-net hunting.

images. The proposed architecture has been tested in both COVID-19 and normal images. This method has yielded 82.1% accuracy because of the lack of training images. Song et al.[17] presents an ensemble DL model for COVID-19 detection. The disadvantage of this model is that it has tested only 88 samples. Hani et al.[18] indicate that the main feature of CT scans related to COVID-19 is bilateral glass opacities. Singh et al.[19] presented a graphical user interface for the diagnosis of COVID-19 using a support vector machine and directional emboss. This is the tailor-made model for clinicians to analyze the infection rate of COVID-19. But the performance of this method is inferior.

Sen et al.[20] presented a two-stage feature extraction and selection method for COVID-19 detection. This method consists of two modules in which; the first module is Convolutional Neural Network (CNN), used to extract the features, and the second module helps select the appropriate features from the extracted one. Ghassemi et al.[21] present the deep model for auto COVID-19 detection based on cyclic Generative Adversarial Network (GAN). The GAN helps augment the CT images to get more CT images to train the deep network. Goel et al.[22] proposed an optimized GAN architecture based on a pre-trained ResNet model for accurate diagnosis of COVID-19. This architecture has been tested with more CT slices to prove the efficiency of the proposed network.

Shi et al.[23] presented attention deep transfer learning network for COVID-19 detection. This network has been divided into two parts: the teacher network extracts the global features, and the student network extracts the irregular lesions from the CT images. Wang et al.[24] proposed the inception network extract graphical features and then diagnose. Xu et al.[25] segmented the infected region from a CT scan image using a 3D deep learning model and then classified between normal, pneumonia, and COVID efficiently 86.7%. Huang et al.[26] quantitatively evaluated the CT images of COVID-19 by the clinical studies.

Chen et al.[27] presented U-net based residual attention network for quantifying the COVID-19 through CT images. The main contribution of this work is aggregated residual mechanism to improve the robustness of the accuracy. The main drawback of the U-Net architecture slows down the training in the middle layers.

Kassani et al.[28] extracted the features from COVID-19 images using different DL models, and these features are fed into Machine Learning (ML) classifiers for classifying COVID-19 cases from the normal. Qi et al.[29] developed a multi-features CNN model from classifying COVID-19, healthy, and pneumonia persons from local phase enhanced CXR images. Abraham et al.[30] developed a multi-CNN model for extracting the COVID-19 features, and a Bayesnet classifier has been used for classification.

Apostolopoulos et al.[31] proposed a transfer learning-based CNN architecture for diagnosing COVID-19. They have used two publicly available datasets for testing their architecture. This architecture has been produced 96.78% of accuracy. The main limitation of this work is tested with few numbers of COVID-19 images. Hassantabar et al.[32] introduced DL based fractal feature extraction model and CNN for diagnosing COVID-19. Castiglioni et al.[33] developed an ensemble CNN architecture for training and testing CXR images for auto diagnosis of COVID-19. This method has used only 250 number of COVID-19 images for their experiment. Gour et al.[34] proposed a stacked CNN model, which consists of 30 CNN layers is called CovNet30 model for feature extraction and logistic regression ML classifier for diagnosis. Jain et al.[35] proposed a four-step detection process that includes data augmentation, preprocessing, stage I, and stage II to detect the COVID-19. The ResNet-50 networks have been used for feature extraction and classification of COVID-19, normal and viral pneumonia. Joshi et al.[36] proposed binary classification and multi-class classification techniques for COVID-19.

The research gap of these studies is the lack of clinical data for testing the networks, a small number of images used, and a lack of ML/DL architectural information. Furthermore, based on the literature survey, all the DL-based methods use CNN to extract the features using the manual hyperparameter selection. None of the existing DL-based methods has selected automatic hyperparameter selection for the CNN model to get optimum performance. This brings the question of whether DL methods performance can be enhanced with a proper tuning mechanism. This motivation to employ WOA as one of the well-regarded recent algorithms to ensure the maximum performance of DL methods.

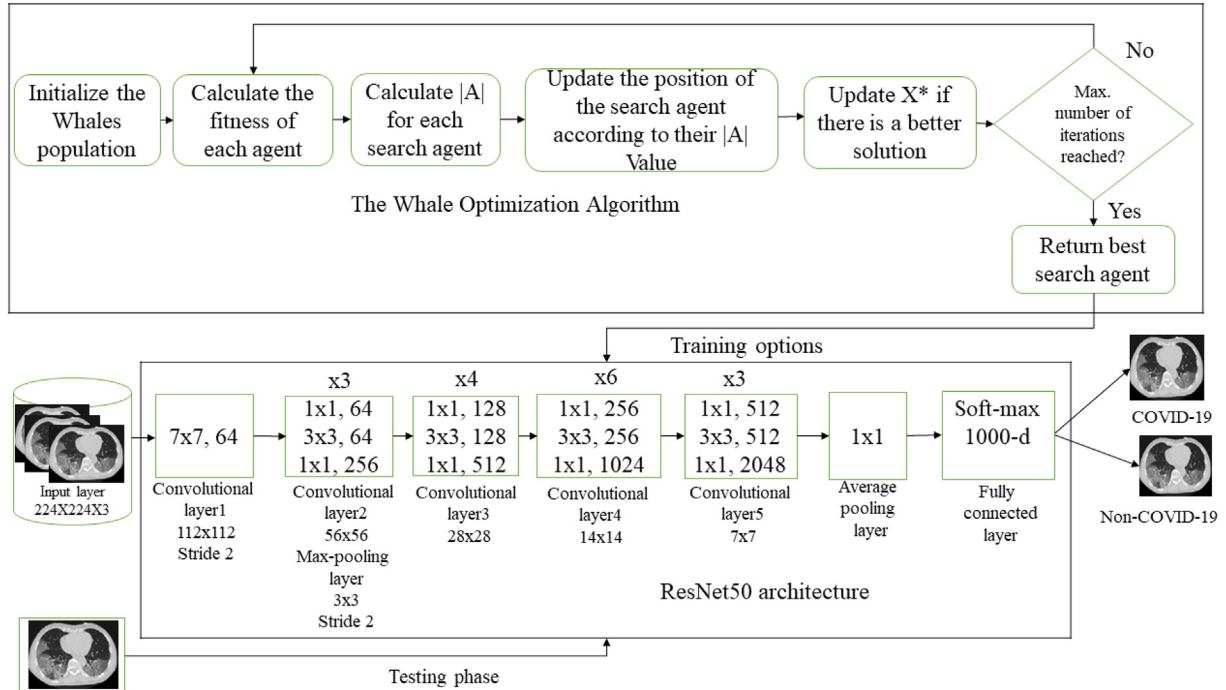


Fig. 3 – Workflow of the proposed Optimized WOANet.

3. The Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) was proposed [15] as an optimizer to solve single-objective problems. This algorithm mimics the searching system of humpback whales in nature. Similar to other population-based meta-heuristic algorithms, WOA makes many random solutions for a given optimization issue. This set is then undergoing several steps of changes based on some rules and principles. What makes this algorithm different is developing such regulations inspiring humpback whale's problem-solving techniques when hunting. The primary mechanism implemented in WOA is the bubble net trap that humpback whales use during foraging.

The main equation given in the algorithm is stated in Eq. (1) and (2).

$$X(t+1) = X^*(t) - A \cdot D; p < 0.5 \quad (1)$$

$$X(t+1) = D' e^{bl} \cos(2\pi t) + X^*(t); p \geq 0.5 \quad (2)$$

where X - position, t - current iteration, D - distance, p - number in $[0, 1]$ as random, A is coefficient vector, X^* - position vector of the best solution and $'\cdot'$ - element by element multiplication.

" $D' = |X^*(t) - X(t)|$ " is the distance of the $'i'$ th whale the prey, $'b'$ - constant for defining the state of the logarithmic spiral and $'l'$ is a number in between -1 and 1 , $D = |CX^*(t) - X(t)|$, C is coefficient vector. $A = 2ar$, $C = 2r$, a decreases from 2 to 0 and r is the vector in between 0 and 1 . A and C are coefficient vectors. This condition permits exchanging between two systems: surrounding preys and twisting bubble net techniques, as demonstrated in Fig. 2.

The algorithm impersonates two stages, such as the exploitation stage and exploration stage. The exploitation stage is circling a prey and spiral bubble net assaulting technique, and the exploration stage is looking arbitrarily for prey. They are both guaranteed in WOA by adaptively tuning the boundaries $'a'$ and $'c'$ in the key condition.

To guarantee investigation and mix, the best plan is the defining moment to refresh the circumstance of different chases specialists when $|X| > 1$. In different conditions, similar to when $|X| < 1$, the best arrangement procured so far accepts the work of the defining moment. The mathematical representation, as found in Eqs. (3) and (4).

$$D = |Cx_{rand} - x| \quad (3)$$

$$x(t+1) = x_{rand} - AD \quad (4)$$

The WOA is very competitive algorithm for solving critical optimization problems compared to existing optimization algorithms. The advantages are: balanced exploitation and exploration stages, lack of gradient, stochastic nature [15]- these motivated attempts to use WOA to train the DL network. Speculatively, WOA should have the choice to train CNN with appropriate objective function.

4. Methodology

The ResNet-50 is one of the DL models, and it has a unique feature extraction of the input image for image classification. The ResNet-50 feature extraction is done by several convolutional and pooling layers. A fully connected and soft-max layer does the classification. The weight and bias values of convolutional and fully commenced layers are tuned using the training algorithm. This training algorithm includes many

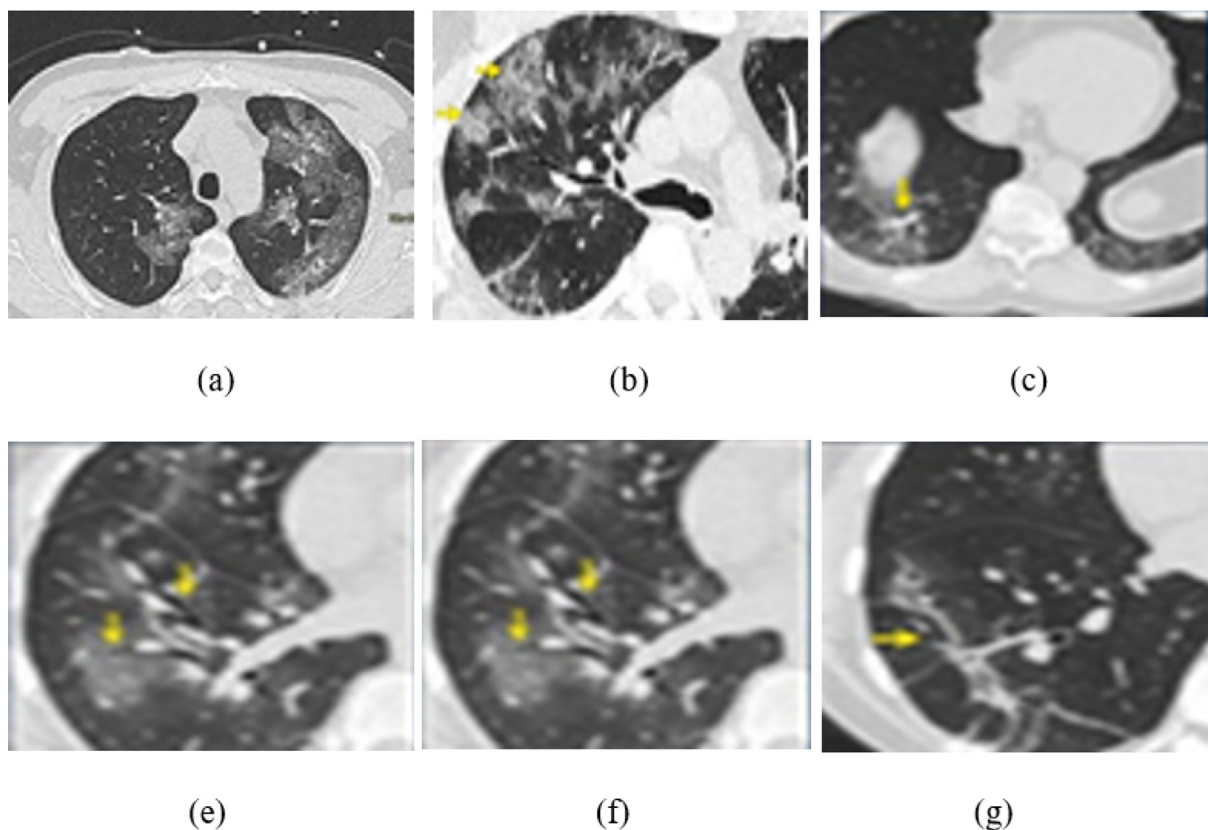


Fig. 4 – (a) GGO of a young COVID positive male; (b) crazy paving also with GGO; (c) widening of vessels under GGO; (d) VD under GGO; (e) TB in the area of GGO.

hyperparameters, which helps to improve the performance of the ResNet-50 model. These parameters are training algorithm, momentum learning, batch size, epoch, and validation frequency. This work presents to optimize these hyperparameters for training the ResNet-50 model to get optimum performance. Testing these hyperparameters is a time-consuming task; hence WOA is proposed in this model to optimize the hyperparameters of ResNet-50 for training the network. Therefore this proposed architecture has been named as WOANet. Fig. 3 shows the architecture of WOANet.

4.1. ResNet-50 network

ResNet-50 is a pre-trained DL network. It's a subclass of CNN, and ResNet-50 is most predominantly used for image classification problems[37]. The advantage of ResNet-50 is the skipping connection of one layer to another. This will help to reduce the overall computational time of the network. It consists of 5 stages, each with convolution and pooling layers, and it has over 23 million trainable parameters[38]. In this work, the ResNet-50 network has been used for both feature extraction and classification. The features extraction has been performed using the convolutional and pooling layers. The classification has been performed using a fully connected and soft-max layer. The ResNet-50 has been trained by optimizing the hyperparameters of the network using WOA.

4.2. Hyperparameter optimization using WOA

The hyperparameter plays an important role in increasing the performance of the DL network. The WOA is used in this work to optimize the hyperparameter of ResNet-50 while training the network. The optimized training procedure is explained in the further steps.

- Step 1: Initialization: created a set of random solutions is generated. The ResNet-50 network configuration for each solution is randomly generated.
- Step 2: Fitness evaluation: Each ResNet-50 network is evaluated using an objective function. The training hyperparameters values of the DL network are automatically updated using WOA, and the fitness function selected for this work is the error rate.

Table 1 – Training Options using WOA.

Training Algorithm	SGDM
Momentum Learning	0.07
Initial Epoch	0.0836
Maximum Batch size	10
Minimum Frequency	32
Validation	30

Table 2 – Experimental results of WOANet.

Accuracy	Sensitivity	Specificity	Precision	F1 Score
98.78	98.37	99.19	99.18	98.37

Step 3: A new set of solutions is created based on the objective value of each solution and WOA's mechanisms.
 Step 4: Stages 2 to 3 are rehashed until the most extreme number of the epoch is reached.

Algorithm 1 presents the pseudocodes of the proposed WOANet for the detection of COVID-19 patients.

Algorithm 1: Pseudo code of Whale Optimized Deep Learning Network

Require: Batch size m , no. of search agents n , dimension k , number of iterations t , hyper parameters α, β, γ , hyper parameter evaluation function.

Initialize: The whales population $Xi(i = 1, 2, 3, \dots, n)$
 Initialize a, A , and C
 Deep Learning Network Parameters: w & b

```

for number of iterations,  $t$ 
    Sample a batch of training data,  $\sum_{i=1}^m \{D^i\}$ 
    Calculate the fitness of each search agent
     $X^*$  = the best search agent
    for each search agent,  $n$ , do
        if  $|A| \leq 1$  then
            Update the position of the current search agent by the equation 1
        else if  $|A| \geq 1$  then
            Select a random search agent  $X_{rand}$  and
            Update the position of the current agent by the equation 3
        end if
    end for
    Update  $a, A$ , and  $C$ 
    Update  $X^*$  if there is a better solution
     $(\alpha, \beta, \gamma) = \text{hyper parameter evaluation function}(X^*)$ 
     $w$  &  $b \leftarrow \text{sgdm}(\alpha, \beta, \gamma)$ 
end procedure
    
```

5.2. Clinical description of CT images in COVID-19 scenario

Recent studies suggested changes in the features of the chest using CT scan follow-up. Some of the chest radiograph findings are Ground Glass Opacity (GGO), Crazy Paving, Vascular Dilation (VD), Traction Bronchiectasis (TB), Subpleural bands, and Architectural distortion, and CT halo sign. Pleural effusion, lymphadenopathy, pericardial effusion, pneumothorax, and cavitation are other imaging patterns seen as the disease's progression. GGO is bilateral, multifocal, and commonly located in the inferior lobe of the right lung. Fig. 4 (a) shows the GGO of a young COVID-19 positive male, having fever for ten days with progressive shortness of breath and cough. Crazy Paving is the widened intralobular and interlobular lines besides GGO. This imaging pattern is seen at the later stage of COVID-19. In Fig. 4(b), yellow arrows show the Crazy Paving also with GGO. VD is the thickened vessels

5. Results

This section presents the dataset used in this study, implementation details, experiments, and the obtained results.

5.1. Dataset and Implementation details

The CT images are collected from a publicly available GitHub repository, namely COVID-CT (<https://github.com/UCSD-AI4H/COVID-CT>) dataset. There are 2460 images are collected from the COVID-CT dataset, out of which 1230 images per subject. Then 2214 images were used for training, and 246 images were used for testing in both subjects. The proposed algorithm is implemented in MATLAB 2020a and executed Windows 10, 64 GB RAM Nvidia GPU, 64 GB RAM computer.

under the GGO (shown in Figure (b)). Fig. 4(c) shows the VD under GGO using a yellow arrow. TB is defined as irreversible dilation of bronchioles in the area of GGO. It is the new biomarker of the infected patient found at the later stage of the disease. Fig. 4 (d) shows the TB in the area of GGO using yellow arrows.

5.3. Training

The ResNet-50 CNN network has been used to diagnose the COVID-19 through CT images. There are 350 COVID-19 and 350 Non-COVID-19 images were used for training. The proposed architecture classifies the image in either of the two categories: Non- COVID-19 and COVID-19, and the images are resized to $224 \times 224 \times 3$. ResNet-50 architecture is used

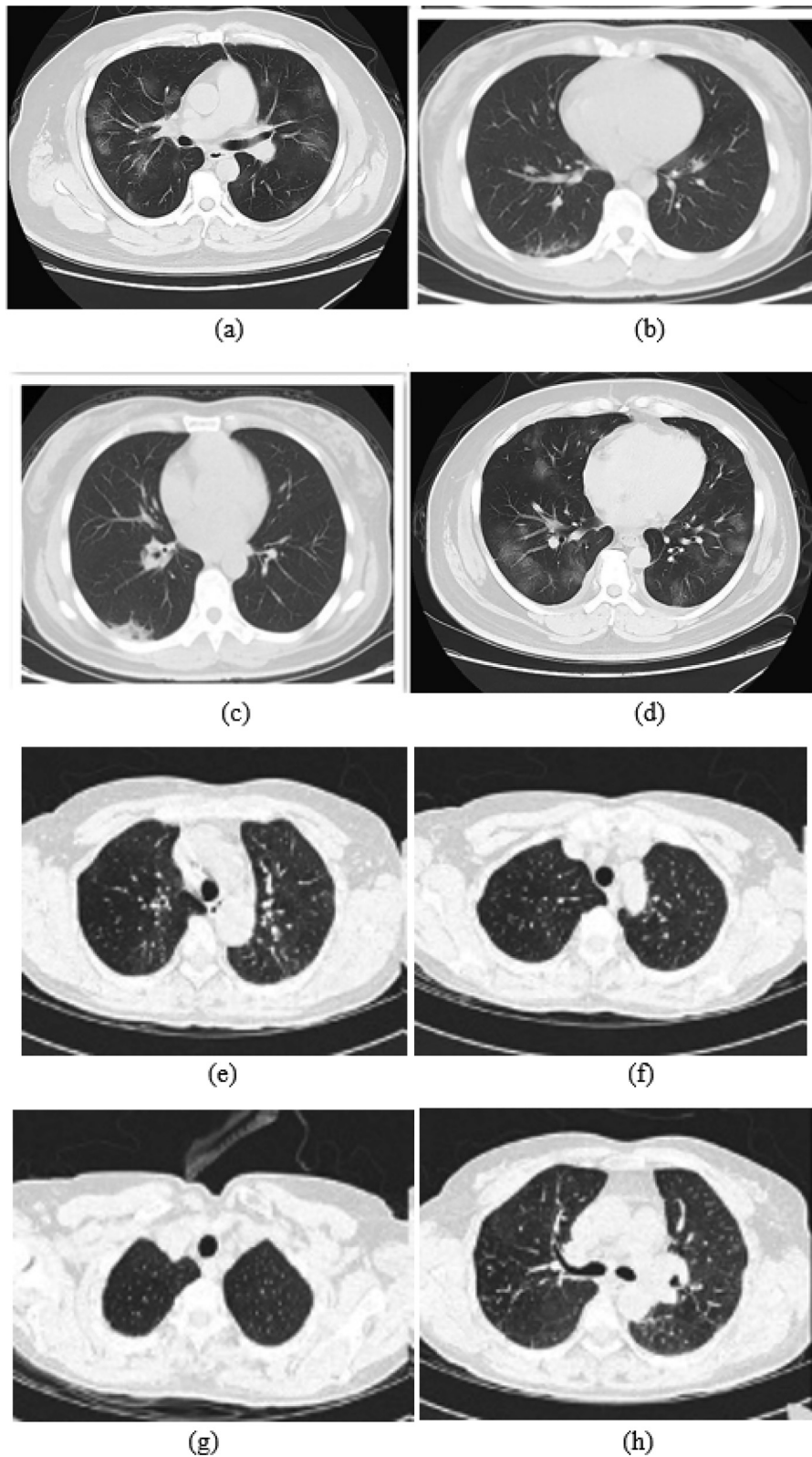


Fig. 5 – Sample training images; (a-d) COVID-19; (e-h) Non-COVID-19 [<https://github.com/UCSD-AI4H/COVID-CT>].

for the classification of the image, and parameters are tuned using Scholastic Gradient Descent with Momentum (SGDM) training, whose parameters are optimized using WOA at the

time of training. The values of training parameters using WOA optimization are presented in Table 1,2, and the training image samples are shown in Fig. 5.

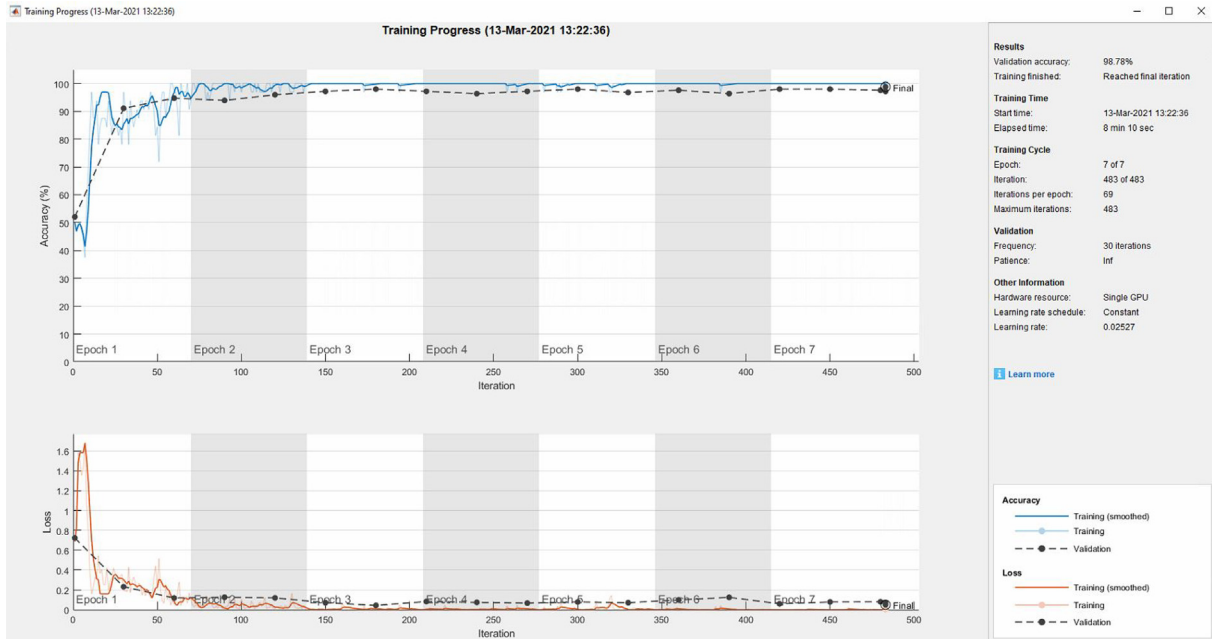


Fig. 6 – Training progress of WOANet.

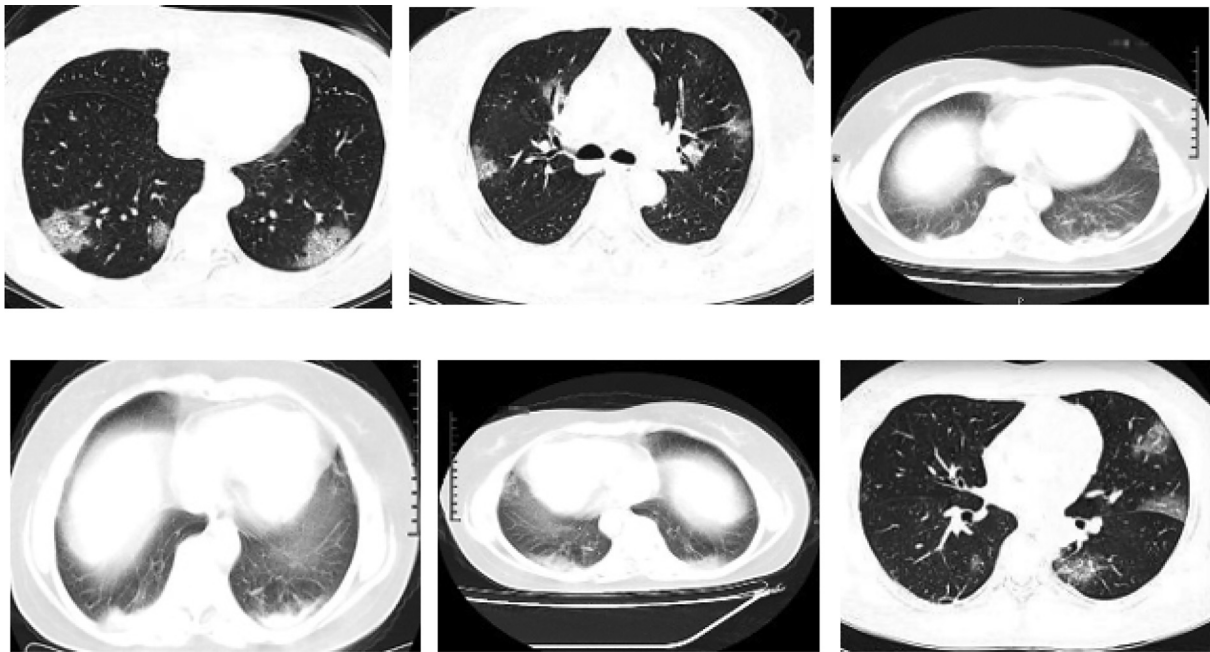


Fig. 7 – Sample testing COVID-19 images [https://github.com/UCSD-AI4H/COVID-CT].

5.4. Training progress

In this work, WOA is used to choose the training parameters of the ResNet-50 to achieve maximum accuracy. The proposed network has achieved the best accuracy and less loss in all the iterations (epochs). The training progress is shown in Fig. 6.

5.5. Testing

The resized $224 \times 224 \times 3$ images are used to test the network. After that, this image is given to a trained, WOA based ResNet-50 pre-trained network. The ResNet-50 first automatically extracts the features from the image and then classifies them into an appropriate class using Fully Connected Layer

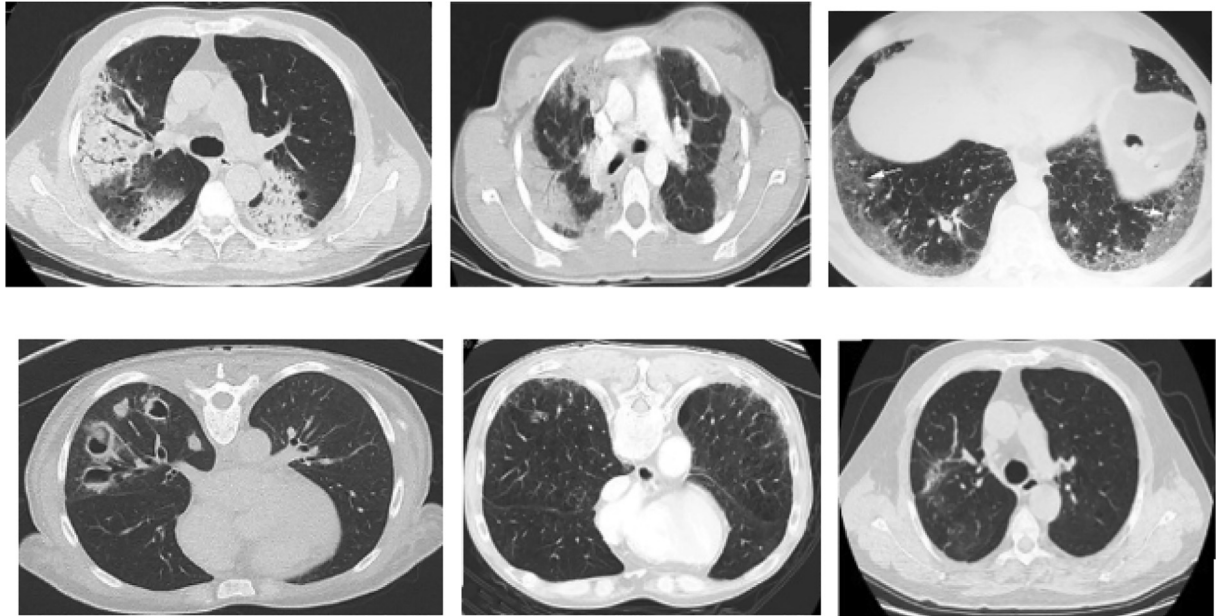
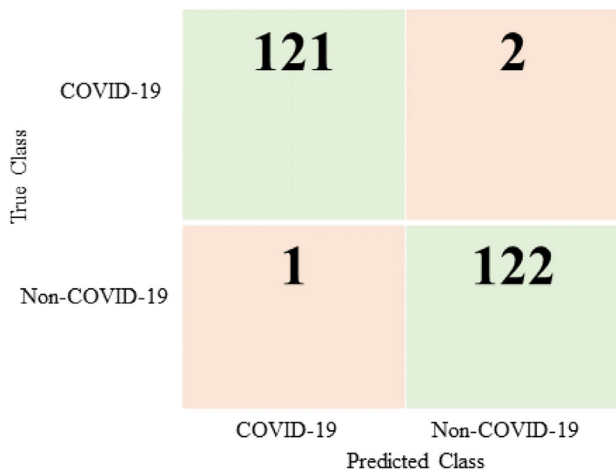


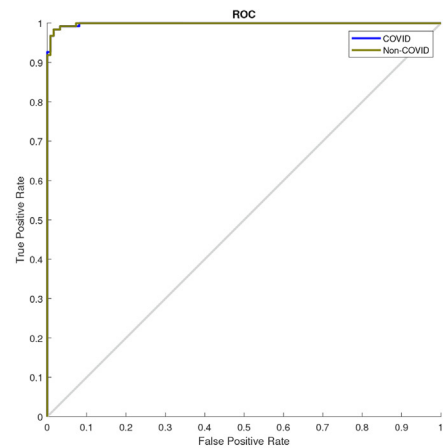
Fig. 8 – Sample testing Non-COVID-19 images[https://github.com/UCSD-AI4H/COVID-CT].

Table 3 – Experimental results of the Proposed Network Model.

Method	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Optimized AlexNet[40]	93.90	98.37	89.93	90.30	94.16
Optimized GoogleNet[41]	95.12	93.68	97.56	97.44	95.00
Optimized SqueezeNet[42]	91.87	94.31	89.43	89.92	92.06
Optimized VGG19[43]	96.34	95.93	96.75	96.72	96.33
Non-optimized ResNet-50[44]	90.65	91.06	90.24	90.32	90.69
Optimized ResNet-50(WOANet)	98.78	98.37	99.19	99.18	98.37



(a)



(b)

Fig. 9 – Results of proposed WOANet; (a) CM; (b) ROC.

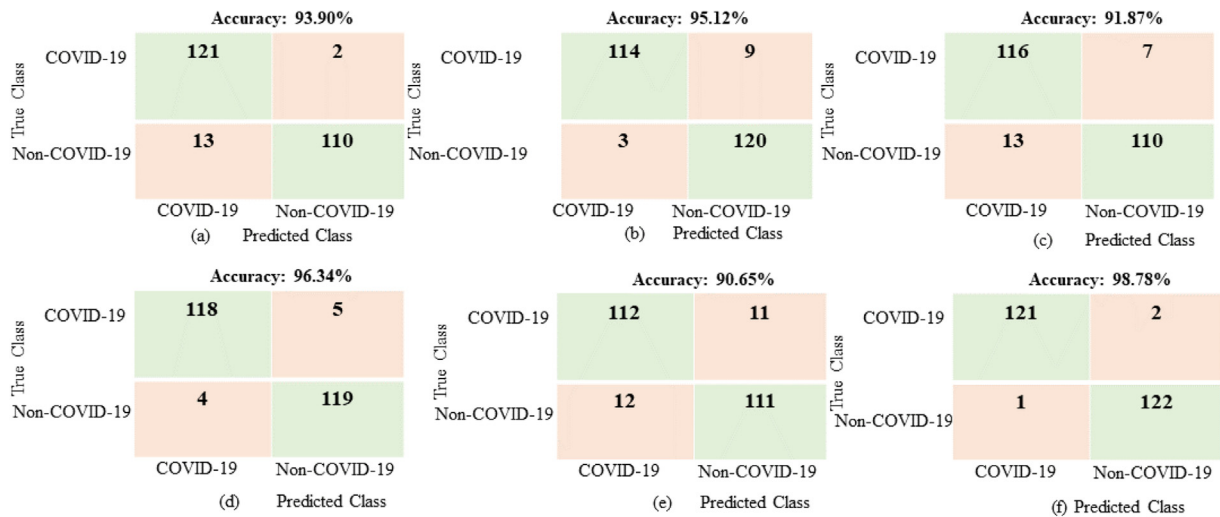


Fig. 10 – CM of: (a) Optimized AlexNet; (b) Optimized GoogleNet; (c) Optimized SqueezeNet; (d) Optimized VGG; (e) Non-optimized ResNet-50; (f) Optimized ResNet-50(WOANet).

(FCL) and soft-max classifier. The sample images of testing are given in Figs. 7 and 8.

The proposed WOANet architecture effectively classifies the COVID-19 or Non-COVID-19 CT images. The architecture also takes very less time for classification, is about 5 s per image. The experimental result of the WOANet is presented in Table 3.

The CM and ROC bend are appeared in Figs. 9 (a) and (b) have been created for the proposed technique to investigate the adequacy of the classification. With the use of the proposed technique in 246 CT images, 98.37% have classified the class of COVID-19, 99.18% were classified the class of Non-COVID-19. The highlight of the proposed classification method is that it produced fewer incorrect classifications in COVID-19 images because of optimized hyperparameter selection; hence, this network will be used for automatic and early detection of COVID-19. This proposed WOANet will substantially help the radiologists overcome the load on the medical system and hospitals.

6. Discussion

The experiment has been conducted to prove the efficiency of the proposed WOANet architecture for diagnosing COVID-19 images using different optimization algorithms and pre-trained DL models. This section presents the performance metrics, experimental results, and discussion in detail.

6.1. Performance metrics

The performance of the proposed technique has to utilize the metrics of accuracy, sensitivity, specificity, precision, F1 Score values, Confusion matrices (CM), and Receiver Operating Characteristic (ROC) to verify the effectiveness of the result [39].

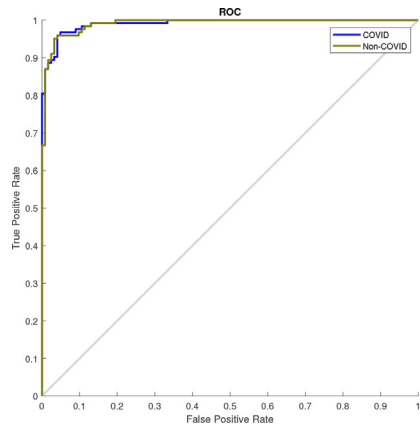
6.2. Performance analysis

The confusion matrix has been generated for WOA optimized benchmark pre-trained models, such as AlexNet[40], GoogleNet[41], SqueezeNet[42], VGG19[43] and ResNet-50[44] and also non-optimized ResNet-50 model (shown in Fig. 10). It is seen that the proposed WOA-based ResNet-50 model performs well than other models. Fig. 11 shows the obtained ROC of the proposed WOANet and other optimized pre-trained models and non-optimized ResNet-50 model. It shows that the WOANet achieves phenomenal results as differentiated and the other models.

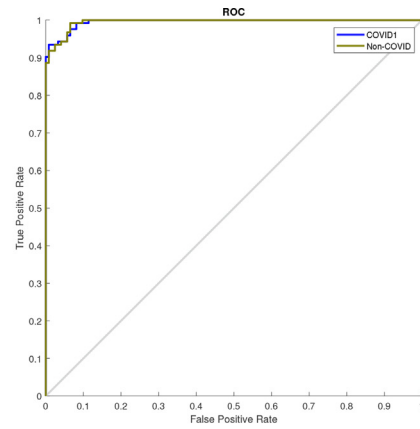
The proposed method performance measures such as Accuracy, Sensitivity, Specificity, Precision, and F1 Score have been compared with other optimized pre-trained networks such as AlexNet, GoogleNet, SqueezeNet, VGG19, and non-optimized ResNet-50 with WOANet. Table 4 shows the analysis of the performance metrics between the proposed and other optimized and non-optimized pre-trained models. It shows that the proposed WOANet accomplishes significant results than other models. Additionally, an experiment has been conducted with other optimization algorithms such as genetic algorithm[45], pattern search[46], simulated annealing[47], particle swarm optimization[48], Grey Wolf Optimization[49] to prove the effectiveness of the proposed architecture. Table 5 shows the performance metrics of the different optimization algorithms. It shows that the proposed WOA has been yielded the best metrics than other algorithms.

6.3. Comparative analysis

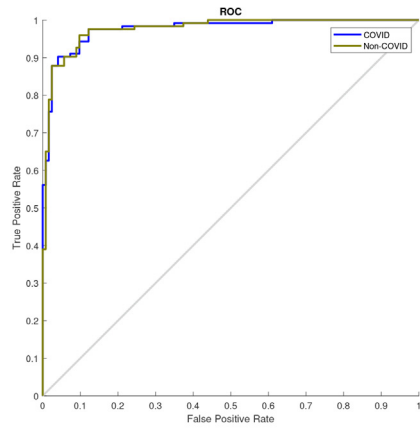
The comparative analysis has been presented in this subsection with the proposed WOANet architecture. A discussion and remarks have been given at the end of this subsection as well.



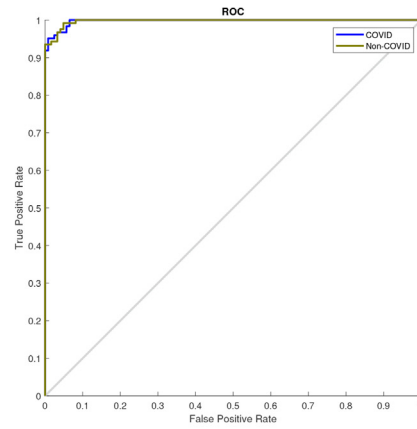
(a)



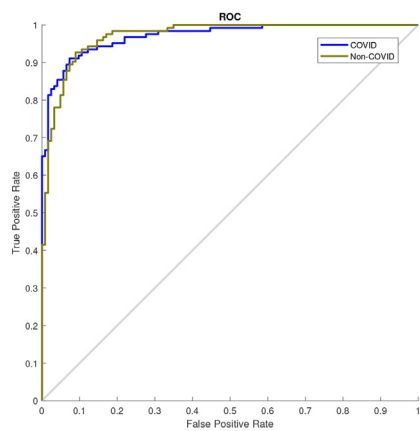
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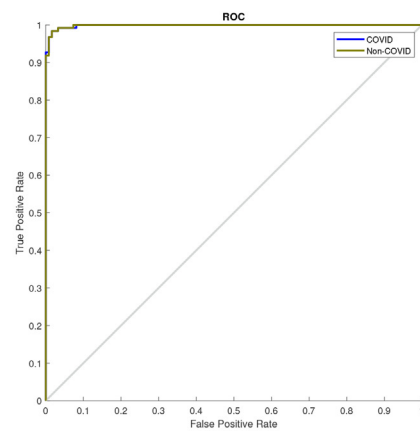
(c)



(d)



(e)



(f)

Fig. 11 – ROC of: (a) Optimized AlexNet; (b) Optimized GoogleNet; (c) Optimized SqueezeNet; (d) Optimized VGG; (e) Non-optimized ResNet-50; (f) Optimized ResNet-50(WOANet).

Table 4 – Experimental results with different optimization techniques.

Method	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Without optimization	90.65	91.06	90.24	90.32	90.60
Genetic Algorithm[45]	92.28	91.06	93.50	93.33	92.18
Pattern search[46]	93.09	89.43	96.75	96.49	92.83
simulated annealing[47]	93.90	90.24	97.56	97.37	93.67
Particle Swarm Optimization[48]	94.31	94.31	94.31	94.31	94.31
Grey Wolf Optimization[49]	96.15	95.93	98.37	98.33	97.12
Proposed WOA	98.78	98.37	99.19	99.18	98.37

Table 5 – Comparison of the results with state-of-the-art pre-trained deep learning networks with CT images

DL model	No.of images	Accuracy(%)	Sensitivity(%)	Specificity(%)	Precision(%)	F1 score(%)
DRE-Net[17]	274	86	96	-	79	87
CNN + ResNet18[25]	618	-	86.7	-	81.3	83.9
ResNet50[35]	1215	97.77	97.14	-	97.14	-
CNN + ResNet-50[52]	1010	-	83	-	-	-
DL Multitask[53]	1369	86	94	79	-	-
CNN + SqueezeNet[54]	757	83	85	81	81.73	83.33
DL model[55]	19291	95	100	-	-	97
ResNet-50[56]	157	-	98.2	92.2	-	-
DenseNet201[57]	2492	96.25	96.21	96.29	-	96.29
UNet + BER algorithm[58]	24	-	95	84	-	-
ShuffleNetV2[59]	1042	91.21	90.52	91.58	-	-
ResNet-50 + 2D CNN[61]	852	93.02	91.46	94.78	95.19	-
DenseNet121[62]	1137	90.8	84	93	-	-
EfficientNetB4[63]	1186	96	95	96	-	-
DeCoVNet[66]	499	-	90.7	91.1	-	-
CovNet[68]	4352	-	90	96	-	-
ResNet34[69]	303	-	-	-	81.3	-
Covid19Net[70]	5372	85	79.35	71.43	-	90.11
UNet++[71]	1136	-	97.4	92.2	-	-
Residual attention U-Net[27]	410	89	-	-	95	-
Proposed WOANet	2700	98.78	98.37	99.19	99.18	98.37

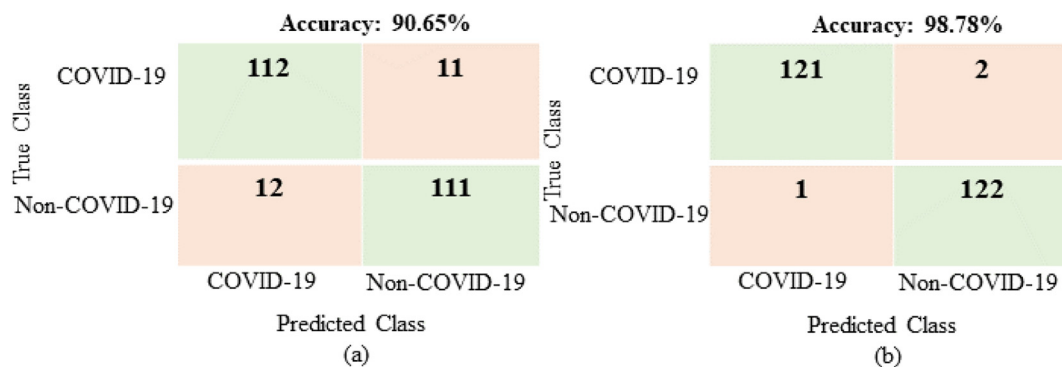


Fig. 12 – CM for the: (a) Nonoptimized ResNet-50; (b) Optimized ResNet-50.

6.3.1. Comparison with nonoptimized ResNet-50

A comparative analysis has been made between the proposed optimized and nonoptimized ResNet-50 in the performance metrics of CM and ROC, which is presented in Figs. 12 and

13. From this performance analysis, the proposed WOANet produced better accuracy than the nonoptimized ResNet-50 architecture.

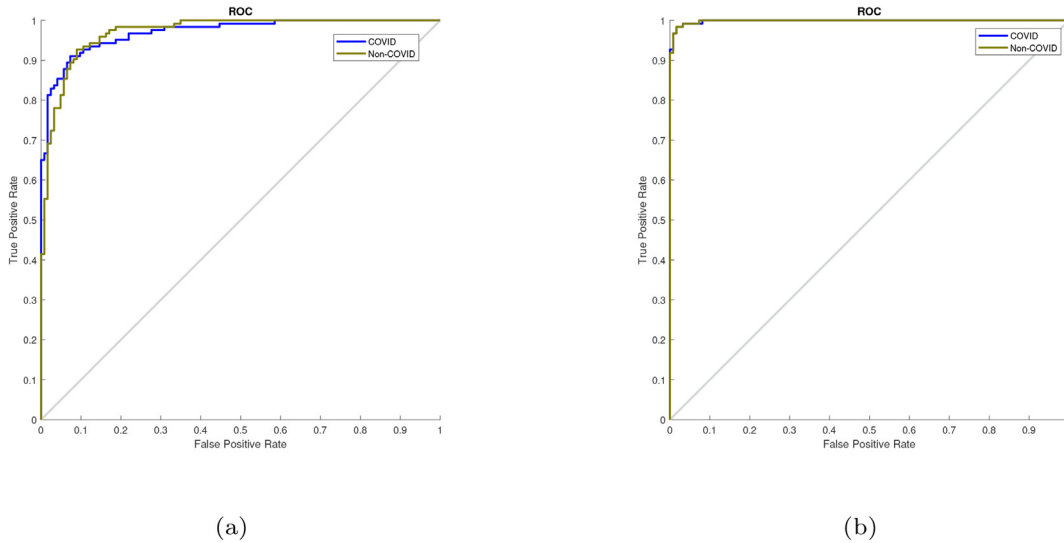


Fig. 13 – ROC for the: (a) Nonoptimized ResNet-50; (b) Optimized ResNet-50.

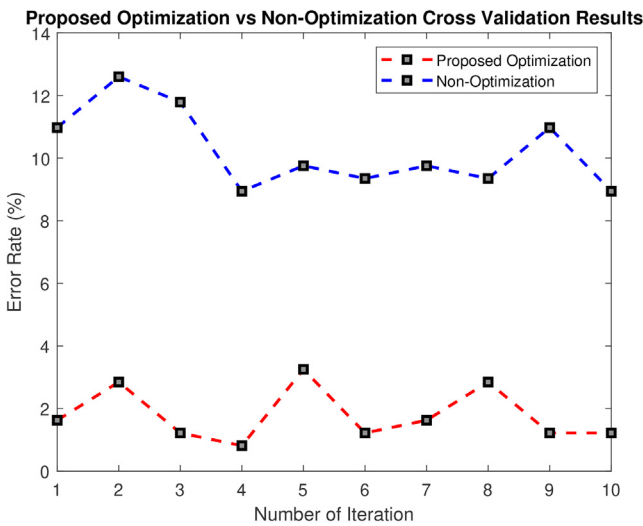


Fig. 14 – Comparison with cross-validation.

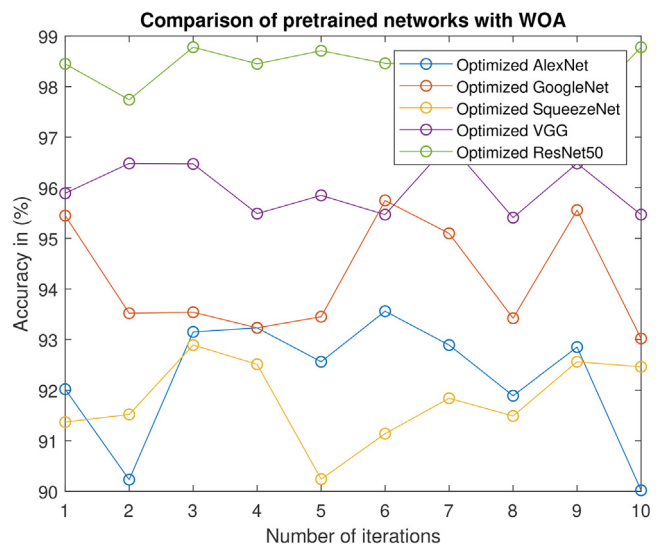


Fig. 15 – Comparison of WOA optimized pre-trained networks with cross-validation.

6.3.2. Comparison using cross-validation

Cross-Validation (CV) is a re-sampling method used to evaluate the proposed model with limited sample size. This subsection compares nonoptimized and optimized pre-trained networks with 10-fold CV to generalize the proposed WOANet. The CV has been performed between iterations and the error rate for nonoptimized and optimized models. The corresponding results have presented in Fig. 14. The proposed optimized model has yielded less error rate than the nonoptimized model. Although the CV has been performed between the number of iterations and the accuracy of different pre-trained models and the corresponding result shown in Fig. 15, it shows that the proposed optimized ResNet50 (WOANet) produced the best results networks in all the iterations. In addition, the overall accuracy has been analyzed using 10-fold CV for the proposed optimized and nonopti-

mized ResNet-50 models in the performance metrics of CM, which is presented in Figs. 16. The proposed WOANet produced better accuracy (98.37%) than the nonoptimized ResNet-50 architecture accuracy(89.83%).

6.3.3. Comparison with grid search optimization

Grid Search Strategy (GSS) is one of the efficient optimization techniques for hyperparameter tuning in most of the DL models[50]. Furthermore, GSS is widely used for many medical image classification problems[51]. The comparative analysis has been performed with GSS to prove the efficiency of the proposed WOA, which is presented in Fig. 17. It depicts that the proposed WOA based network yielded less error rate concerning the percentage of training images than GSS.

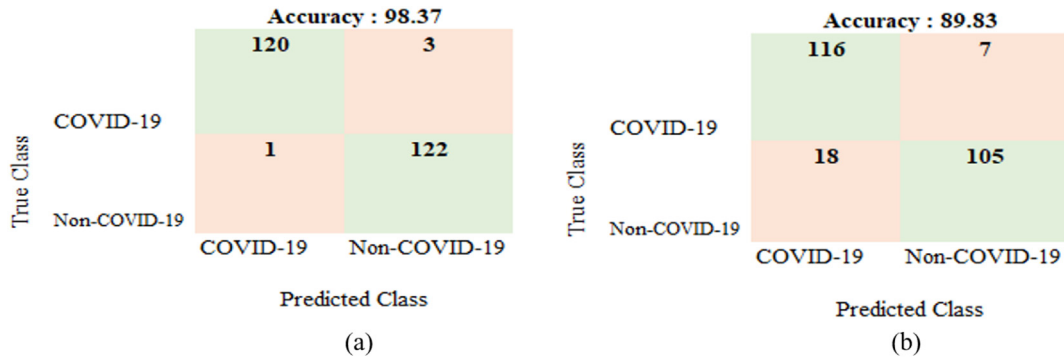


Fig. 16 – CM for the: (a) Nonoptimized ResNet-50; (b) Optimized ResNet-50.

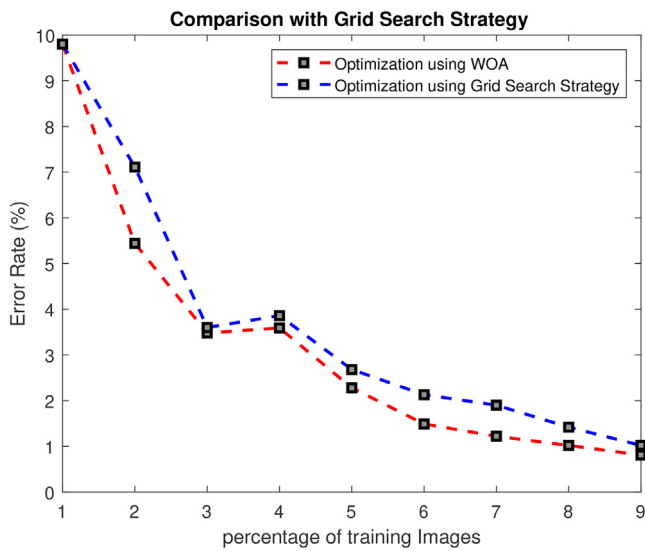


Fig. 17 – Comparison of WOA with GSS.

6.3.4. Comparisons of the results with other DL models

Tables 5 and 6 have investigated our proposed WOANet with state-of-the-art DL networks and CNN networks, respectively, for COVID-19 diagnosis. As shown in Table 5, we have analyzed 2700 CT images, 900 COVID, 900 Pneumonia, and 900 normal, that are available as open-source with the highest

accuracy, specificity, sensitivity, precision, recall, and F1 score. The DRE-Net proposed by Song et al.[52] has produced only 86% of accuracy and the total number of images used for their experiment is very less. The author Xu et al.[25] used an ensemble network which includes CNN and ResNet-50 model, and the achieved accuracy is very less than the other methods. The DL multi-task network proposed by Amyar et al. [53] has also produced less accuracy. Another ensemble network which includes CNN and SqueezeNet, has been proposed by Polsinelli et al.[54] yields less accuracy.

Comparable datasets are used by Wang et al.[50] who investigated 924 COVID images using two DL networks: DenseNet121 for segmentation and COVID-19Net for classification. The use of two DL networks increases the computational complexity with 85% accuracy. The DL model proposed by Ni et al.[55] achieved reasonably good accuracy and sensitivity, but the number of images tested in the experiment also large number but the computation cost if this method is too high. The ResNet-50 networks have been tested by Gozes et al.[56] for COVID-19 diagnosis; this method did not report the accuracy rather achieved reasonably good sensitivity and specificity. The DenseNet21 network has been used by Jaiswal et al.[57] achieved better accuracy but than ours.

Another combination of CNN and ResNet-50 has been proposed by Song et al.[17] used 1010 images and reported 83% of sensitivity. The DeConvNet architecture has been proposed by Zhang et al.[14] for testing COVID-19 from the normal cases.

Table 6 – Comparison of the results with state-of-the-art CNN with CT images

DL model	No.of images	Accuracy(%)	Sensitivity(%)	Specificity(%)	Precision(%)	F1 score(%)
CNN[28]	134	98	-	-	-	-
Multi-CNN[29]	12174	95.57	-	-	-	-
Multi-CNN[30]	502	97.44	-	-	-	-
CNN[31]	142	96.78	98.66	98.46	-	-
CNN[32]	682	93.2	96.1	-	-	-
CNN[33]	500	-	78	82	-	-
CNN[36]	2339	99.81	-	-	-	-
CNN[60]	1125	94.98	94.06	95.47	-	-
CNN[67]	1065	82.9	-	-	-	-
CNN[72]	806	90	90	90	-	-
Proposed WOANet	2700	98.78	98.37	99.19	99.18	98.37

This architecture has been produced very less sensitivity and specificity. Again the ResNet 50 network has been used by Jain et al. [35], this method reported good performance metrics but less than ours. The U-Net architecture has been tested by Pu et al. [58] has shown a marginally good detection rate, but this method has tested very few COVID-19 images, and it fails to prove the efficiency of this method.

The pre-trained network ShuffleNetV2 has been experimented with by Hu et al. [59] has tested a good amount of COVID-19 images, but the accuracy is less than ours. The U-Net++ architecture has been used by Jin et al. [60], this method fails to report the accuracy. Pathak et al. [61] proposed a combination of two networks such as ResNet = 50 and 2D-CNN, but the number of images used for testing is very less by this method. The pre-trained networks DenseNet121 has used by Harmon et al. [62] and EfficientNetB4 proposed by Nai et al. [63] reported less performance metrics than proposed by us. Another large dataset examined by Li et al. [64] used 1296 COVID images and proposed a 3D DL network for COVID diagnosis. But, the hardware requirement for training a 3D DL network is expensive with less performance than the proposed model.

The ResNet34 model has been used by Xia et al. [6], this method fails to prove the performance metrics other than precision. The residual attention U-Net architecture has been proposed by Chen et al. [65], this method produced the detection rate is the only 89%. The 30 layers CNN network is called "CovNet30" has been proposed by Goes et al. [56], this method has been tested a good amount of images, but the accuracy is 92.11, which is less than ours. The method [52] tested data are low resolution, so extracting the feature sign is quite difficult in COVID-19 images. The method [55] achieved 100% sensitivity, but the specificity value is very less, and this method is not suitable for real-time diagnosis. The methods [64,25,66] exhibited more imaging artifacts while acquiring the images. The methods [67,52,58] has obtained only few performance metrics and it these methods fails to prove the efficiency of the methods.

The proposed approach's main advantage is that no fine-tuning has required for various databases. The proposed method can successfully classify the images of any database without tuning parameters. By and large, the proposed approach yielded the best performance metrics than other cutting-edge techniques.

Table 6 shows the comparative analysis of our proposed WOANet with state-of-the-art CNN networks. The methods [28,31],32,33,60,67,72 used the CNN networks for classifying COVID-19 images into others. All these methods are produced reasonably good accuracy but less than the proposed WoANet. Qi et al. [29] [28] proposed multi-features CNN networks to examine 12174 X-ray images to give 95.57% accuracy. First, the images are enhanced using a local phase-based enhancement technique, and then a CNN network is proposed for COVID diagnosis. In our proposed model, there is no need for image enhancement which decreases the computational complexity and saves time. Another comparable dataset is used by Joshi et al. [36], who use transfer learning to extract the features of the input X-ray images from the DarkNet53 pre-trained network. In comparison to this, we proposed a

WOANet DL network whose hyperparameters are optimized as per chest CT images to give the maximum accuracy.

Over the globe, millions of people have been infected by COVID-19; therefore, an efficient and effective diagnosis tool is required urgently. The proposed WOANet architecture can diagnose either COVID-19 or normal through CT scan images. The proposed WOANet has trained and tested a large number of CT scan images. It provides a 98.78% of accuracy, which is the best one than other methods. The proposed optimized network has been compared with different optimization algorithms and pre-trained networks to show its efficiency. This method can directly be used to diagnose the COVID-19 in hospitals without the need for any trained radiologists. It also helps to diagnose the patients quickly. Finally, the proposed WOANet avoided the overfitting issues and proposed the best results than other recent methods.

7. Conclusions and future work

This paper presented an optimized deep learning network for diagnosing COVID-19 from CT scan images. The WOA was employed to optimize the hyperparameters of the ResNet-50 DL network in training. Using hyperparameters optimization for training the DL network improved the accuracy, sensitivity, specificity, precision, and F1-score. The proposed model has tested more CT scan images, including COVID-19 and Non-COVID-19 cases. A comparison of the proposed optimized DL framework with different optimization and different pre-trained networks was conducted as well. It was observed that in the proposed method, there is no need for pre-processing and ROI extraction. The network takes a raw input image and extracts the features using several convolutional and pooling layers. Therefore, the proposed model can alleviate the burden of radiologists for automatically identifying the infected individual within a couple of seconds. In the future, the 3D CT scan images using a 3D convolutional neural network will help further improve the accuracy of diagnosis.

CRedit authorship contribution statement

R Murugan: Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Tripti Goel:** Conceptualization, Methodology, Software, Validation, Writing - review & editing. **Syedali Mirjalili:** Visualization, Investigation, Writing - review & editing. **Deba Kumar Chakrabarty:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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