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Research article

CNGOD-An improved convolution neural network with grasshopper optimization for detection of COVID-19

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Abstract: The world is facing the pandemic situation due to a beta corona virus named Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). The disease caused by this virus known as Corona Virus Disease 2019 (COVID-19) has affected the entire world. The current diagnosis methods are laboratory based and require specialized testing kits for performing the test. Therefore, to overcome the limitations of testing kits a diagnosis method from chest X-ray images is proposed in this paper. Chest X-ray images can be easily obtained by X-ray machines that are readily available at medical centres. The radiological examinations augmented with chest X-ray images is an effective way of disease diagnosis. The automated analysis of the chest X-ray images requires a highly efficient method for identifying COVID-19 from these images. Thus, a novel deep convolution neural network (CNN) optimized using Grasshopper Optimization Algorithm (GOA) is proposed. The deep learning model comprises depth wise separable convolutions that independently look at cross channel and spatial correlations. The optimization of deep learning models is a complex task due the multiple layers and their non-linearities. In image classification problems optimizers like Adam, SGD etc. get stuck in local minima. Thus, in this paper a metaheuristic optimization algorithm is used to optimize the network. Grasshoper Optimization Algorithm (GOA) is a metaheuristic algorithm that mimics the behaviour of grasshoppers for food search. This algorithm is a fast converging and is capable of exploration and exploitation of large search spaces. Maximum Probability Based Cross Entropy Loss (MPCE) loss function is used as it minimizes the back propogation error of cross entropy and improves the training. The experimental results show that the

proposed method gives high classification accuracy. The interpretation of results is augmented with class activation maps. Grad-CAM visualization algorithm is used for class activation maps.

Keywords: COVID-19; diagnosis; deep learning; machine learning; Grasshopper Optimization

1. Introduction

The world is currently facing a serious threat to human life due to the novel corona virus disease (COVID-19). The disease was reported in the month of December in 2019 and originated from Wuhan City, China. The disease spreads from human to human through respiratory droplets, physical contact and through fecal-oral transmission [1]. The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) causes COVID-19 [2]. The pandemic has affected the populations and healthcare systems globally. The entire world is still working towards developing methods to cope up with the current situation. The diagnosis of the disease has become a real challenge as patients without any symptoms also act as carriers of the disease. Multiple advances are coming up in the lab-based testing techniques as testing for COVID-19 is a significant and immediate step towards the control of the disease [3]. It is important to have highly accurate tests. Any false negative will be threat to the society and may lead to increased spread of the disease. Any individual who are incorrectly identified as negative despite of being positive may relax social distancing and other safety measures. This may lead to a cluster of new cases who come in direct or indirect contact with such individuals. Since the lab-based testing is constrained by the testing kits thus some other diagnosis methods are required. The use of computer tomography (CT) images and X-ray images have emerged as a solution to these problems. The automated analysis of these images using machine learning methods can help doctors in diagnosis of COVID-19. As COVID-19 has resemblance with pneumonia it can be observed in chest X-ray images.

Machine learning based methods have become quite popular in various fields like manufacturing, healthcare and many advanced algorithms are developed by different researchers. The use of computer vision and deep learning in medical diagnosis is popular amongst researchers as well as healthcare professionals [4]. There are multiple automated methods for diagnosis of diseases using deep learning-based methods [5]. Diseases like tumor types, cancer of various kinds [6], diabetic retinopathy [7] and other skin diseases can be diagnosed using automated methods. The use of similar methods for the diagnosis of COVID-19 has proved to be beneficial in improving the diagnosis capability of health centres. Many researchers have used deep learning and computer vision for automated diagnosis methods [8]. In a recent publication, a deep CNN called Decompose, Transform and Compose (DeTrac) network is proposed. The network is tuned to classify chest X-ray images as COVID-19 and non-COVID-19 classes. The method was applied to a dataset consisting of chest X-ray images of covid infected and normal patients [9]. DarkCovidNet performs binary as well as multiclass classification for COVID-19 from chest X-ray images [10]. The network was used to train the “you look only once” (YOLO) object detection system. Singh et al. (2020) presented an inception net model utilizing depth-wise convolutions for multiclass classification of chest X-ray images [8]. The authors classified the chest X-ray images into three classes namely normal, COVID-19 and Pneumonia images. This method had improved accuracy due to the use of depth-wise convolutions. The significance of accuracy in case of COVID-19 is crucial thus more accurate methods are required for diagnosis. The deep convolution networks are often limited in performance as they get stuck in local optima problem. These networks are trained by optimizing a loss function using an optimizer. Multiple loss functions are used by neural networks based on softmax activation functions. These loss functions include Mean Square Error (MSE), Cross Entropy (CE) and so on. But the limitation of MSE is that its gradient disappears when softmax is utilized. CE suffers from back propogation error but has fast convergence. Therefore, multiple variants of loss functions are available in literature [11].

In this paper, Maximum Probability Based Cross Entropy (MPCE) loss Function is used. It is based on the maximum probability of prediction. The advantage of using this loss function is that it decreases the error due to back propagation, convergence is fast and thus improves the training of the model [11]. Optimization of deep learning models is a complex task due to the multiple layers and non-linearities present. Thus, there is a need of an efficient optimization algorithm to optimize the loss function and improve the generalization of the model. Multiple optimizers are available for optimizing deep learning models these include RMSprop, momentum, and Adam. Initially, RMSprop and momentum were used for optimizing the deep learning model. But the researchers soon discovered that these optimizers are inefficient for large dataset having multiple parameters [12]. The Adam optimizer utilizes the benefits of both these and became quite popular. However, some researchers observed that despite superior training time, the Adam optimizer fails to converge to an optimal solution for some applications. Specifically in the case of image classification the Adam optimizer is inefficient [13]. Thereafter, many researchers worked on analyzing the poor generalization of Adam. But these solutions were not generalized and worked in some specific cases only [14]. To overcome these limitations and for optimizing the proposed model GOA is used for optimizing the loss function. GOA mimics the grasshopper food search strategy [15]. It utilizes two kinds of forces attractive and repulsive. These forces balance the search strategy and thus make GOA capable of providing the optimal solution with fast convergence. This algorithm has high exploration and exploitation capability. Other metaheuristic algorithms like Particle swarm, ant colony, artificial bee etc. lack the capability of exploiting a large search space [16]. The deep convolution network has proved to be efficient in object recognition from digital images. However, the deep convolution neural network also faces the problem of local minima like other conventional networks. Thus, in the proposed method a bio inspired optimization algorithm is used for optimizing the deep learning model. Several bio-inspired optimization algorithms are available in the literature [17]. These optimization algorithms can solve optimization problems in the most efficient way. Therefore, in the proposed method the network weights are initialized using the optimal weights obtained from Grasshopper Optimization algorithm (GOA). The choice of GOA in the proposed method is motivated by the high exploration and local optima avoidance quality of this algorithm. The repulsive force amid the grasshoppers results in extensive exploration of the search space by the search agents. Thus, the local optima are not reached in case of GOA. On the other hand, the high attractive force amid the grasshoppers leads to fast convergence of the algorithm. There is a proper balance between exploitation and exploration in case of GOA. In the proposed method a novel deep convolution network with MCPE loss function and GOA optimizer is presented. The chest X-ray images are preprocessed using Contrast Limited Adaptive Histogram Equalization (CLAHE) [18]. It enhances the images in a specified level and prevents over enhancement of noise. The preprocessed images are used by the proposed deep network. The model is trained by optimizing the MPCE loss function using GOA optimizer. The trained network is used to classify the images into three classes

COVID, Pneumonia and Normal. The result interpretation is improved using class map activations. The class map activation visualization is done using Grad-CAM algorithm.

2. Background

2.1. Grasshopper Optimization Algorithm (GOA)

One of the most popular meta heuristic algorithms is Grasshopper Optimization Algorithm (GOA) [15]. This algorithm is inspired by the swarm behaviour of grasshoppers for search of food. The grasshoppers are found in two stages nymph and adults. Both the nymph and adult grasshoppers show swarm behaviour. The nymph jumps and their movement is like a rolling cylinder. Their movement is slow, and steps are small. When the grasshoppers become adult, they cover long range and have abrupt movement. This behaviour can be used for solving complex problems. The optimization problems may be segmented into exploration and exploitation. During exploration, the search agents need to cover long range abruptly while exploitation requires slow movement locally. The adult grasshopper movement is modelled for exploration, nymph movement is used for exploitation. The target achievement is inspired by the food searching behaviour of the grasshoppers. Figure 1 shows the attraction and repulsion forces that work amid the grasshoppers.

The mathematical model for GOA is shown in Eq (1):

$$X_i = S_i + G_i + A_i \tag{1}$$

The position of the i_{th} grasshopper is denoted by X_i.

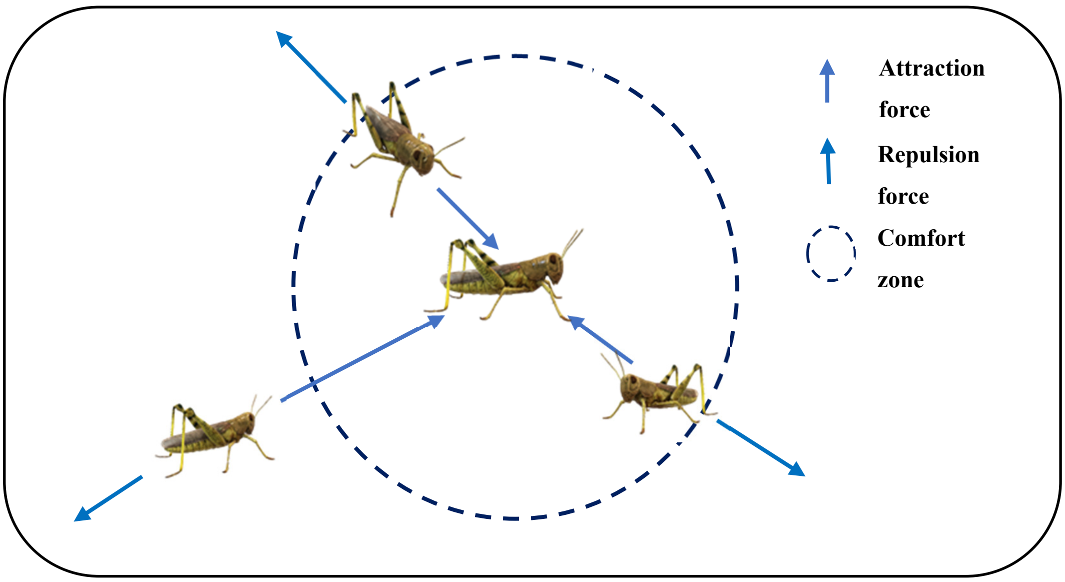

Figure 1. Attraction and repulsion force amid grasshoppers.

This is the sum of the social interaction (S_i), gravity force (G_i) and the wind advection (A_i). The random behaviour of the algorithm is achieved by adding random variables r_1, r_2, r_3 in the range [0, 1]. Equation (2) represents the position of the ith grasshopper with randon behavior.

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \tag{2}$$

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij}) \overline{d_{ij}} \tag{3}$$

where d_{ij} is the distance between i-th and j-th grasshopper

$$d_{ij} = |X_j - X_i| \tag{4}$$

s is the designed function.

The G component in Eq (1) is computed using Eq (5):

$$G_i = -g\widehat{e_g} \tag{5}$$

where g is gravitational constant and e_g is the unity vector towards the centre of earth. A is computed as

$$A_i = u\widehat{e_w} \tag{6}$$

where u is a constant drift and e_w is a unity vector in the direction of wind.

2.2. Deep convolution network

Deep convolution networks are being widely used in image classification problem. These networks are capable of self feature extraction and do not require any explicit feature extraction methods. Deep convolution networks have a more complex architecture than the traditional networks. These comprise of input, output and multiple hidden layers. In this section the details of the network layers including convolution, pooling and fully connected layers is discussed.

2.2.1. Convolution layer

In this layer a convolution filter is applied on the input and the output is generated as follows. If $X = \{x_1, x_2, x_3, \ldots\ldots x_n\} \in \mathbb{R}^n$ is the input vector of size n. Then the output vector y_i is computed as follows using Eq (7):

$$y_i = \sum_{j \epsilon N_i} w_j x_j \tag{7}$$

In Eq (7) N_i represents the size of the filter, w_j and x_j represent the weight and neighbours respectively. Equation (7) depicts the convolution operation of the input vector by the weight vector of the filter. Thus, it can be further simplified to Eq (8)

$$y = x * w \tag{8}$$

where $w = (w_o, w_1, \ldots., w_{0-1}) \in \mathbb{R}^o$, the convolution operator is represented by *. $Y = \{y_1, y_2, y_3, \ldots\ldots y_n\} \in \mathbb{R}^n$ represents the output vector obtained after convolution layer.

2.2.2. Pooling layer

The dimensions of the feature map generated after convolution layer is controlled by the pooling layer. This layer is used to diminish the number of parameters to be learnt. This further aids in reducing the computation done by the network. The features present in the region are summarized by this layer. Mathematically, it is represented as Eq (9):

$$y_j = \frac{1}{p} \sum_{k=0}^{p-1} x_{pj+k} \ , y \in \mathbb{R}^m \tag{9}$$

In Eq (9) p represents the number of parameters to be reduced. Whereas m is computed as,

$$m = \frac{n}{p} \tag{10}$$

2.2.3. Activation function

Activation function significantly affects the performance of the network. It is crucial in the learning of the network from the training data. In this paper, Rectified Linear activation (ReLu) [19] is used. ReLU is used since it has a high convergence rate and overcomes the problem of vanishing gradient. The function is represented as:

$$f(x) = \max(0, x) \tag{11}$$

From Eq (11) it can be interpreted that function maps all negative values to 0 without making any changes to the positive values.

Softmax activation function is applied in the last layer of the network.

$$Softmax(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{12}$$

x_i represents the observed output.

3. Proposed method

In this paper, a meta heuristically optimized deep convolution network is proposed for the detection of COVID-19 from chest X-ray images. The proposed methodology is shown in Figure 2.

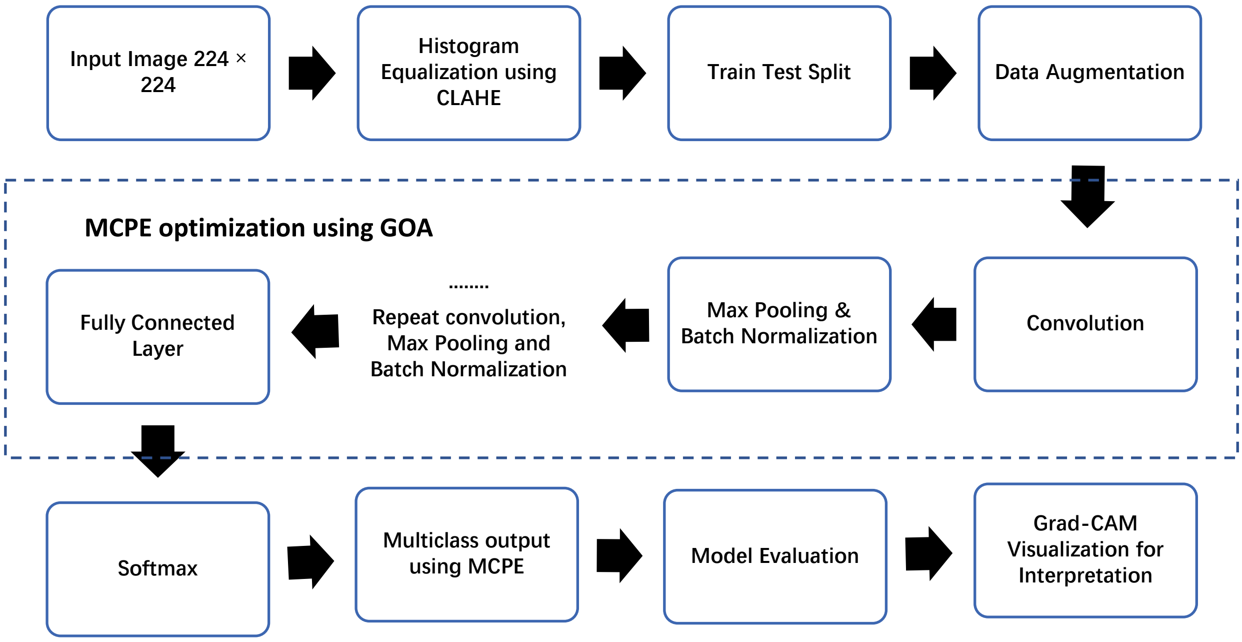

Figure 2. Proposed methodology.

The flowchart of the proposed method is shown in Figure 3.

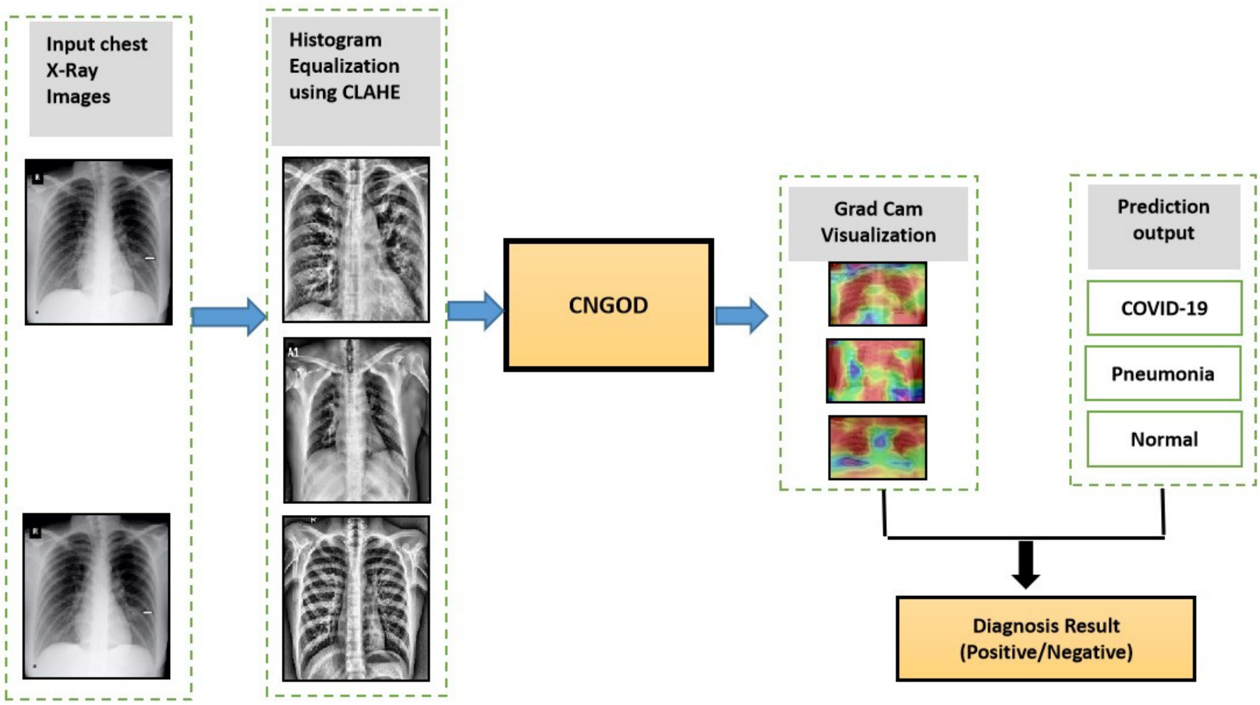

Figure 3. Flowchart of the proposed method.

The various steps involved in the proposed method are as follows:

Step 1 Input Chest X-ray images: The chest X-ray images collected from [20,21] are given as input to the proposed network. The chest X-ray images are collected from three classes of individuals. These include chest X-ray images of normal individuals i.e., those without any abnormality in the chest. The other two classes include patients suffering from COVID-19 and pneumonia. These images are used for training and testing the developed model. The dataset comprises of total of 1419 images of three classes viral pneumonia, COVID and normal cases. The data is split in the ratio of 80:20. The training set is 80% and for validation 20% data is used.

Step 2 Pre-processing using CLAHE: The chest X-ray images have low contrast and therefore CLAHE is used for histogram equalization. The histogram equalization algorithm is as follows:

Input: Chest X-ray input images
Output: Preprocessed histogram equalized image
Method: CLAHE

Begin

For each image compute:

$$x_k(i,j) = \frac{(x_{kmax} - x_{kmin})}{\mathrm{P}(x_k)}$$

where $x_k(i,j)$ is the pixel value at location (i,j) for the k_{th} image

End

The pre-processed images obtained from this step are used as input to the proposed deep learning network. Figure 4 shows the effect of applying the pre-processing algorithm. The histogram of the images shows the effect of applying CLAHE on the low contrast chest X-ray image.

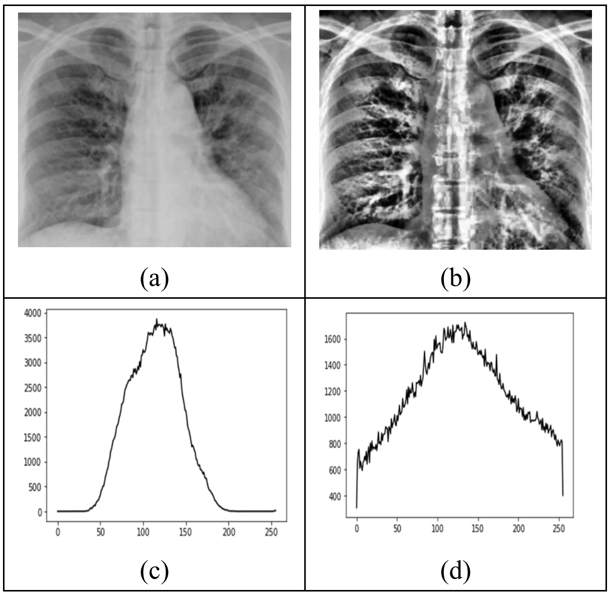

Figure 4. (a) Original chest X-ray image; (b) Pre-processed image; (c) Histogram of original image; (d) Histogram of pre-processed image.

Step 3 Initialize deep CNN: The network architecture used is shown in Figure 5. The deep network used in this work is motivated by the design of the traditional XceptionNet. This network comprises of depth wise separable convolutions that independently look at cross channel and spatial correlations [22]. There are five convolution blocks comprising of both regular and depth wise convolution layers. The first block has two layers of size 16 × 16. And second block has size 32. This is followed by convolution blocks 3–5. This is shown in Figure 5. Finally, fully connected layers are added to assign classes to the input image. A dropout value of 0.2 was used to avoid overfitting of the network [9].

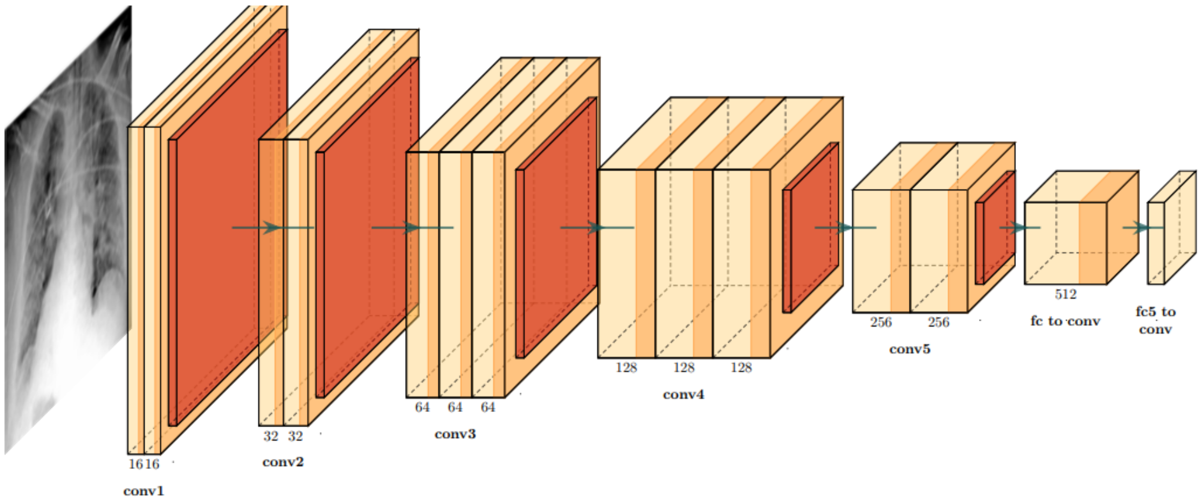

Figure 5. Model architecture.

Step 4 Network Training: The optimal filter weight vectors are used to train the network. The loss function used for training is maximum probability based cross entropy loss as discussed in the next step. The network is trained using 100 epochs.

Step 5 Maximum Probability Based Cross Entropy Loss: For improving the training of the model. MPCE loss function is used. It reduces the back propagation error of CE and makes the convergence fast. The mathematical formulation of MPCE is shown in Eq (13).

$$f^t(W) = -\sum_{i=1}^{m} y_i' log(y_i) = -\sum_{i=1}^{m} (y_{max} - y_u)\bar{y}_i log(y_i) \tag{13}$$

where, y_{max} is the maximum amongst m classes with the true class being the u_{th} class. The uth coordinated $\bar{y}$ is 1, $\bar{y}$ is the vector of real classes. And y_i' is the i_{th}coordinate of the vector y'.

Step 6 Loss Optimization using GOA: The training of the deep learning model involves the modification of weights at each epoch and minimization of loss function. The selection of the optimization algorithm is significant in reducing overall loss and network accuracy. Choosing the best optimizer for the given application is an essential requirement for accurate results. The most used optimization algorithm is Adam optimizer and some of its variants [12]. In the proposed work, the grasshopper optimization is used for finding the optimal weights. The aim of using GOA is to minimize the total classification error that is used as the objective function for GOA. The fitness function that is the classification error is evaluated and the positions of the grasshoppers are updated.

Step 7 Prediction using trained Model: The model is trained to classify the input into one of the three classes, i.e., COVID-19, pneumonia or normal.

Step 8 Grad-CAM Visualization: The classification results obtained from the classifier can be used to make the clinical decision. But since the false positive and negative rates in case of COVID-19 will lead to serious repercussions. Therefore, the classification results are augmented with Grad-CAM visualization. The combined information can be used by the doctors to make the diagnosis decision for any patient.

4. Experimental results

The experiments are conducted in python with GPU acceleration. The keras module is used for implementing the deep learning model. The performance of the proposed method is evaluated using the various evaluation metrics [23]. The following metrics are used:

Sensitivity represents the correctness of classification. The calculation of sensitivity is done using the Eq (14).

$$Sensitivity = \frac{TP}{TP+FN} \tag{14}$$

Precision is defined as the number of misclassifications. This can be computed by

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

Another metric used is F1-score which is the harmonic mean of precision and sensitivity. Thus, it is computed as

$$F1 - Score = 2 \times \frac{precision \times sensitivity}{precision+sensitivity} \tag{16}$$

The overall accuracy is also computed using

$$Overall\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{17}$$

where TP, FP and FN represents the true positive, false positive and false negative, respectively.

The confusion matrix of the proposed method for the three classes namely normal, COVID-19, pneumonia is presented in Table 1. The confusion matrix is computed by taking random samples from all three classes. The number of samples from each of the three classes are 135, 28 and 121. The number of misclassifications in the Normal class is 4, in COVID-19 class one sample is classified as Normal and two are classified as viral pneumonia. Similarly, the samples in Viral Pneumonia have also been misclassified as normal and COVID-19. The misclassification is very low in the proposed method. The augmentation of Grad-CAM visualizations along with these prediction results will completely minimize the chances of any wrong diagnosis. Table 2 summarizes the evaluation results for all the three classes.

Table 1. Confusion matrix.

		Predicted Result		
		Normal	COVID-19	Viral Pneumonia
Actual Result	Normal	**131**	0	4
	COVID-19	1	**25**	2
	Viral Pneumonia	1	1	**119**

Table 2. Accuracy results.

Disease Type	Accuracy (%)	Precision	Sensitivity	F1-score
Normal	97.19	0.98	0.97	0.98
COVID-19	98.94	0.96	0.89	0.93
Viral Pneumonia	96.13	0.95	0.98	0.97

The result obtained are also compared with the other existing state of the art methods. Four methods are selected for the comparative study this includes DarkCovidNet, DeTracResnet18, DWCNN [8].

Table 3. Comparison results.

Methods	Accuracy	Precision	Sensitivity	F1-score
DarkCovidNet	87.02	89.96	85.35	87.37
DeTraC-ResNet18	95.12	93.36	97.91	95.58
DWCNN	95.80	96.16	95.60	95.88
CNGOD	96.83	96.52	96.63	97.08

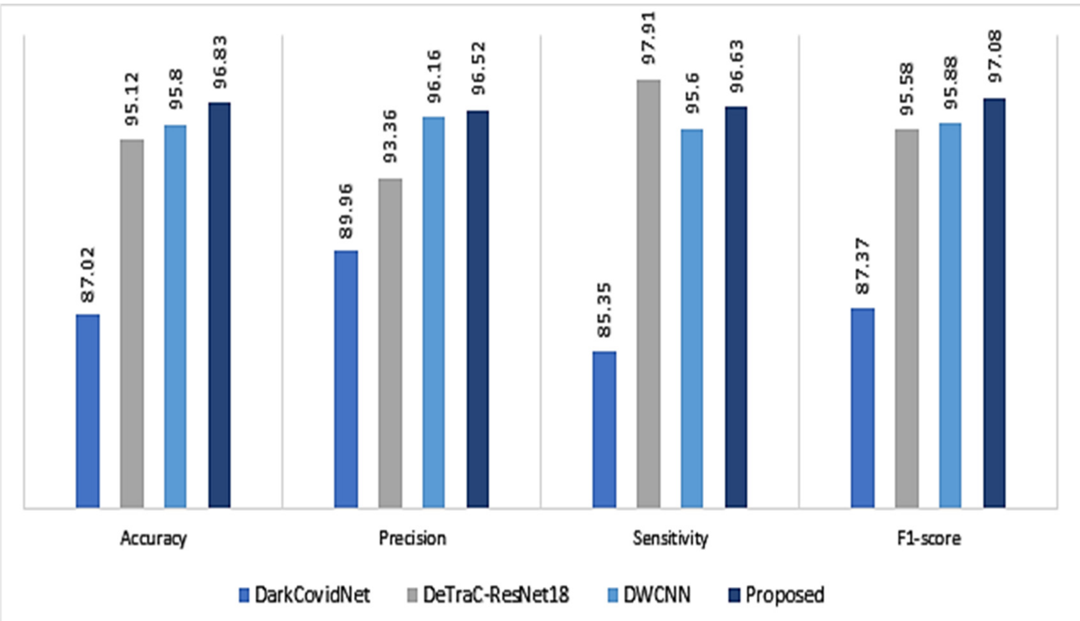

Figure 6. Comparison results.

The method used in DarkCovidNet is based on YOLO network containing seventeen layers. The second method utilizes the pretrained Resnet18 and it is further fine-tuned for the detection of COVID-19 from chest X-ray images. The third paper utilizes a depth wise convolution network is tuned to diagnose COVID-19. The accuracy of DarkCovidNet is 87%, DeTracResNet18 is 95.12 and that of DWCNN is 96.83%. The experiments show that the deep learning methods can be used for effective covid detection. The proposed method has high accuracy and thus will perform effectively in automated detection of COVID-19 from chest X-ray images.

5. Conclusions

This paper presents, a novel method for diagnosis of COVID-19 from chest X-ray images. The use of chest X-ray images for diagnosis is quite beneficial for COVID-19. A deep convolution network optimized using grasshopper optimization algorithm is proposed. The deep convolution neural network is optimized using the GOA algorithm. The error function used in this work is MPCE as it minimizes the back propagation error of cross entropy and improves the training. The experiments are conducted on the chest X-ray images dataset. The dataset consists of chest X-ray images of normal, pneumonia and COVID-19 affected patients. The model is trained to classify the images into one of these classes. The results are also augmented with Grad-CAM visualizations to reduce the false negatives and improve the diagnosis accuracy. The proposed method is compared with three other states of the art methods. The evaluation metrics like Accuracy, Precision, Sensitivity, Specificity, F1-score are computed and compared. The method achieves high accuracy and can be used for diagnosis of COVID-19 from chest X-ray images. In future the proposed method can be further improved by using a more detailed dataset with larger number of images of all the three classes.

Conflict of interest

The authors declare there is no conflict of interest.

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