

# A Novel Multi-Objective Rat Swarm Optimizer-Based Convolutional Neural Networks for the Diagnosis of COVID-19 Disease

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Received March 8, 2021; revised July 30, 2021; accepted August 23, 2021

**Abstract**—Early detection of coronavirus disease (COVID-19) is considered an essential task for disease control and cure. Thus, an automated diagnosis of COVID-19 is highly desirable. This paper introduces a novel diagnosis approach, namely, RSO-AlexNet-COVID-19. The proposed hybrid approach is based on the rat swarm optimizer (RSO) and convolutional neural network (CNN). RSO is used to find the optimal values for the hyperparameters of the AlexNet architecture to achieve a high level of diagnostic accuracy of COVID-19. It obtained overall classification accuracy of 100% for CT images datasets and an accuracy of 95.58% for the X-ray images dataset. Moreover, the performance of the proposed hybrid approach is compared with other CNN architecture, Inception v3, VGG16, and VGG19.

**Keywords:** coronavirus, multi-objective, hyperparameters optimization, convolutional neural networks, rat swarm optimizer

**DOI:** 10.3103/S0146411622030075

## 1. INTRODUCTION

The new coronavirus disease was aroused in China in January 2020 and has increasingly spread all over the world. It was announced by World Health Organization (WHO) that the pandemic outbreak of the coronavirus is a public health emergency of international concern at the end of January 2020. In February 2020, they called this kind of disease COVID-19 [1]. Due to the continuous extensive increase in mortalities and morbidities, it leads to worse situations of the international medical health day after day. Up till now, there are millions of confirmed infected cases all around the world. Therefore, there is a high need to detect the disease at its early stage, especially with the unavailability of the drug for COVID-19. An efficient rapid effective diagnostic test will save a lot of people's life and will effectively achieve a proper early detection of the patients carrying COVID-19 [2]. Thus, the researchers from all around the world have started to use machine learning algorithms and to develop an automated diagnosis for COVID-19.

Recently, deep learning algorithms proved their efficiency for dealing with large medical images datasets such as prediction of microbial interactions, histopathological classification of gastric and colonic epithelial tumors as in [3–5]. Additionally, deep learning algorithms eliminate the need of extracting the relevant features manually. Thus, many research works uses deep learning architectures, especially convolutional neural networks (CNN) for the diagnosis of COVID-19.

Authors in [6] used convolutional long short term memory for the detection of COVID-19. The experimental results showed that their proposed architecture achieves an accuracy of 98.91% for CT images. Another approach is proposed in [7]. In this approach, ResNet-101 is adopted for COVID-19 diagnosis. The experimental result on X-ray dataset images demonstrated that their proposed approach achieved 98% accuracy. Authors in [8] developed a new CNN architecture called CoroDet for COVID detection. The results of CoroDet obtained an accuracy of 91.2% for four classes' classification, 94.2% for three classes' classification, and 99.1% for two classes' classification.

Although the high classification accuracy is achieved by CNN architectures, all of these architectures have a large number of hyperparameters. These parameters can highly affect the efficiency of CNN architectures. Thus, they can downgrade achieving better results. Therefore, the intertwining of hyperparame-

ters is considered a challenging and critical task, especially for large and complex networks. Manually tuning these parameters is tedious and very time-consuming. However, few studies consider this problem. The authors in [9] use distributed particle swarm optimization to tune the hyperparameters associated with CNNs. The results on classification benchmarks datasets revealed that the proposed approach can effectively find the optimal values for the CNN model with high classification accuracy. In [10], the authors used the genetic algorithm to tune the parameters of deep long short-term memory (LSTM). The experimental results showed that using a dynamic tuning approach performs better than static tuning of LSTM.

This paper proposes an efficient approach for tuning AlexNet using one of recent swarm intelligence algorithms proposed in 2020 called rat swarm optimizer (RSO) [11]. The main inspiration of RSO came from the fighting and the chasing behavior of the rats with their prey. The authors of the original RSO showed the efficiency of RSO in solving real-world optimization problems compared with the other well-known swarm intelligence algorithms. Additionally, the authors investigated the convergence ability of RSO for a better understanding of its behavior. The experimental results revealed that RSO converges very quickly toward the optimum compared with eight other meta-heuristic optimization algorithms. This is due to RSO maintaining a good balance between exploitation and exploration phases of the search space. The parameters  $A$  and  $C$  used in RSO are responsible for better exploitation and exploration through the optimization process. One of the main advantages of the RSO algorithm is that it has few parameters to adjust. This advantage can make the algorithm using less memory space. In this paper, RSO is used to optimize the hyperparameters of AlexNet to achieve high performance of AlexNet CNN architecture. The proposed hybrid approach called RSO-AlexNet-COVID-19 is evaluated on two COVID-19 datasets. The best of our knowledge that this is the first time to introduce RSO with AlexNet. The main contributions of this study can be summarized as follows:

- (1) This paper considered a new hybrid approach based on CNN and RSO.
- (2) The performance of the proposed RSO-AlexNet-COVID-19 approach is evaluated on two COVID-19 datasets with different images modalities.
- (3) Furthermore, the performance of RSO-AlexNet-COVID-19 is compared with Inception v3, VGG16, and VGG19.
- (4) Several measurements are used for the evaluation purpose such as accuracy, sensitivity, specificity, prevalence, and computational time.

## 2. RAT SWARM OPTIMIZER (RSO)

Rat swarm optimizer (RSO) is one of the recently published swarm intelligence algorithms proposed in late 2020 [11]. Rats are medium-sized and long-tailed rodents. There are two main species of rats. These species are black rats and brown rats. The main inspiration of RSO came from the fighting and the chasing behavior of the rats with their prey. Rats use their social agnostic behavior to chase the prey in the group. The mathematical model of both chasing and fighting behavior is defined as follows.

### 2.1. Chasing the Prey

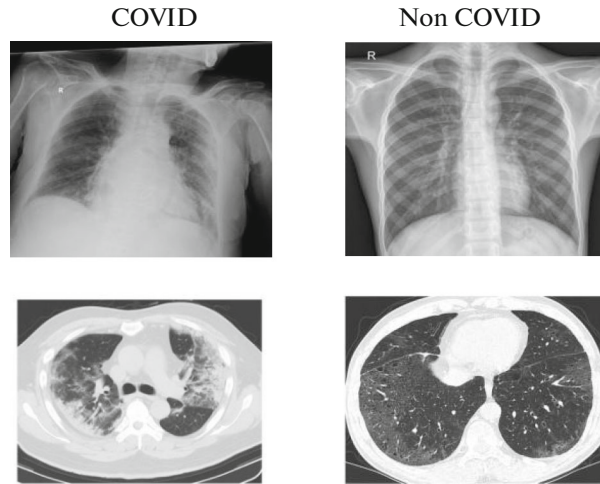
Suppose that the optimal rat (search agent) has previous knowledge about the prey's location. The rest of the rats update their position based on the best position of the rat using the following equation:

$$\vec{X} = A \cdot \vec{X}_i + C \cdot (\vec{X}_{\text{best}} - \vec{X}_i), \quad (1)$$

where  $\vec{X}_i$  is the rat position in  $i$ th iteration and  $\vec{X}_{\text{best}}$  is the position of the best rat (optimal solution).  $C$  and  $A$  are the control parameters. They are used to control the exploration and exploitation phases through the optimization process. The mathematical definition of these two parameters is defined as follows:

$$C = 2 \cdot \text{rand}(), \quad A = r - i \left( \frac{r}{\text{Max}_{\text{iter}}} \right), \quad (3)$$

where  $C$  is random parameter generated in range 0 and 2;  $r$  is random parameter generated in range 1 and 5, and  $i = 0, 1, 2, \dots, \text{Max}_{\text{iter}}$ .



**Fig. 1.** Samples of COVID and Non COVID images.

## 2.2. Fighting with Prey

The following are the mathematical representation of rats with prey

$$\bar{X}_{i+1} = |\bar{X}_{\text{best}} - \bar{X}|, \quad (4)$$

where  $\bar{X}_{i+1}$  is the position of the next rat, where the position of next rat is updated based on the position of the best rat and other rats.

## 3. COVID-19 DATASET DESCRIPTION

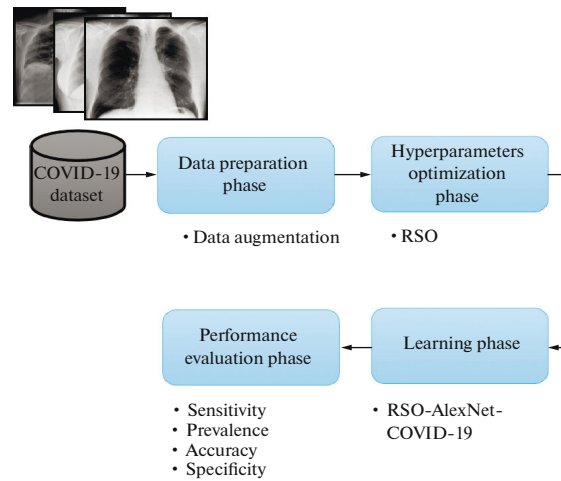
In this paper, two benchmark COVID-19 datasets are adopted. The first dataset is the Kaggle Chest X-ray dataset [12]. The dataset consists of 6786 X-ray images, 930 images represent COVID cases, 1583 images represent normal cases, 4273 images represent pneumonia cases. The second COVID dataset is CT scan images dataset [13]. The dataset consists of two classes, 349 images represent COVID cases and 397 images represent normal cases. Figure 1 shows samples of the adopted datasets.

## 4. THE PROPOSED RSO-ALEXNET-COVID-19 APPROACH

The proposed RSO-AlexNet-COVID-19 approach is comprised of four main phases. These phases are the data preparation phase, hyperparameters optimization phase, learning phase, and performance evaluation phase. Figure 2 shows the building structure of the proposed RSO-AlexNet-COVID-19 approach. Each phase will be explained in detail in the following sections.

### 4.1. Data Preparation Phase

In this phase, many data augmentation techniques are adopted. As previously mentioned in the dataset description, the first dataset is an imbalanced dataset, where there are only a few samples of COVID images compared with the normal and pneumonia images cases. Machine learning algorithms in most cases failed to handle this problem. This is due to most of the available information belongs to the dominant category in this type of dataset. Thus, machine learning algorithms do not learn to classify the other minor categories. They only learn to classify the dominant class. However, data augmentation techniques prove their efficiency to handle this problem by generating more images from the existing ones. Thus, the number of training samples will be increased. This will result in decreasing the overfitting of CNN architectures and improving the generalization [14]. The used data augmentation techniques are summarized in Table 1.



**Fig. 2.** The structure of the proposed RSO-AlexNet-COVID-19 approach.

#### 4.2. Hyperparameters Optimization Phase

In this phase, multi-objective RSO is used to tune four main parameters of AlexNet. These parameters are batch size, dropout rate, learn rate dropout period, and the number of epochs. Therefore, the search space is four-dimensional. The solution of the multi-objective optimization problem can be divided into the scalarization method and the Pareto method. The Pareto method is applied if the desired solutions are separate and produce a compromise solution (trade-off). Although, the scalarization method is applied if the desired solution and performance indicators component that forms a scalar function integrated into a single fitness function. In this paper, we used the scalarization method, where the used fitness function composes of two objectives with equal weights. The best position of the rat is the one that maximizes the sensitivity with specificity. It is mathematically defined as follows:

$$f(\vec{X}) = S_n + S_p, \quad (5)$$

where  $S_n$  represents the sensitivity and  $S_p$  represents the specificity.

The algorithm starts with random initialization of the population of candidate solutions. Each candidate solution (rat's position) is a mixture of these four hyperparameters. The search boundary for these four hyperparameters is defined in Table 2. Through the optimization process, each position of the rat is evaluated based on Eq. (5). Then, it is compared with the fitness value of the position of the best rat. This process is repeated over and over till the algorithm reaches the maximum number of iterations. The rest of the parameters including the population size, the number of dimensions, and the maximum number of

**Table 1.** The used data augmentation techniques

Augmentation technique	Value/Range
Rand X reflection	True
Rand Y reflection	True
Rand X translation	[-5, 5]
Rand X shear	[-0.05, 0.05]
Rand Y shear	[-0.05, 0.05]
Rand Y translation	[-5, 5]
Rand X scale	[0.1, 1.1]
Rand Y scale	[0.1, 1.1]
Colour normalization	True

**Table 2.** The searching boundary of the proposed multi-objective RSO

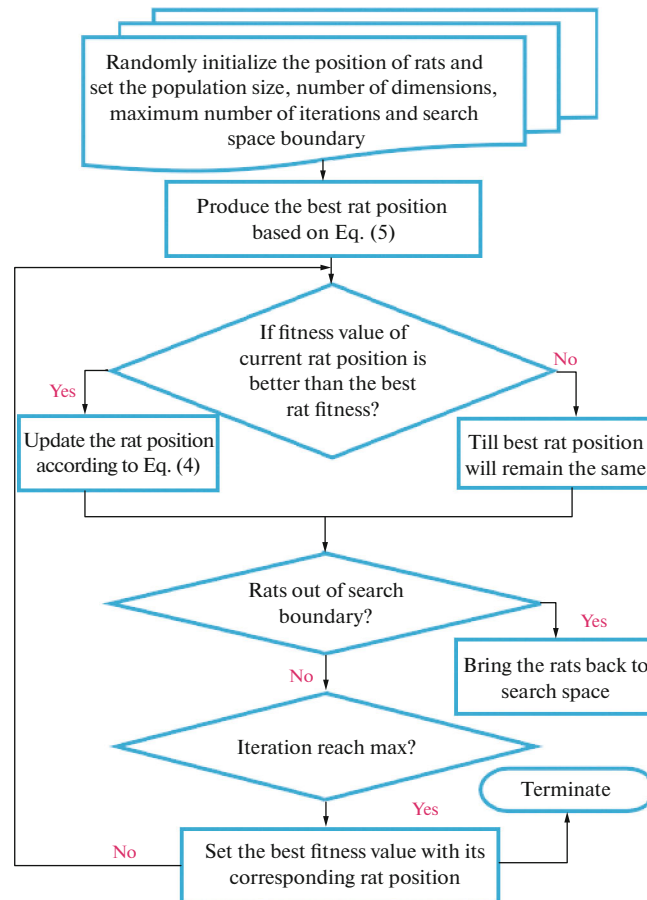
Hyperparameter	Range
Batch size	[1, 64]
Learning dropout rate	[0.1, 0.9]
Learning dropout period	[2, 10]
# Epochs	[2, 20]

**Table 3.** The optimal hyperparameters determined by the proposed multi-objective RSO

Hyperparameter	Optimal value (Dataset 1)	Optimal value (Dataset 2)
Batch size	64	6
Learning dropout rate	0.6	0.4
Learning dropout period	2	2
# Epochs	20	12

iterations are set to 20, 4, and 30, respectively. The flowchart of the proposed multi-objective RSO is showed in Fig. 3.

Table 3 shows the optimal values of the hyperparameters obtained from RSO for CT COVID-19 image datasets with two classes' categories and chest X-ray COVID-19 images datasets with three classes' categories. These values will be further used to feed the next phase.

**Fig. 3.** The proposed multi-objective RSO flowchart.

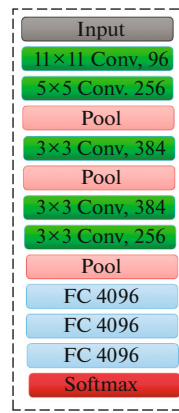


Fig. 4. AlexNet block diagram architecture.

#### 4.3. Learning Phase

CNN architectures are considered very powerful tools and prove their efficiency for image classification. This is due to their hierarchical and efficient structure of feature extraction from an image. AlexNet is one of CNN architectures. It has eight layers deep with 61 million parameters. AlexNet architecture composes of a convolution layer followed by a pooling layer, normalization, convolution pooling normalization layer, and then multiple convolution layers, pooling layer, and finally several fully connected layers. These convolutions and pooling operations are used to monitor and evaluate the potential feature of COVID-19 datasets.

Figure 4 shows the network architecture of AlexNet [15]. As it can be seen, there are five convolution networks and three fully connected networks with rectified linear unit (ReLU) activation function. Moreover, the numbers like  $11 \times 11$ ,  $5 \times 5$ ..., etc., represent the kernel size for each layer in AlexNet. The rest of the numbers like 96, 256, 384..., etc., are the number of output produced from each layer. AlexNet proves its efficiency to address the over-fitting problem by using dropout layers. Fine-tuning techniques and feature extraction are used to prepare the proposed optimized AlexNet architecture to learn from COVID-19 datasets. The proposed multi-objective RSO algorithm determines the optimal value of batch size, dropout rate, learn dropout period, and number of epochs. These optimized parameters are used to feed AlexNet architecture to classify COVID-19 datasets.

#### 4.4. Performance Evaluation Phase

In this phase, four different measurements calculated from the confusion matrix are adopted to evaluate the performance of the proposed RSO-AlexNet-COVID-19 approach. These measurements are accuracy, specificity, sensitivity, and prevalence. Accuracy is the most common measurement used to evaluate the performance of a classifier algorithm. It is mathematically defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \quad (6)$$

Specificity is the number of true negatives divided by the total number of true negatives and the number of false positives as described in Eq. (7). It measures among all people that do not have COVID-19, how many detected as negative COVID-19.

$$\text{Specificity} = \frac{TN}{TN + FP}. \quad (7)$$

While sensitivity or recall measures how many are predicted as positive COVID-19 out of all of the positive COVID-19 cases. It is mathematically defined as follows:

$$\text{Sensitivity} = \frac{TP}{TP + FN}. \quad (8)$$

Finally, prevalence is the number of actual COVID-19 cases divided by the total of COVID-19 and non-COVID-19. It measures how often we find a person with COVID-19 from all people. The mathematical representation is defined in Eq. (9):

$$\text{Sensitivity} = \frac{TP}{TP + FN}. \quad (9)$$

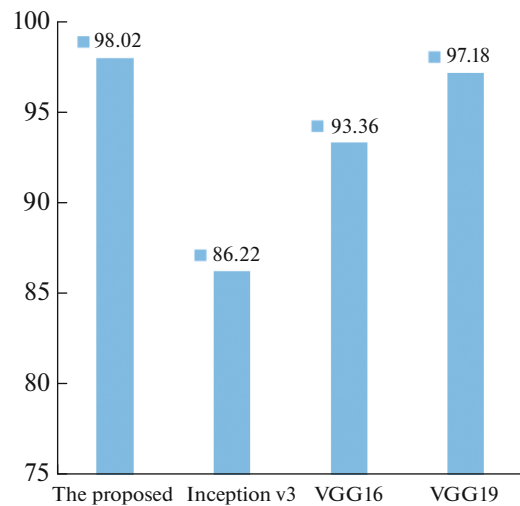


Fig. 5. Comparison of the proposed approach with Inception v3, VGG16, and VGG19 in terms of sensitivity for dataset 1.

## 5. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, several experiments are conducted to analyze and evaluate the performance of the proposed RSO-AlexNet-COVID-19 approach. It should be mentioned that all the experiments are performed on MATLAB2020, where deep learning and parallel optimization packages are included. Additionally, all the experiments were performed on a PC with 16 GB DDRAM, a core of i7 processor, and a graphic card NVIDIA GeForce RTX. The experimental results are divided into two main experiments. The goal of the first experiment in Section 5.1 is to evaluate the performance of the proposed RSO-AlexNet-COVID-19 approach for CT COVID-19 images dataset, where there are only two classes, COVID-19 or non-COVID-19. The second experiment in Section 5.2 aims to evaluate the performance of the proposed approach for X-ray chest COVID-19 images dataset, where three classes are included. These classes are COVID-19, normal, and pneumonia. In all the experiments the performance of the proposed approach is compared with well-known and most commonly used CNN architectures. This architecture is Inception v3, VGG16, and VGG19. VGGNet is one of CNN architectures designed to reduce the number of the training parameters of convolution layers. VGG16 [16] and VGG19 [17] are two variants of VGGNet. Inception is another CNN architecture. It consists of multiple inception modules. Each module consists of a  $1 \times 1$  convolution layer,  $3 \times 3$  convolution layer,  $5 \times 5$  convolution layer, and max-pooling layer [18]. It should be noted that in all the experiments, the optimized hyperparameters of AlexNet using multi-objective RSO are compared with a manual search of Inception v3, VGG16, and VGG19. Manual search means that the values of hyperparameters of these architectures are randomly chosen. This is due that this paper is only considered the optimization of AlexNet architecture. AlexNet is chosen because it is the faster training process. Thus, it has a faster execution time [19].

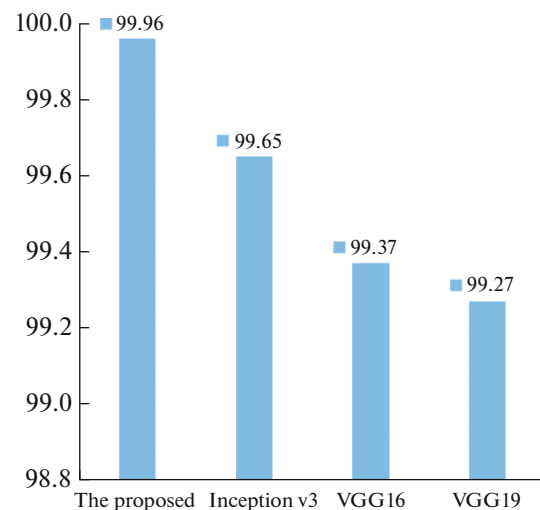
The performance of the proposed RSO-AlexNet-COVID-19 approach for dataset 1: In this phase, the performance of the proposed approach is evaluated on multiclass, where three classes of X-ray chest COVID-19 images dataset are considered. Figure 5 compares the performance of the proposed approach with Inception v3, VGG16, and VGG19 in terms of sensitivity. As it can be seen that proposed optimized CNN approach is superior compared with the other CNN architectures. Figure 6 compares the performance of the proposed approach with other CNN architectures in terms of specificity. As it can be seen, the best results were obtained from the proposed optimized AlexNet architecture using RSO. Another finding is that Inception v3 is in second place, VGG16 is in third place, and VGG19 is in fourth place.

Figure 7 compares the performance of the proposed approach with Inception v3, VGG16, and VGG19 in terms of accuracy. As it can be observed, the proposed RSO-AlexNet-COVID-19 approach is very competitive compared with the other CNN architectures.

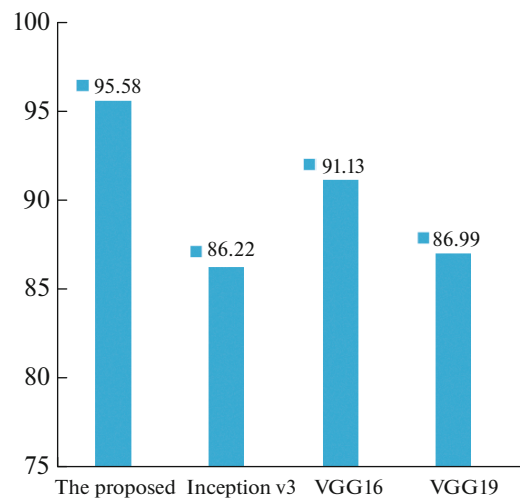
The performance of the proposed RSO-AlexNet-COVID-19 approach for dataset 2: In this phase, the performance of the proposed RSO-AlexNet-COVID-19 approach is evaluated for the binary classification problem, where only two classes are considered.

These classes are COVID or non-COVID. Additionally, it compared with Inception v3, VGG16, and VGG19 in terms of accuracy, sensitivity, specificity, and prevalence. Specificity is used to evaluate the





**Fig. 6.** Comparison of the proposed approach with Inception v3, VGG16, and VGG19 in terms of specificity for dataset 1.

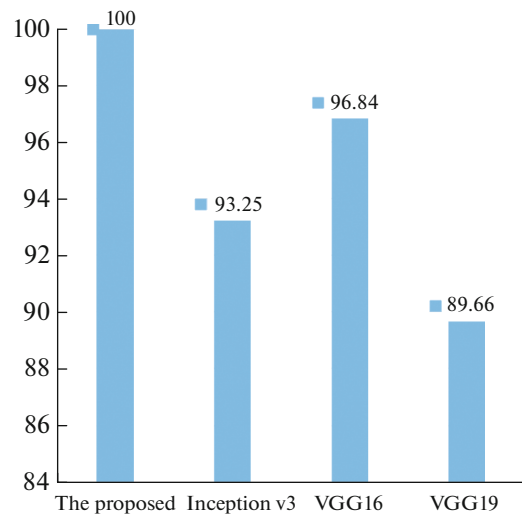


**Fig. 7.** Comparison of the proposed approach with Inception v3, VGG16, and VGG19 in terms of accuracy for dataset 1.

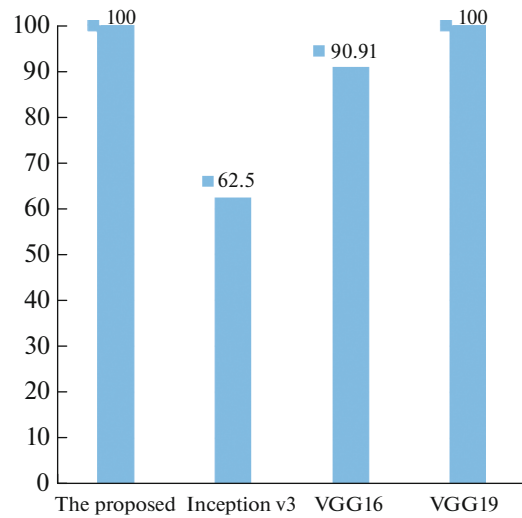
ability of an algorithm of a screening test to detect the true negative. In other words, it is used to measure the number of correctly identifying people that do not have COVID-19. Sensitivity is the adequacy of the screening test. It measures the probability of screening test of correctly identified as COVID-19. Accuracy measurement is used to measure the ability of an algorithm to differentiate between healthy and unhealthy people. Finally, prevalence is used to measure how common is the actual COVID-19 cases among all cases. Figs. 8, 9, 10, and 11 compared the performance of the proposed hyperparameter tuning of AlexNet using RSO with the manual search of Inception v3, VGG16, and VGG19 in terms of sensitivity, specificity, accuracy, and prevalence, respectively. As it can be observed, the proposed RSO-AlexNet-COVID-19 approach is superior compared with the other CNN architectures. It is obtained an overall accuracy of 100%, the sensitivity of 100%, specificity of 100%, and prevalence of 100%. Another finding is that VGG16 architecture is in second place for accuracy and sensitivity results. Moreover, it is in third place for specificity and prevalence.

To further evaluate the performance of the proposed algorithm, the computational time is calculated. Table 4 compares the computational time of the training process in seconds for the proposed algorithm with Inception v3, VGG16, and VGG19 architectures. As it can be seen the proposed algorithm obtained less computational time compared with the other CNN architectures. This is due to AlexNet has a small number of learnable parameters with a minimum number of convolution layers. It has 60M learnable

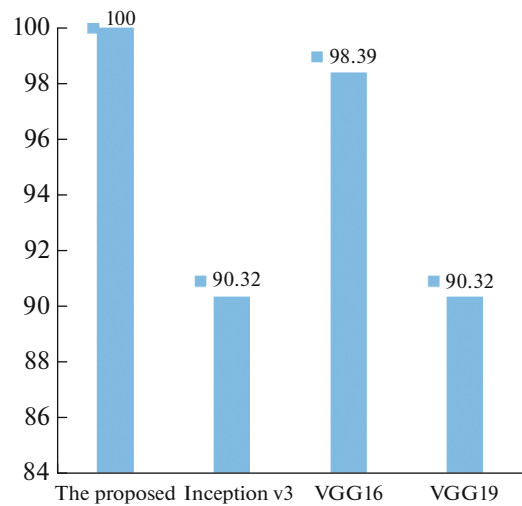




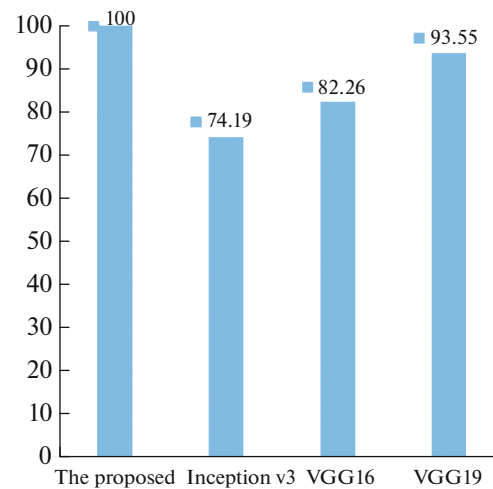
**Fig. 8.** Comparison of the proposed approach with Inception v3, VGG 16, and VGG 19 in terms of sensitivity for dataset 2.



**Fig. 9.** Comparison of the proposed approach with Inception v3, VGG 16, and VGG 19 in terms of specificity for dataset 2.



**Fig. 10.** Comparison of the proposed approach with Inception v3, VGG 16, and VGG 19 in terms of accuracy for dataset 2.



**Fig. 11.** Comparison of the proposed approach with Inception v3, VGG16, and VGG19 in terms of prevalence for dataset 2.

**Table 4.** Comparison of the proposed approach with Inception v3, VGG16, and VGG19 in terms of computational time for dataset 1 and dataset 2

Hyperparameter	Computational time dataset 1 (S)	Computational time dataset 2 (S)
The proposed algorithm	1320	54
Inception v3	2100	840
VGG16	1680	300
VGG19	1800	360

parameters with 8 convolution layers compared with VGG16 has 138M parameters with 16 convolution layers, VGG19 has 144M parameters with 19 convolution layers, and finally, Inception v3 has 21M parameters with 48 convolution layers. The same observation is presented in [19].

From all the obtained results, it can be concluded that tuning the hyperparameters of CNN architecture can significantly improve the performance and thus obtain better results. Moreover, it can be concluded that the produced results are quite satisfactory, but there will be room for improvement. These results can be used as a screening tool for COVID-19.

## 6. CONCLUSIONS

This paper introduces a new hybrid approach for the diagnosis of COVID-19 based on CNN and RSO called RSO-AlexNet-COVID-19. The proposed approach consists of four main phases. These phases are the data preparation phase, hyperparameters optimization phase, learning phase, and, finally, performance evaluation phase. In the first phase, different data augmentation techniques are applied such as translation, shearing, vertical and horizontal flip, and shift. In the second phase, RSO is adopted to find the optimal values of hyperparameters in AlexNet CNN architecture. In the third phase called the learning phase, the optimized CNN architecture is applied for the COVID-19 diagnosis. In the last phase called the performance evaluation phase, several measurements are adopted. These measurements are accuracy, sensitivity, specificity, prevalence, and computational time. Two different datasets are used in the simulation to evaluate the reliability of the proposed hybrid approach. The first one contains a set of CT images divided into COVID and normal. The second one contains a set of X-ray images divided into COVID, normal, and pneumonia. The proposed RSO-AlexNet-COVID-19 achieved an accuracy of 95.58% for the first dataset and an accuracy of 100% for the second dataset. Meanwhile, the performance of the proposed approach compared with Inception v3, VGG16, and VGG19 CNN architecture. The comparison results showed the effectiveness and the robustness of the proposed approach additionally, the experimental results revealed that the proposed optimized CNN approach can be adopted and considered for quick screening of COVID-19.

## CONFLICT OF INTEREST

The author declares that he has no conflicts of interest.

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