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Article

COVID-19 Severity Prediction Using Enhanced Whale with Salp Swarm Feature Classification

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Abstract: Computerized tomography (CT) scans and X-rays play an important role in the diagnosis of COVID-19 and pneumonia. On the basis of the image analysis results of chest CT and X-rays, the severity of lung infection is monitored using a tool. Many researchers have done in diagnosis of lung infection in an accurate and efficient takes lot of time and inefficient. To overcome these issues, our proposed study implements four cascaded stages. First, for pre-processing, a mean filter is used. Second, texture feature extraction uses principal component analysis (PCA). Third, a modified whale optimization algorithm is used (MWOA) for a feature selection algorithm. The severity of lung infection is detected on the basis of age group. Fourth, image classification is done by using the proposed MWOA with the salp swarm algorithm (MWOA-SSA). MWOA-SSA has an accuracy of 97%, whereas PCA and MWOA have accuracies of 81% and 86%. The sensitivity rate of the MWOA-SSA algorithm is better that of than PCA (84.4%) and MWOA (95.2%). MWOA-SSA outperforms other algorithms with a specificity of 97.8%. This proposed method improves the effective classification of lung affected images from large datasets.

Keywords: PCA; WOA; CT-image; lung infection; COVID-19

1 Introduction

COVID-19 is a virus infection that has changed human life in various aspects including finance, education, health care, and supply chains. People with COVID-19 infection are facing respiratory problems and can recover with appropriate treatment effectively [1]. Many studies have been done in implementing classification and determining the presence of COVID-19 as well as in detecting the severity of pneumonia. CT and X-ray image modalities are non-invasive and used to detect and severity of lung infection [2,3]. In this study, we used principal component analysis (PCA) for feature extraction of CT images and a modified whale optimization algorithm (MWOA) for feature selection. To classify COVID-affected images from a large dataset and detect severity using the modified whale optimization algorithm (MWA) with the salp swarm algorithm (MWOA-SSA). The main disadvantage of existing algorithms are inefficiency, high execution time, and maximized error rate. To overcome these issues, our proposed MWOA-SSA has high potential in detecting the severity of lung infections such as pneumonia and classifying COVID-19 in affected and unaffected images from a large dataset effectively and quickly.

To predict coronavirus, X-ray images play a more important role than CT because the former is less sensitive. Furthermore, X-ray images are used to diagnose the early and mild stages of coronavirus patients. CT images are also is used in the diagnosis of coronavirus and improving efficiency in terms of dosage in radiation [4]. To enhance the improvement in scanning images in a sliced manner effectively by using multi-slice computerized tomography (MSCT) [5]. To achieve improvement in larger temporal resolution achieved by dual source CT image [6].

Machine learning algorithms have been used for the last decades in medical applications for computer-based diagnosis, helping physicians diagnose at earlier stages of diseases and providing better customized therapies to patients [7,8]. Approaches to find the best solution from all possible solutions of a particular radiology problem are known as meta-heuristic algorithms. The acceptable best solution of the optimization technique requires less computational effort within a stipulated time [9]. For the feature selection, the proposed MWOA is implemented with a binary optimizer in terms of average select size, error rate, mean, standard deviation, average fitness, best fitness, and worst fitness. The main contributions of this study are as follows,

1. A COVID-19 classification based on proposed algorithms for feature classification of WMOA-SSA is developed.
2. A novel approach in detecting severity of lung infection based on severity level is implemented.
3. The proposed WMOA-SSA can effectively classify the input CT images as COVID-19 or non-COVID-19.

The paper has been organized as follows. Section 2 presents the literature review. Section 3 introduces the classification of COVID-19 images using MWOA-SSA. Section 4 discusses the experimented results. Section 5 concludes the paper and provides future directions.

2 Review of Literature

This section describes the recent literature on feature classification and prediction of coronavirus. COVID-19 has affected human beings in every aspect of their daily lives. To diagnosis the coronavirus disease by using various modalities of image such as CT and X-ray image. Through these images, physicians scan and diagnose at early stages and during disease progression. Many studies have been published on the prediction of coronavirus. Our aim is to achieve effectiveness in classifying COVID-19 case images from a large dataset and detect the severity of lung infections such as pneumonia. A previous paper [10] proposed evaluating the infection rate in CT scans of lungs using visual and coronal axes. By using visual inspection COVID-19 disease is used to identify the lung infection [11].

Another paper [12] proposed implementing a visual infection-based method to detect lung infection using lung CT scan. Authors in [13] implemented deep learning algorithms to identify and screen COVID-19 patients using the modality of CT images accurately. By using an artificial intelligence (AI) technique for diagnosis, COVID-19 patients are identified based on convolutional neural network (CNN) using CT slices images, helping accurately classify COVID-19 from non-COVID-19 groups [14]. The machine learning algorithm fractional multichannel exponent moments method is used to extract features from the chest X-ray image and used to classify COVID-19 or non-COVID-19 patients [15]. Tab. 1 shows a summary of recent research work in COVID-19.

Table 1: Survey on existing algorithms

Author name	Modality of image	Methods
Hu et al. (2020) [16]	CT image	Supervised deep learning
Nour et al. (2020) [17]	X-Ray image	CNN, support vector machine (SVM)
Wu et al. (2020) [18]	CT image	ResNet50 based deep learning
Ardakani et al. (2020) [14]	CT image	ResNet-101 based deep learning
Zhang et al. (2020) [19]	CT image	AI based ResNet
Panwar et al. (2020) [20]	X-Ray image	Transfer learning, deep CNN
Butt et al. (2020) [21]	CT image	CNN
Al-Tashi et al. (2019) [22]	CT image	Hybrid grey wolf optimization
Ye et al. (2019) [23]	CT image	Adaptive statistical iterative reconstruction-V technique
Yamashita et al. (2018) [24]	X-ray image	CNN
Fu et al. (2018) [25]	CT, X-Ray image	Multimodal CNN
Walker et al. (2017) [26]	CT, X-Ray image	Multimodal CNN

3 Enhanced Whale with Salp Swarm Optimization Methodology

This work introduces the concept of classification of affected lung disease and its severity. This proposed work has four stages. First, a median filter is used for pre-processing. Second, PCA is used for texture feature extraction. Third, A MWOA is used for selecting features. Fourth, the proposed MWOA-SSA is used for classification and identifying the severity. The architecture of our proposed method is given in Fig. 1. CT scan images are collected and preprocessed using a median filter. PCA is used to remove unwanted textures in the images. Then, the images are processed using MWOA-SSA to classify the affected image.

This proposed work consists of four phases:

Phase 1: Pre-processing using a median filter.
Phase 2: Feature extraction using PCA.
Phase 3: Feature selection using MWOA.
Phase 4: Proposed work on classification of infected lung images from a large dataset using MWOA-SSA.

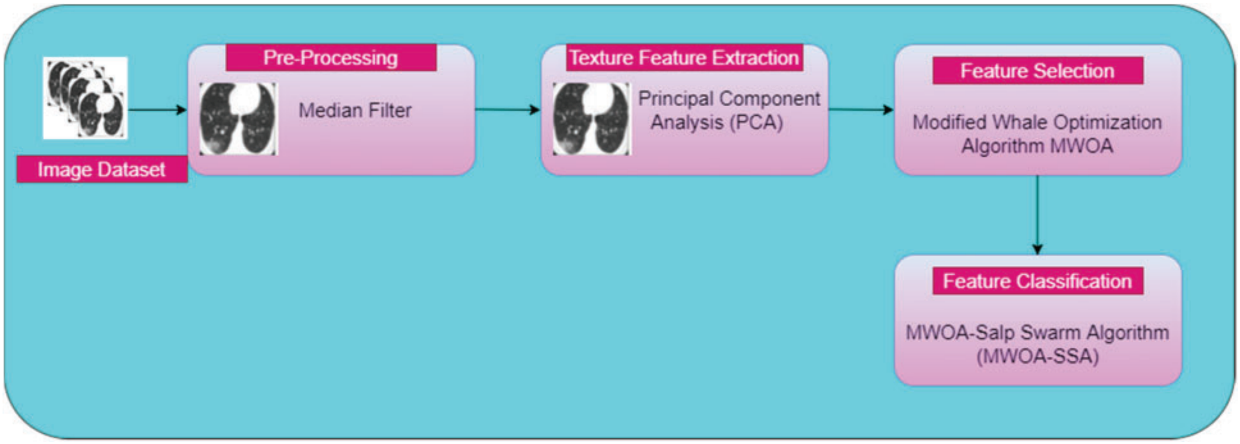

Figure 1: Architecture of proposed work

3.1 Pre-Processing

The aim of pre-processing is to improve the high quality of the CT scan chest image. We need to denoise the image by applying a median filter. This median filter scans the entire image using an 8×8 matrix and replaces the center pixel value by choosing the median of all pixel values inside the 8×8 matrix by using

$$img[a, b] = median\{imgo[i, j], \{i, j) \in y\} \tag{1}$$

where y is the neighborhood pixel value represented by the user and i, j is the center pixel value's location.

3.2 Texture Feature Extraction Using PCA

The idea behind PCA is to map m-dimensional features to n dimensions that have a set of orthogonal feature values. Feature extraction using PCA meets the variance of sample pixel values after reduction of dimensionality and minimizes the error rate. The steps needed for texture feature extraction using PCA are given below, and Fig. 2. Provides an overview of PCA operation.

Algorithm 1: Texture Feature Extraction using PCA

Step 1: To standardize the original pixel values, subtract all sample pixel values from the mean value of corresponding feature value by using s s

$$\overline{A_j} = \frac{1}{n} \sum_{i=1}^{n} A_{ij} \tag{2}$$

Step 2: Evaluate the covariance matrix C $(c = (A_{jk})_{n \times n}$ where n is the number of features; A_{jk} is the correlation between jth and kth feature value, where $j = 1, 2, \ldots, n; k = 1, 2, \ldots, n$.

$$C = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \tag{3}$$

(Continued)

Algorithm 1: Continued

Step 3:

For the covariance matrix, calculate the eigen value of λ_i, and the eigenvector value is ei_i.

$$\lambda_i ei_i = Cei_i \tag{4}$$

Step 4: Store the output values of eigenvector from large to small values

$\lambda_1 \geq \lambda_2 \geq \ldots \lambda_n$ and calculate the rate of contribution for each principal component. The rate of contribution is given below:

$$\frac{\lambda_k}{\sum_{k=1}^{n} \lambda_k} \tag{5}$$

Step 5: Transform the original matrix A into a new matrix B ($B = (B_{jk})_{n \times n1}$, where j=1,2...n and k=1,2,...n.

$$B = A \times f_1, f_2, \ldots, f_{n1} \tag{6}$$

where $f_1, f_2, \ldots, f_n$ denotes a new feature space which is composed of n1 vector feature values, and n1 is extracted features by PCA. Fig. 2 shows the working principle of PCA.

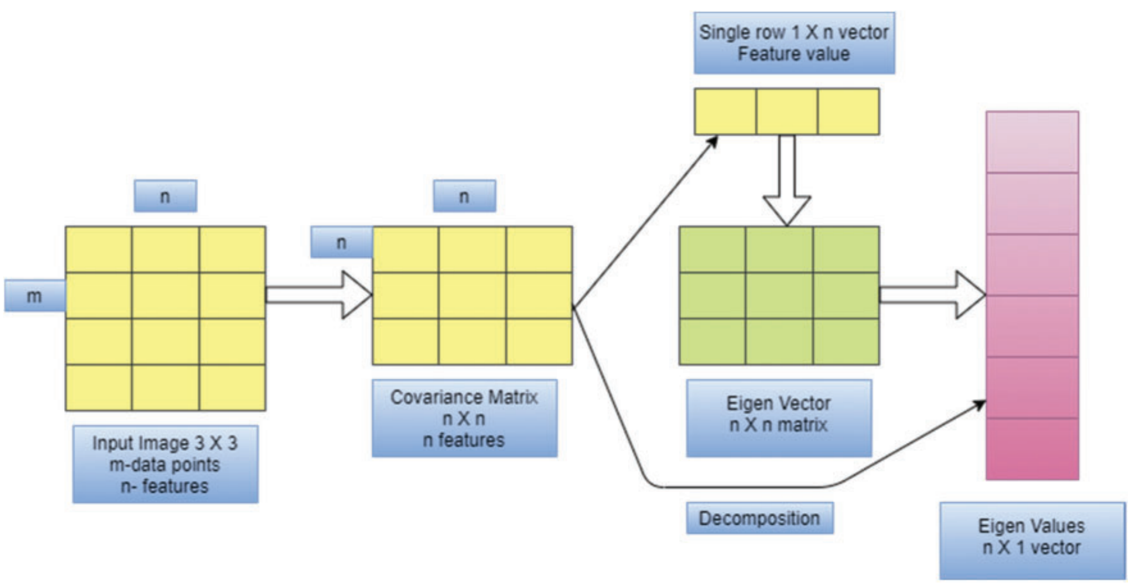

Figure 2: Overview of PCA

3.3 Feature Selection Using MWOA

Feature selection of brain image using MWOA, which is based on the behavior of whales, in which for trapping the prey bubbles are involved for searching in a spiral-shaped [27,28]. The whale is randomly selected, and it can be updated by the best whale value that gives the optimal solution.

$$\vec{F}(n+1) = \overrightarrow{F_{rand}} - \vec{A} \,.\, \vec{D} = |\vec{c} \,.\, \overrightarrow{F_{rand}} - \vec{F}| \tag{7}$$

To improve this result, the performance of three whales are randomly chosen, and it cannot be affected by the leader's position. Eq. (6) is modified as follows:

$$\vec{F}(n+1) = \vec{w_1} * \vec{F}_{rnd1} + \vec{x} * \vec{w_2} * (\vec{F}_{rnd2} - \vec{F}_{rnd3}) + (1 - \vec{x}) * \vec{w_3} * (\vec{F} - \vec{F}_{rnd1}) \tag{8}$$

where, $\vec{F}_{rnd1}$, $\vec{F}_{rnd2}$ and $\vec{F}_{rnd3}$ are randomly chosen solutions (prey). $\vec{w_1}$ is a random value between [0,0.5]. $\vec{w_2}$ and $\vec{w_3}$ are random values between [0,1]. $\vec{x}$ decreases the value and smoothens exploration and exploitation by using

$$\vec{x} = 1 - \left(\frac{it}{Max_{it}}\right)^2 \tag{9}$$

where t represents iteration number, and Max_{it} represents the maximum number of iterations.

The algorithm is given as follows:

Algorithm 2: MWOA

Input: Lung Image
Output: Detecting COVID presence images
Step 1: Initialize Population $\vec{F_i}\,(i = 1, 2, \ldots n)$, maximum iteration max_it, function of fitness Fi_n.
Step 2: Initialize parameters of WOA $\vec{B}$, $\vec{b}, \vec{c}, \vec{u_1}, \vec{u_2}, \vec{r_3}, h$ and modified parameters $\vec{w_1}$, $\vec{w_2}$, $\vec{w_3}$.
Step 3: Initialize t=1.
Step 4: Convert output into binary values as 0 or 1.
Step 5: Evaluate fitness value Fi_n for each $\vec{F_i}$.
Step 6: Find best individual value by $\vec{F^*}$.
Step 7: While $n \leq$ max_$iter$ do
Step 8: For $i = (1; i < n + 1)$ **do**
Step 9: If $(\vec{u_3} < 0.5)$ **then**
Step 10: If $(|\vec{B}| < 1)$ **then**
Step 11: Update current position of agent for search by using Eqs. (2), (3).
Step 12: Else
Step 13: Choose three search agents randomly $\vec{F}_{rnd1}, \vec{F}_{rnd2}, \vec{F}_{rnd3}$.
Step 14: Update agent's exponential form by using Eq. (9).
Step 15: Update current position of agent for search in exponential form by using Eq. (8).
Step 16: End if
Step 17: Else
Step 18: Update current position of agent for search by using

$$\vec{F}\,(t+1) = \vec{D'}\,.e^{bh}.\cos(2\pi h) + \vec{F^*}\,(t)$$

Step 19: End if
Step 20: End For
Step 21: for $(i = 1; i < n + 1)$ **do**
Step 22: Evaluate $\vec{F_i^*} = Gaussian(\mu\vec{F^*}\,,\,\sigma) + (\eta \times \vec{F^*} - \eta' \times \vec{P_i})$
Step 23: End For
Step 24: Update $\vec{B}, \vec{b}, \vec{c}, \vec{w_3}, h$

(Continued)

Algorithm 2: Continued

Step 25: Binary optimizer the updated solution/prey by using

$\overrightarrow{F_n^{(t+1)}} = \begin{cases} 1 \; if \; sigmoid(F_{best}) \geq 0.5 \\ 0 \qquad\qquad Otherwise \end{cases}$

$sigmoid(F_{best}) = \frac{1}{1 + exp^{-10(F_{best}-0.5)}}$

Step 26: Evaluate fitness value Fi_n for each $\overrightarrow{F_i}$.

Step 26: Find best individual value by $\overrightarrow{F^*}$.

Step 27: $t = t + 1$

Step 28: End While.

Step 29: Return $\overrightarrow{F^*}$.

3.4 Proposed Feature Classification Using MWOA-SSA

In this phase, classification of infected lung images from a large dataset is done using MWOA-SSA. To improve the accuracy and optimal solution, the SSA) is used with MWOA. This SSA randomly initializes the swarm of N salps. The swarm is represented by the 2-D matrix *mat*. Searching food for swarm is represented as sf , and leader's movement in the form of a chain is denoted as sx_i'. It is represented by using

$$sx_i' = \begin{cases} sf_i + r_1((upl_i - lowl_i)r_2 + lowl_i), & r_3 \geq 0.5 \\ sf_i + r_1((upl_i - lowl_i)r_2 + lowl_i), & r_3 < 0.5 \end{cases} \tag{10}$$

where i is swarm's dimension position, and it is updated. sf_i is the i^{th} position for a source of food. upl_i and $lowl_i$ are the upper and lower limits of the i^{th} element. r_1 is a dynamic variable for iteration. r_2 and r_3 are random numbers between [0,1] calculated as

$$r_1 = 2e^{-(4it/iter)^2} \tag{11}$$

where it represents the current iteration and $iter$ is the maximum number of iterations. r_1 is a control variable that controls the balance between exploitation and exploration of the optimization algorithm. It is represented as

$$sx_i' = 0.5(sx_i' - sx_i^{i-1}) \tag{12}$$

The procedure for SSA is given as follows.

Algorithm 3: Feature Classification using MWOA-SSA

Input: Lung CT Scan Image

Output: COVID-detected image

Step 1: Initialize population $\overrightarrow{F_i}\,(i = 1, 2, \ldots n)$, maximum iteration max_it, function of fitness Fi_n.

Step 2: Initialize parameters of WOA $\vec{B}$, $\vec{b}, \overrightarrow{c}, \overrightarrow{u_1}, \overrightarrow{u_2}, \overrightarrow{r_3}, h$ and modified parameters $\overrightarrow{w_1}$, $\overrightarrow{w_2}$, $\overrightarrow{w_3}$.

Step 3: Initialize t = 1 and swarm of salps $sx_i i = 1, 2, \ldots.., n$.

Step 4: Convert output into binary values as 0 or 1

Step 5: Evaluate fitness value Fi_n for each $\overrightarrow{F_i}$.

Step 6: Evaluate fitness value for each salp of the swarm

(Continued)

Algorithm 3: Continued

Step 7: Find best individual value by $\overrightarrow{F^*}$.
Step 8: Assign F as best salp's position.
Step 9: Update r_1 by Eq. (11).
Step 10: While $n \leq$ max_*iter* do
Step 11: For $i = (1; i < n + 1)$ **do**
Step 12: If $(\overrightarrow{u_3} < 0.5)$ **then**
Step 13: If $(|\vec{B}| < 1)$ **and** $(i == 1)$ then
Step 14: Update current position of agent for search by using Eqs. (2) and (3).
Step 15: Update position of leader by using Eq. (10).
Step 16: Else
Step 17: Update position of followers by using Eq. (12).
Step 18: Choose three search agents randomly $\vec{F}_{rnd1}, \vec{F}_{rnd2}, \vec{F}_{rnd3}$.
Step 19: Update agent's exponential form by using Eq. (9).
Step 20: Update current position of agent for search in exponential form by using Eq. (8).
Step 21: End if
Step 22: Else
Step 23: Update current position of agent for search by using

$$\overrightarrow{F}(t+1) = \overrightarrow{D'} . e^{bh} . \cos(2\pi h) + \overrightarrow{F^*}(t)$$

Step 24: End if
Step 20: End For
Step 21: for $(i = 1; i < n + 1)$ **do**
Step 22: Evaluate $\overrightarrow{F_i^*} = Gaussian(\mu \overrightarrow{F^*}, \sigma) + (\eta \times \overrightarrow{F^*} - \eta' \times \overrightarrow{P_i})$
Step 23: End For
Step 24: Update $\vec{B}, \vec{b}, \vec{c}, \overrightarrow{w_3}, h$
Step 25: Binary optimize the updated solution/prey by using

$$\overrightarrow{F_n^{(t+1)}} = \begin{cases} 1 \ if \ sigmoid(F_{best}) \geq 0.5 \\ 0 \qquad Otherwise \end{cases}$$

$$sigmoid(F_{best}) = \frac{1}{1 + exp^{-10(F_{best}-0.5)}}$$

Step 26: Evaluate fitness value Fi_n for each $\overrightarrow{F_i}$.
Step 26: Find best individual value by $\overrightarrow{F^*}$.
Step 27: $t = t + 1$
Step 28: End While.
Step 29: Return $\overrightarrow{F^*}$, F.

4 Results and Analysis

For the experimental result, data are collected from the Kaggle dataset [29], which has 1,500 CT images of COVID-19 and non-COVID 19. MWOA-SSA is compared with the existing algorithms MWOA [30] and SSA [31] by using performance metric measures of sensitivity, specificity, accuracy, precision (PPV), F-score, and negative predictive value (NPV).

$TP - True\ Positive,\ TN - True\ Negative,\ FN - False\ Negative,\ FP - False\ Positive,$

These metric measures are defined by using:

Sensitivity

It is also called true positive rate or recall.

$$sensitivity = \frac{TP}{TP + FN} \tag{13}$$

Specificity

It is called true negative rate (TNR).

$$Specificity = \frac{TN}{TN + FP} \tag{14}$$

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

Precision

It is called positive predictive value (PPV).

$$PPV = \frac{TP}{TP + FP} \tag{16}$$

Negative Predictive Value

It evaluates true negatives for all negative values by using

$$NPV = \frac{TN}{TN + FN} \tag{17}$$

F-Score

It is used to measure sensitivity and mean of harmonic by using

$$F - Score = 2 \times \frac{PPV \times TPR}{PPV + TPR} \tag{18}$$

Tab. 2 shows the performance metric measures of feature extraction.

Table 2: Performance metric measures of feature extraction

Algorithm	Sensitivity	Specificity	PPV	NPV	F-score
PCA	84.4%	77.2%	74.6%	81.3%	75.1%
MWOA	95.2%	89.5%	82.1%	85.2%	83.2%
MWOA-SSA	97.8%	91.7%	88.3%	93.6%	96.4%

Tab. 2 shows that for the sensitivity rate, MWOA-SSA is better than PCA (84.4%) and MWOA (95.2%). MWOA-SSA outperforms other algorithms with a specificity of 97.8%. For PPV, MWOA-SSA has a percentage of 88.3%. For NPV, MWOA-SSA has 93.6%. MWOA-SAA outperforms other algorithms with an F-score of 96.4%.

4.1 Feature Selection

MWOA-SSA is used for feature selection, and it is compared with existing algorithms of PCA and MWOA in terms of average fitness, average error, best fitness, mean, standard deviation, and worst fitness. The parameter values for the fitness function are 0.97 and 0.03.

Average Error

It shows the classifier's accuracy for the feature selection for the COVID-19 dataset, and it is calculated by using

$$AverageErr = 1 - \frac{1}{R}\sum_{j=1}^{R}\frac{1}{S}\sum_{i=1}^{N} Comp(Cl_i, lb_i) \tag{19}$$

where Cl_i is classifier's label for the pixel i and lb_i is the class label for the pixel i of the image and *Comp* calculates the matching between two inputs.

Mean

$$Mean = \frac{1}{R}\sum_{j=1}^{M} me_j^* \tag{20}$$

Standard Deviation

$$SD = \sqrt{\frac{1}{N-1}\sum^{(me_j^*-mean)^2}} \tag{21}$$

where mean is obtained from Eq. (17)

Best Fitness

It calculates the minimum function of fitness, and it is calculated as

$$Bestfit_n = Min_{j=1}^{M} me_j^* \tag{22}$$

Average Fitness

The average size of features in the COVID-19 dataset is calculated as

$$Avgsize = \frac{1}{M}\sum_{j=1}^{M}\frac{size(me_j^*)}{D} \tag{23}$$

Worst Fitness

The worst solution of fitness is calculated as

$$worstfit_n = Max_{j=1}^{M} me_j^* \tag{24}$$

Tab. 3 shows the performance of the proposed algorithm in feature selection

The results of the proposed MWOA-SSA algorithm in Tab. 3 show the lower error and select features from the COVID-19 dataset. The MWOA-SSA algorithm achieved the minimum average error of 0.1114 in selecting the features of infected lung images. The minimum errors for PCA, MWOA, and MWOA-SSA are used to select the features from best fitness to worst fitness. The proposed algorithm MWOA-SSA outperforms other existing algorithms, and the best fitness value is 0.1034, the worst fitness value is 0.2115, and the average fitness value is 0.2034.

Table 3: Performance metric measures for feature selection

Optimizer	PCA	MWOA	MWOA-SSA
Average error	0.1652	0.1547	0.1114
Average select size	0.3234	0.3548	0.0715
Mean	0.3452	0.4134	0.1573
Standard deviation	0.0367	0.0678	0.0123
Best fitness	0.1264	0.1598	0.1034
Worst fitness	0.2763	0.2356	0.2115
Average fitness	0.2287	0.2419	0.2034

4.2 Detection and Severity Classification of COVID-19

To detect the infection severity, lung images have been examined by using ground truths of CT0–CT4 as given below. Tab. 4 presents the severity levels in the lungs.

Table 4: Severity levels for infection in lungs [32,33]

Class	Infection in %
Healthy	0
Mild	1 – 25%
Moderate	26 – 50%
Severe	51 – 75%
Critical	76 – 100%

In this work, we collected data on 500 patients with COVID-19 infection. Infection was confirmed by a nasopharyngeal swab using a U-TOP COVID-19 Detection Kit. Age, gender, d-dimer, ferritin levels, C-reactive protein test (CRP), and O2 were collected. Patient's age was classified into <20, 21–40, 41–49, 50–60, 61–70, and >70 years. The correlation ($p < 0.05$) between CT severity score was used to detect lung infection. Tab. 5 shows a survey of 500 patients who are affected by pneumonia. Fig. 3. shows the CT severity of COVID-19 patients.

Table 5: Demographic data of 500 patients

Age in years	Male (300 patients)	Female (200 patients)
5 to 20	53	40
21 to 40	87	35
41 to 60	65	45
61 to 70	35	35
More than 71 years	60	45

Fig. 3 shows that negative disease was mainly seen in the age group of 21 to 40 (30%), mild lung mainly infection was seen in the 41 to 60 age group (60%). Moderate lung infection was mainly seen in the 61 to 70 age group (68%), and severe lung infection was mainly seen in the age group of 41 to 60 (70%). This is the highest risk factor for COVID-19 affected patients [34–37]. Fig. 4. shows the time taken for the classification of COVID-19 affected cases and non-COVID-19 cases from the large dataset.

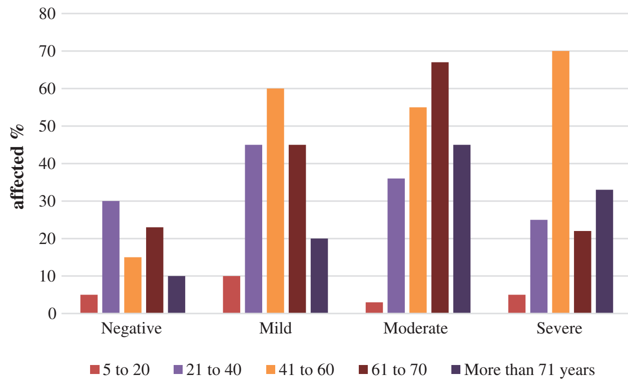

Figure 3: CT-COVID severity score

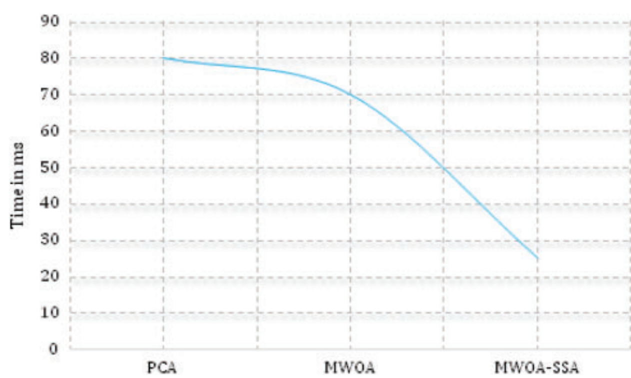

Figure 4: Execution time (proposed method executes faster than PCA and MWOA)

5 Conclusion

MWOA-SSA is used for the classification of COVID-19 cases in four phases. In the first phase, to classify accurate COVID-19 and non-COVID-19 images from a large dataset, pre-processing work has been done using a median filter. Features are extracted for the training CT images by PCA. For the feature selection of CT lung images, MWOA is implemented. For the selected features of the CT image, MWOA-SSA is implemented to classify the COVID-19 and non-COVID-19 images from the large dataset. This paper also proposes detecting and identifying the severity of lung infection by using different severity levels of COVID-19 cases. The main advantage of MWOA-SSA is that it efficiently and quickly classifies COVID-19 and non-COVID-19 cases and detects severity of lung infection using severity levels. MWOA-SSA has an accuracy of 97%, whereas PCA and MWOA have accuracies of 81% and 86%. In future work, we suggest the use of various deep learning algorithms and various modalities of images and clinical reports.

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