Enhancing COVID-19 Diagnosis Through a Hybrid CNN and Gray Wolf Optimizer Framework

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***Abstract*—Covid-19 is an infectious respiratory disorder brought about using a brand-new coronavirus first found in 2019. The severity of symptoms can vary from mild to life-threatening. No vaccine or specific treatment has been developed to address Covid-19. Hence the most effective preventive measure is to practice social distancing and adhere to good hygiene practices. Medical imaging and convolutional neural networks are used in Covid-19 research to quickly identify infected individuals and detect changes in the lung tissue of those infected. Convolutional neural networks can be used to analyze chest CT scans, detecting potential signs of infection like ground-glass opacities, which indicate the presence of Covid-19. This article introduces a powerful framework for classifying COVID-19 images utilizing a hybrid of CNN and an improved version of Gray Wolf Optimizer. To demonstrate the efficiency of the projected framework, it is verified on a standard dataset and compared with other methods, with results indicating its superiority over the others.**

Keywords—Covid-19; respiratory disorder; medical imaging; convolutional neural networks; improved gray wolf algorithm

I. Introduction

This In Wuhan, Hubei Province, China, a cluster of pneumonia cases with an undetermined reason was described in Dec. 2019. Middle East Respiratory Syndrome (MERS-CoV) and severe acute respiratory syndrome (SARS-CoV) are just two examples of the diverse diseases that can be brought on by the coronaviruses (CoV) family of viruses. Formerly undetected in people, the coronavirus illness (Covid-19) is a new type that was discovered in 2019.

The way of transmission of Covid-19 makes it a very dangerous disease. The disease can be transmitted by airborne droplets (discharges that appear invisibly when talking, sneezing, or coughing.). Medical imaging is also essential in determining the severity of COVID-19 and providing guidance for treatment. Medical imaging can be used to diagnose pneumonia.

Automated CT or X-ray analysis techniques based on artificial intelligence exist for the detection, monitoring and quantification of the coronavirus. They are used to detect infected patients from healthy individuals. At first, blood tests were taken from patients hospitalized with corona symptoms after some time, and it took 2 to 3 days to confirm their infection. It was dangerous and caused the number of patients to increase for a long time. The beginning of this decade should be marked by the coronavirus pandemic, spurring the development and advancement of various digital technologies to combat multiple diseases and clinical issues.

Machine learning, a subdivision of artificial intelligence, enables a system to gain knowledge from prior data, detect patterns, and make decisions with little human input. Examples of algorithms include logistic regression [1], SVM [2], K-means clustering [3], etc.

DL (Deep Learning) is a type of ML (machine learning) that utilizes multiple layers of computation to analyze and learn data representations, extracting features at various levels of abstraction. CNNs methods are one example of DL and are employed in various uses related to Covid-19 identification.

For example, A DL-based technique for diagnosing the Covid-10 utilizing X-ray images was offered by [4]. The researchers employed chest X-ray radiographs to identify coronavirus pneumonia in patients by utilizing five transfer learning-based convolutional neural networks, namely ResNet101, ResNet50, InceptionV3, Inception-ResNetV2, and ResNet152. Five-fold cross-validation was implemented, and three binary categorizations were established containing four groups (viral pneumonia, bacterial pneumonia, and COVID-19, normal (healthy)). Findings presented that the ResNet50 system can provide the greatest segmentation efficiency among the other 4 utilized models, according to the performance findings.

Using chest CT X-ray pictures, Aslan et al. introduced two DL methods for the automated detection of positive COVID-19 patients [5]. These suggested designs used ANN methodology to autonomously conduct lung segmentation (pre-processing) on CT images (ANN). The AlexNet architecture was included in both designs. Hence, a pre-trained application is the suggested approach. The second suggested design, meanwhile, had a combined configuration since it included a BiLSTM (Bidirectional Long Short-Term Memory) layer that also considered temporal aspects. The findings show that the suggested architecture performs very well at detecting infections. Consequently, this research contributes to previous studies with its advanced architectural design and high segmentation accuracy.

A structure for COVID-19 image segmentation that combines deep learning and metaheuristics was suggested in [6]. As a deep learning system, appropriate visual representations were learned and extracted using MobileNetV3 as the foundation for feature extraction. To reduce the dimension of the image representations and improve classification precision, the Aquila Optimizer was used as a characteristic selector and metaheuristic method. Two datasets, including CT COVID-19 and X-ray images, were applied to verify the suggested framework. The tests' findings

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demonstrated that the suggested framework performed well regarding segmentation precision and dimension decrease throughout the characteristic extraction and choice stage. The Aquila Optimizer feature selection algorithm demonstrated superior performance metrics than other prior approaches.

However, despite the advancements in deep learning techniques for COVID-19 identification using medical imaging, there is still a need for more efficient and accurate classification frameworks. While previous studies have demonstrated the effectiveness of convolutional neural networks (CNNs) in analyzing chest CT scans and X-ray images, there is room for improvement in terms of classification performance and computational efficiency. Furthermore, the existing literature lacks research on the utilization of hybrid models that combine CNNs with optimization algorithms to enhance the classification accuracy of COVID-19 images. Optimizers play a crucial role in fine-tuning the model parameters and improving its overall performance. Therefore, there is a gap in the literature regarding the development and evaluation of a hybrid CNN framework incorporating an improved version of the Gray Wolf Optimizer for COVID-19 image classification. Closing this gap in the research is essential as it can lead to the development of a more effective and accurate framework for identifying COVID-19 infections. Such a framework would not only assist in the timely diagnosis of the disease but also aid in monitoring the severity of the infection and providing appropriate treatment guidance. Additionally, an enhanced classification model would contribute to the efforts in containing the spread of the virus by enabling the rapid identification of infected individuals.

The approach outlined in this article for detecting and identifying covid-19 from medical photos is based on the combination of the Improved Gray Wolf Algorithm and Convolutional neural networks. There are two critical steps in this process. The photos are subjected to pre-processing in the first stage to minimize and eliminate the noise. To identify the kind of tumor through data training, the operation of segmentation and extraction of brain tumor features is performed in the second phase. This section describes the pre-processing processes, formulation of the Improved Gray Wolf Algorithm, and convolutional neural networks.

II. Pre-processing Stage

Category of image pre-processing is one of the most basic stages of image processing because the images that are given to the computer system mainly have noise in their pixels. These noises should be reduced as much as possible and ideally eliminated. Medical images of Covid-19 are no exception to this rule.

The noise image is considered in the form of an initial image, and after that, the noise removal operation is performed by the MFT filtering method [7]. To achieve the constituent structure and components of the images and their analysis, as well as their small and large details, the quantum MFT filtering method was considered. The output of the pre-processing step is a set of decomposed coefficients.

In this process, a set of these coefficients is randomly selected to perform the reconstruction operation. The parts used in this process consist of median filtering, Gaussian filtering, quantum matching, criterion change, single-point columns and rows, point detection and point-to-point matching. In Gaussian filtering, a Gaussian filter is applied to the image. The value of this filter is chosen by chance. This value can be 3×3 or 5×5 pixels. After performing this filtering, the median filter is utilized for the image. In the following, the total pixels are randomly multiplied by a suitable criterion. This numerical value is in the interval between 0.7 and 1.3. Once the appropriate criterion is chosen, the process of quantum adaptation must begin.

In this step, the amount of light in each part of the image is matched by the quantum processing method of the MFT filtering method. In a single-point row and column steps, pixels are determined randomly. In the point-to-point matching phase, each pixel of the decomposed coefficients is determined randomly until the new image is generated. In the last step, all row, column and diagonal points are identified by MFT filtering to reduce image noise. After completing the mentioned operation, the whole image is sorted by the unique pixel values they have. Threshold functions and active contours have two characteristics which are oscillating and wave, and they are written according to the below Equation:

$$\int_{-\infty}^{0} |\psi(t)|^2 dt < \infty \quad (1)$$

where, the maximum energy in $\psi(t)$, which is proportional to time and changes according to it, has a time interval assigned to it, expressed according to the below formula.

$$\int_{-\infty}^{0} \psi(t) dt < 0 \quad (2)$$

Considering that reducing the noise of the images is intended, its relationship is written as follows:

$$Min - Noise = \left(\sum_{\Omega} \sqrt{1 + (\beta|\nabla l|)^2} \right) + \frac{\lambda}{2}(l - I)^2 \quad (3)$$

In this equation, several parameters are involved, each serving a specific purpose in the noise reduction process:

l represents the target image, which refers to the ideal or noise-free image that we aim to reconstruct or approximate.

I denotes the noisy image, which is the input image that contains the noise and requires denoising.

∇l represents the total variation of the determination period. Total variation is a measure of the image's smoothness or the amount of changes between neighboring pixels. By considering the total variation, the algorithm can effectively preserve the edges and important features while reducing noise.

β is the balance level parameter. It controls the trade-off between noise reduction and preserving image details. Adjusting β allows for fine-tuning the denoising process to achieve the desired level of noise reduction while maintaining important image characteristics.

λ is the regularization parameter, also known as the smoothing parameter. It controls the smoothness of the denoised image and balances the fidelity to the noisy input image. A higher value of λ promotes smoother results, while a lower value preserves more details but may not effectively suppress noise.

Ω represents the total points in the image, indicating the spatial domain over which the noise reduction process is applied.

By minimizing the expression in Equation (3), the algorithm aims to reduce the noise in the input image (I) while preserving important image details and minimizing artifacts introduced during the denoising process. This noise reduction step is essential to enhance the quality and accuracy of the COVID-19 image analysis, facilitating more reliable classification and diagnosis. Overall, incorporating the noise reduction relationship into the proposed framework contributes to improving the robustness and effectiveness of COVID-19 image classification by reducing unwanted noise and enhancing the clarity of the images.

The performance of Equation (3) is such that it always considers the edge of the corresponding image and preserves its important features. The expression $(l-I)^2$, which is present in Equation (3), shows the amount of verification and confirmation of the validity of the existing image during review and processing with the base image.

III. Methods and Tools

In this investigation, the concept of DL is used to train the network. DL is a type of ML that utilizes a variety of algorithms to represent abstract concepts numerically in the form of a graph. Deep models comprised multiple layers of linear and non-linear transformations. In other words, it is based on learning to display knowledge and features in model layers, which are based on artificial neural networks that model very complex networks.

A. Deep Learning

Its impact has been felt in almost all scientific fields and has changed businesses and industries. Recently, deep learning method has been widely utilized in the automatic identification of COVID-19 in patients [8-9]. Since then, numerous CNN designs have been created to classify images, and it has been demonstrated that these architectures outperform humans on the same dataset [10]. In order to forecast picture class labels, connectivity loss, as well as operational parameters (e.g., convolution kernels), are learnt from peripheral images [11].

A convolutional neural network is generally comprised of input, convolution, activation, fully connected, and output layers.

1) Convolution layer: The convolution layer is the maximum essential layer in a CNN. It can automatically identify features of an image without the need for manual definition. This layer can be expressed mathematically as follows:

$$f(g(t)) \cong \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau \quad (4)$$

where, convolution is determined by taking the integral of the product of two functions after inverting and altering one of them. As stated in Equation 4, $g(t)$ serves as the filter that is reversed and shifted across the input function $f(.)$. The result of this intersection between $g(.)$ and $f(.)$ is the convolution value.

The "stride" parameter indicates the intervals at which the filter function traverses the input function. The stride is the distance the filter function $g(.)$ moves across $f(.)$. Generally, after a convolution operation, the output feature map will have a reduced size compared to the inputs. To prevent this from happening and maintain the dimensions of the output map, "padding" is utilized.

2) Activation layer: Activation layers, which typically follow convolution layers and are nonlinear in nature, play a crucial role in the selection of neurons to be activated. The input of the activation layer is an actual number that is transformed by a nonlinear operation.

3) Pooling layer: Pooling layers are usually placed between convolutional layers to reduce the three-dimensional size of the demonstration and decrease the number of variables and computations in a system. A pooling layer filters out important pixels and eliminates noise from the output feature map of a convolutional layer. Furthermore, pooling layers are utilized to increase the spatial invariance of the network.

4) Fully connected layers: The fully associated layers, which receive the output from the characteristic extraction layers, are typically positioned at the end of the neural network. The principal objective of the Dense layer is to assess all of the characteristics generated by preceding layers and use them for classification tasks. The following is a description of this notion.

$$L = \sum_{i=1}^{N}\sum_{j=1}^{k} -D_k^j \log Z_k^j \quad (5)$$

where, N is the sample count, D describes the chosen output vector, and Z_k^j shows the actual output vector for the mth class as determined by the following formula:

$$Z_k^j = \frac{exp(f_j)}{\sum_{j=1}^{k} exp(f_j)} \quad (6)$$

The function L is developed to contain a value to raise the weights' η values, and this is done with the weight penalty:

$$L = \sum_{i=1}^{N}\sum_{j=1}^{k} -D_k^j \log Z_k^j + \frac{1}{2}\eta \sum_P \sum_Q \omega_{p,q}^2 \quad (7)$$

where, L describes the whole number of layers, K defines the layer q connections, and p is the connection weight. A block schematic of a typical CNN for skin cancer detection is shown in Fig. 1.

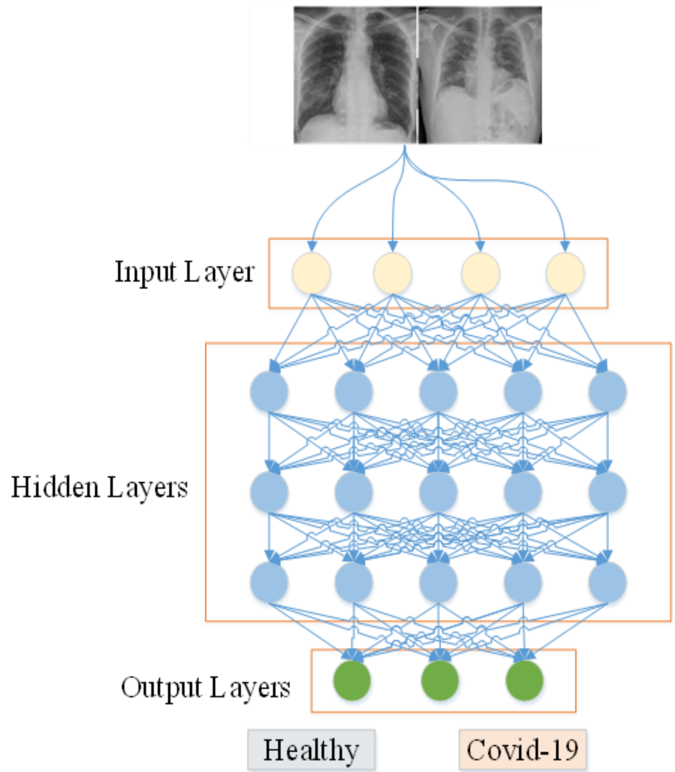


Fig. 1. The convolutional neural network's common construction.

B. Improved Gray Wolf Algorithm

The Gray Wolf Optimization (GWO) algorithm draws inspiration from the collective behavior of gray wolves while hunting, which is a variety of Swarm Intelligence Algorithm. The wolves' location in the issue-solving area shows how the issue can be solved [12]. Gray wolves live and hunt in groups.

The wolves employ a strategic approach to hunting, first forming a perimeter around the targeted prey and gradually tightening the circle until the animal is exhausted. They begin to attack in succession, taking direction from the alpha wolf and eventually bringing down their target [13]. Gray wolves exhibit a hierarchical social structure. This hierarchy is shown in Fig. 2 and explained below:

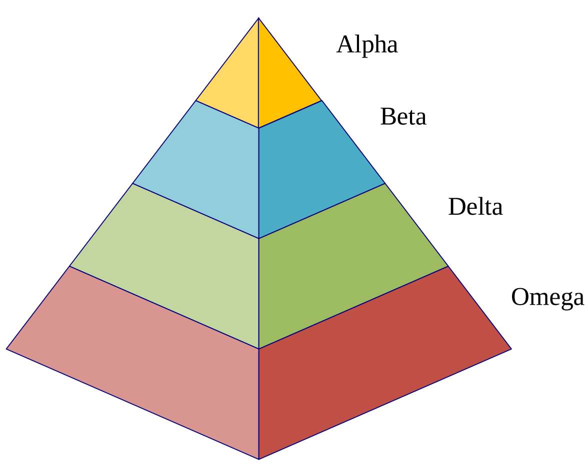


Fig. 2. The gray wolf hierarchy.

- The alpha category (α) is known as the group leader and is responsible for making decisions about hunting. Alpha decisions apply to the entire group.
- The beta wolves (β) constitute the second hierarchical class within a wolf pack and are relied upon for making decisions and performing other duties. These wolves are often called upon to assume the alpha position when the existing alpha reaches advanced age or passes away.
- The Omega wolves (ω) can be classified as the lowest hierarchical order in the wolf pack. This group of wolves functions similarly to a Peshmerga, requiring obedience from all other members of the pack and being the last to receive sustenance.
- Wolves which are not included in the aforementioned social structure are referred to as Delta wolves (δ). These wolves are subordinate to Alpha and Beta but have a higher rank than Omega.

Gray wolves surround their victim when hunting, as was already described. The following relationships are employed to model hunting:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \qquad (8)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - A.D \quad (\qquad 9)$$

Hence, t denotes the coefficients, A and C represent the vector of hunting position and the vector of position for the gray wolf.

$$\overrightarrow{A2} = \vec{a}.\overrightarrow{r_1} - \vec{a} \tag{10}$$

$$\vec{c}(t+1) = 2.\overrightarrow{r_2} \tag{11}$$

In the above Equations, i is equal to the repetition of the algorithm. Vectors A and C are the vector coefficients of the prey location, and X is the location of the gray wolf. a is linearly decreased from 2 to 0 throughout iterations. $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are accidental vectors in the interval between 0 and 1. X_p is the bait position.

It is assumed that the position of prey X_p is uncertain in the search space. Therefore, the hunting position is considered the alpha position (the best solution obtained). With this assumption, the position of the wolves is obtained by considering the hierarchy:

$$\overrightarrow{X_1} = \overrightarrow{X_a} - \overrightarrow{A_1}.\left(\overrightarrow{D_a}\right).\overrightarrow{X_2}$$

$$= \overrightarrow{X_\beta} - \overrightarrow{A_2}.\left(\overrightarrow{D_\beta}\right).\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_1}.\left(\overrightarrow{D_\delta}\right) \tag{12}$$

where,

$$\overrightarrow{D_a} = \left|\overrightarrow{C_1}.\overrightarrow{X_a} - \vec{X}\right|.\overrightarrow{D_\beta}$$

$$= \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right|.\overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \tag{13}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \tag{14}$$

By using these relationships, the position of the wolves is obtained in each iteration. Finally, when the stop condition is met, the algorithm ends.

In the following, the proposed improved algorithm will be presented. The gray wolf algorithm is one of the powerful optimization algorithms based on collective intelligence. But the performance of collective intelligence algorithms decreases when faced with complex cost functions [14]. Therefore, to cover this weakness, the developed gray wolf algorithm is introduced in this section. Discovery and extraction features are two fundamental pillars of efficient optimization. The meaning of exploration is to search the entire space of variables. Having this feature will make the algorithm able to explore the entire search space and avoid getting stuck in local extremes. The presence of parameter A in the gray wolf algorithm creates a balance between exploration and extraction properties.

When the parameter A is in the range $A > 1$ or $A < -1$, the algorithm works in a heuristic manner, and when this parameter is in the range $-1 < A < 1$, the extraction property of the algorithm will increase[15]. This parameter is defined as $\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a}$ and its value depends on the value of a. In the main algorithm, the amount of this variable is equivalent to 2 at the beginning of the algorithm, and as the repetitions pass, it reaches zero value linearly. To improve the efficiency of this algorithm, in the suggested technique, the following relationship is used to apply changes to a:

$$a = cos\left(\frac{\pi i}{T}\right) + 1 \tag{15}$$

where, i and T represent, in turn, the iteration of the algorithm and the maximum algorithm iteration.

The values of parameter a in the proposed method in the exploration stage are larger than its values in the original method. This means increasing the power of discovery in this stage of the proposed method. On the other hand, the values of parameter an in the extraction stage are lower than those in the main algorithm. This helps to increase the convergence velocity of the improved algorithm compared to the original technique.

In addition to using Equation (15) to update the parameter, in order to improve the efficiency of the algorithm, instead of averaging the position of wolves α, β and δ in Equation (14), their weighted average is used. In this way, the weight coefficient of each position is considered proportional to the inverse of the resulting cost function. Therefore, instead of using the relation (14), the following relations can be used to obtain the position in the next iteration.

$$\vec{X}(t+1) = \frac{L_1\overrightarrow{X_1}+L_2\overrightarrow{X_2}+L_3\overrightarrow{X_3}}{L_1+L_2+L_3} \tag{16}$$

where,

$$G_\alpha = \frac{1}{cost_a} \tag{17}$$

$$G_\beta = \frac{1}{cost_\beta} \tag{18}$$

$$G_\delta = \frac{1}{cost_\delta} \tag{19}$$

where, $cost\ t$ describes the value of the cost function of the corresponding position, and L_1, L_2, and L_3 represent three weights of the updated Equation.

C. Optimized CNN

Different studies are conducted to improve the structure of a CNN. The application of optimization algorithms to CNNs has produced interesting results. This paper introduces a new optimized approach to optimize CNN structure. The construction of the projected CNN has been shown in Fig. 5, and the input images are 32x32 pixels in size. The proposed algorithm is clearly illustrated in Fig. 3.

For this issue, the size of the sliding window is denoted by "max", and the smallest value that can be accepted of the max-pooling minimum (which is 2 here) is labeled "min" to cut down the error of the system. It's worth mentioning that the amount of the sliding window must be less than the input data. As a result, a selection of answers has been randomly obtained.

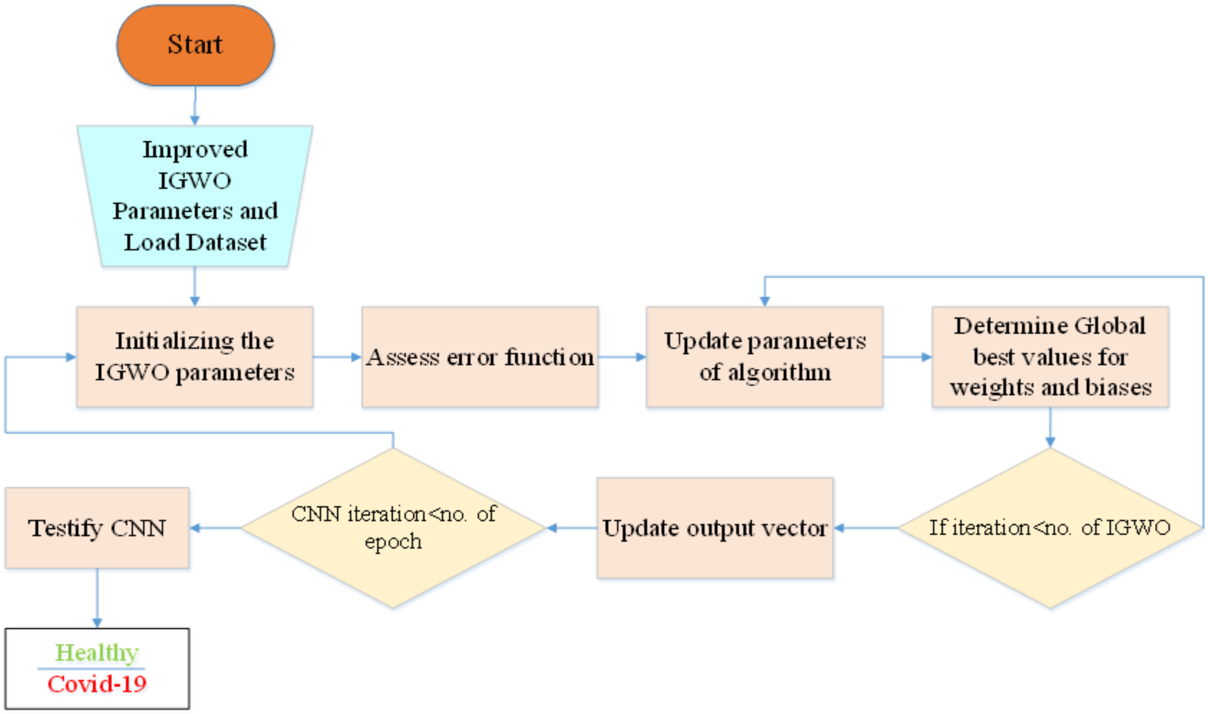


Fig. 3. Schematic representation of the suggested CNN/IGWO.

CNN training is paramount for achieving the best outcomes from layer parameters so that each layer is properly connected and identifies the image accurately. Utilizing the gradient descent algorithm to optimize the parameters of a model, such as convolution filters and fully connected layer weights, is commonplace. In particular, the latter layer plays an integral role in image classification. Thus, it is imperative to refine the training of its weight vector by utilizing an enhanced Whale Optimization Algorithm. The number of search agents should be set at fifty, and a maximum of two hundred iterations with vectors varying linearly between 0 and 2 can be applied. To minimize CNN, a fitness function should be used:

$$E = \frac{1}{T}\sum_{i=1}^{n_t}\sum_{j=1}^{n_{ol}}(D_{ji} - Z_{ji})^2 \quad (20)$$

where, D_{ji} and Z_{ji} denote the chosen output and the output amount generated by the Convolutional Neural Network (CNN), respectively, where and n_{ol} and n_t represent the number of output layers and the amount of training samples, respectively.

This research utilized the half-value precision function to validate the optimized Covid-19 by accurately determining the parameters of the algorithms and applying them to a Convolutional Neural Network. Parameter initialization and evaluation of the function value were conducted, and then the Improved Gray Wolf Algorithm was utilized to update the algorithm parameters. This iterative process was repeated until termination criteria were met. The two essential CNN parameters of weights and biases were selected for optimization in accordance with this research.

$$W = [w_1, w_2, \dots, w_p]$$

$$b_n = [b_{1n}, b_{2n}, \dots, b_{Ln}] \quad (21)$$

$$A = [a_1, a_2, \dots, a_A] \quad (22)$$

$$w_n = [w_{1n}, w_{2n}, \dots, w_{Ln}] \quad (23)$$

With A denoting the whole number of agents, L specifying the whole number of layers, l representing the layer index, n representing the number of agents, and w_{in} Signifying the amount of the weight in layer i; l ranges from 1 to L and n from 1 to A.

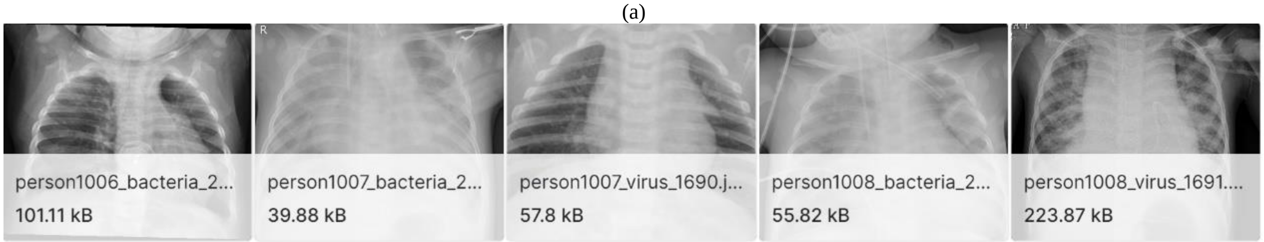
By employing the Improved Gray Wolf Algorithm for error minimization instead of backpropagation, we can optimize both weights and biases with ease since it does not require any backward computation.

IV. Simulation Results

A. Dataset Explanation

The open-source repository on GitHub, run via Dr Joseph Cohen, was used to obtain 65 X-ray images of people with COVID-19 for this study[16]. The majority of the patients in this repository have severe acute respiratory syndrome (SARS), COVID-19, Middle East respiratory syndrome (MERS), or acute respiratory distress syndrome (ARDS) pneumonia. Chest X-ray Images (pneumonia) from the Kagel repository, which contains 65 standard X-ray images, have also been used [17]. Our investigation utilised a dataset composed of chest X-ray images from 65 healthy individuals and 65 patients diagnosed with COVID-19. A total of 130 images were collected and resized to 224×224 pixels. As illustrated in Fig. 4(a) and 4(b), samples of chest X-ray images of both usual and Covid-19 cases are presented.

(a)



(b)

Fig. 4. Some chest X-ray image examples to (a) Normal and (b) Covid-19 cases.

B. System Configuration

Utilizing MATLAB R2018b with 64-bit Windows, our algorithm was programmed and executed on an Intel Core i7 CPU 2.00GHz, 2.5GHz, 16GB RAM and 64-bit operating system. In addition to the variable of the competitive algorithms, we set the population size (N = 50), maximum iterations (tmax = 200), and 10 independent runs for each optimization problem. This ensures a reliable and effective optimization process.

The dataset was partitioned randomly into two subsets: 75% for training and 25% for testing. K-fold cross-verification was employed to validate the results, which are presented in Fig. 5 with five different values of k.

C. Operation Criteria

The proposed system's efficiency was validated by employing five criteria for evaluating deep transfer learning models; Sensitivity, particularity, precision, and positive and negative predictive value (PPV and NPV).

$$Sensitivity\ (\%) = \frac{TP}{TP+FN} \tag{24}$$

$$Specificity\ (\%) = \frac{TN}{FP+TN} \tag{25}$$

$$Accuracy(\%) = \frac{TP+TN}{TP+FP+FN+TN} \tag{26}$$

$$PPV(\%) = \frac{TP}{TP+FP} \tag{27}$$

$$NPV(\%) = \frac{TN}{FN+TN} \tag{28}$$

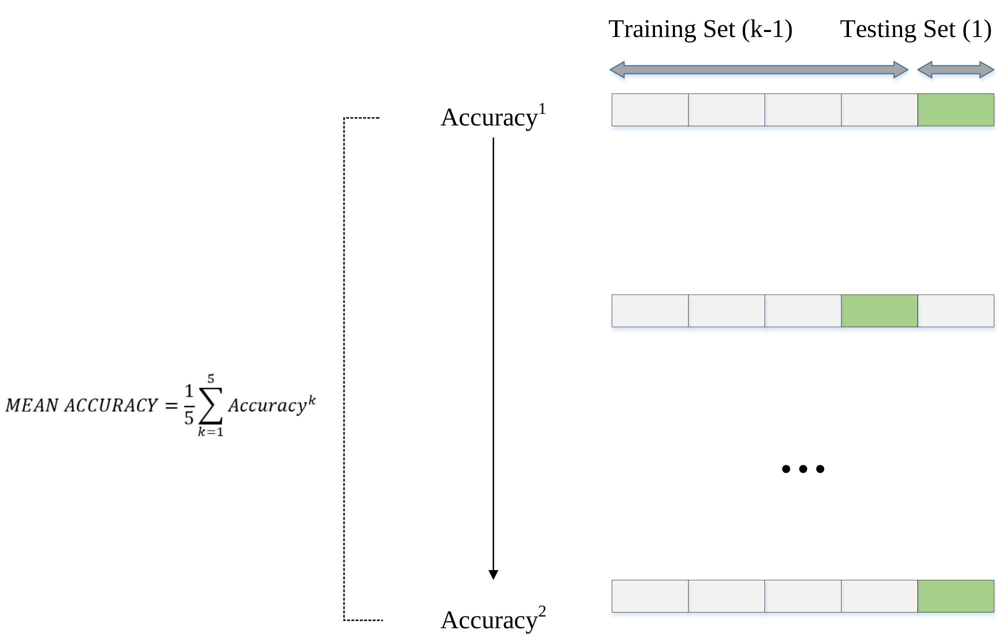


Fig. 5. Visual representation of test and training data sets for five-fold cross-validation.

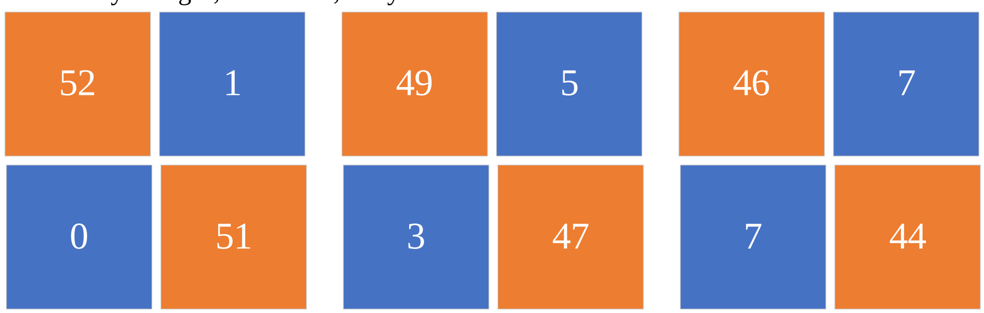
The percentage of examples correctly classified as positive is known as True Positive (TP), while the percentage of examples incorrectly classified as positive is known as False Positive (FP). The False Negative (FN) count corresponds to the number of examples that is falsely labeled as negative. In contrast, the True Negative (TN) count corresponds to the amount of example that is correctly declared negative. Concerning a given dataset and test model, the True Positive (TP) count denotes the amount of positive COVID-19 cases the model has accurately identified. The number of false positives (FP) is the number of normal results that were incorrectly classified as positive for COVID-19. In contrast, the number of true negatives (TN) is the number of normal results that have been correctly identified. The number of false negatives (FN) is the amount of positive COVID-19 results that are misclassified as negative.

D. Results and Discussions

1) Confusion matrix and accuracy analysis: In this investigation, chest X-ray images are utilized to forecast Covid-19 cases. The outcomes of the simulation were trained and assessed on chest X-ray images, and then, they were compared to traditional convolutional neural networks [18] and CNN/GWO methodology. As previously explained, the k-fold cross-validation method has been used to prevent overfitting. According to the analysis of the graphs in the proposed CNN/IGWO model in fold-2, according to the graphs and the confusion matrix, it performs better. Also, in the CNN/GWO model, fold-1 performs better according to the graphs and the confusion matrix, shown in Fig. 6.

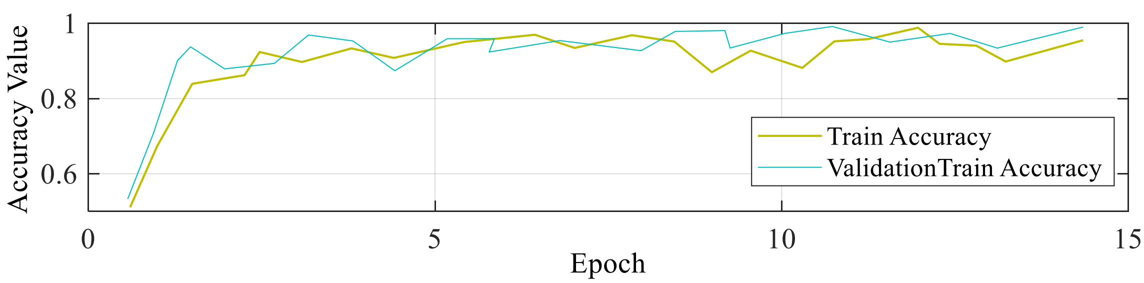
As can be observed, Fig. 6 clearly demonstrates that the proposed CNN/IGWO model outperforms the CNN/GWO model and CNN model in terms of predictive performance, as evidenced by the various metric indicators. The CNN/IGWO model astoundingly recognized COVID-19 contaminated illness (65 images) as accurate positive and ordered images (65 images) as true negative with an impressive 99 percent accuracy score upon analyzing the uncertainty matrix.

Fig. 7 and Fig. 8 reveal the remarkable improvement in precision and loss of a CNN optimized by the IGWO algorithm using the Joseph Cohen dataset, compared with CNN [18] and CNN/GWO methodology.

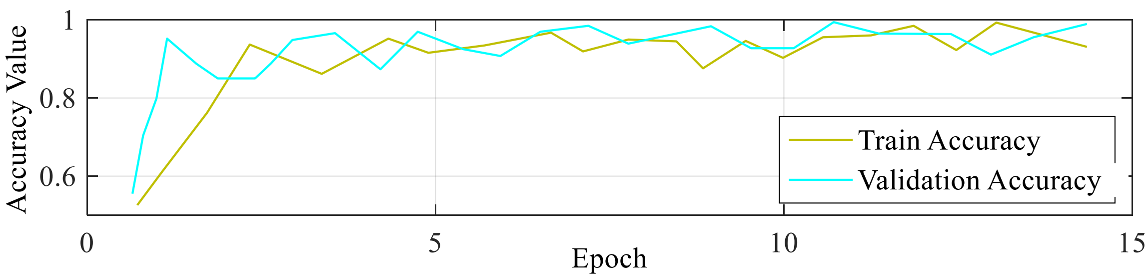


(A) (B) (C)

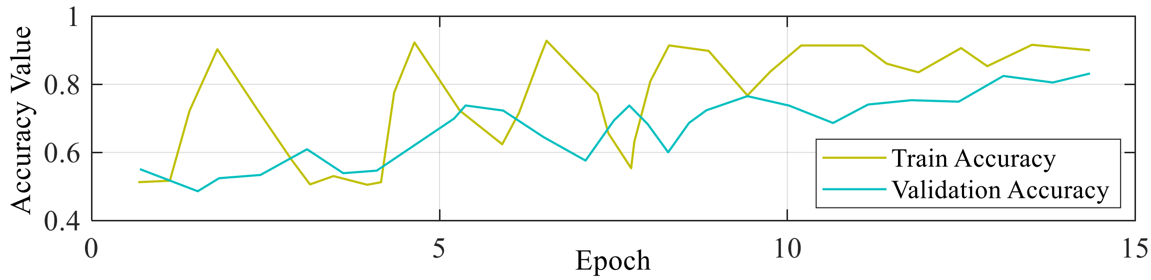
Fig. 6. Confusion matrix of (A) CNN/IGWO, (B) CNN/GWO, and (C) CNN/GWO.



(A)

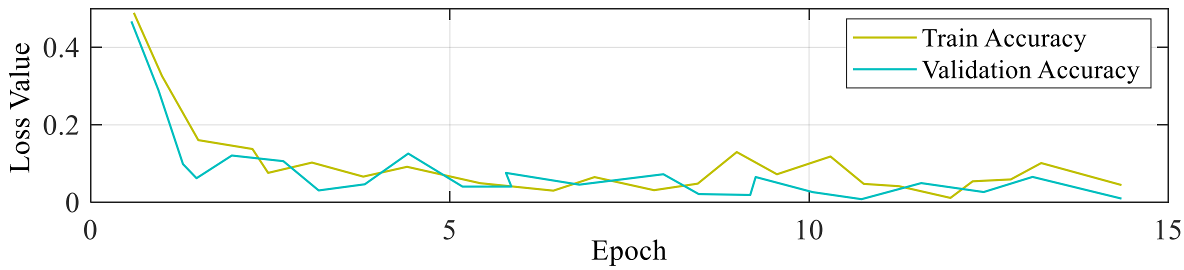


(B)

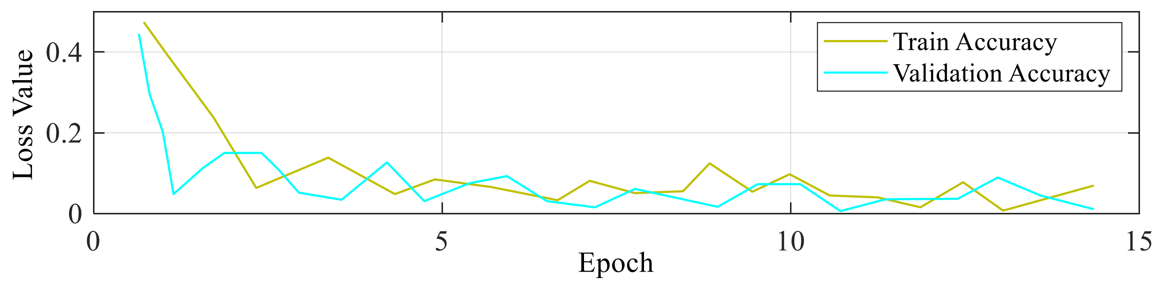


(C)

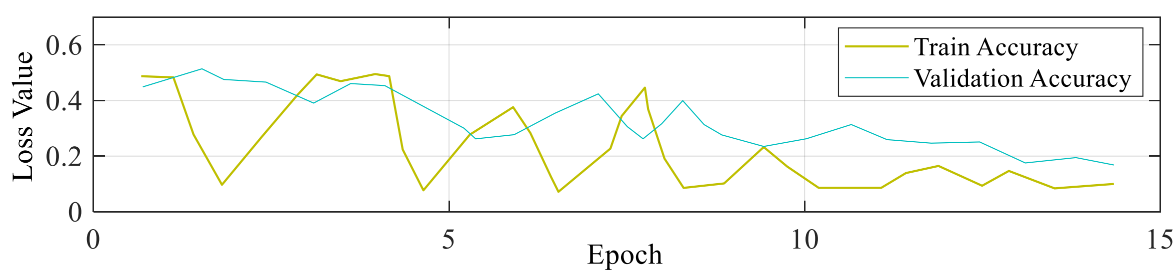
Fig. 7. Accuracy value of (A) CNN/IGWO, (B) CNN/GWO, and (C) CNN/GWO.



(A)



(B)



(C)

Fig. 8. Loss value of (A) CNN/IGWO, (B) CNN/GWO, and (C) CNN/GWO.

According to the results from accuracy and loss diagrams in Fig. 7 and Fig. 8, it can be understood that the maximal the number of epochs, the more the precision of the CNN/IGWO method increases and the less the error in this model. Therefore, if we want to compare these two models in general, the CNN/IGWO model has a better performance

2) Comparison of two models based on test data: As mentioned before, the method was compared with standard CNN [18] and CNN/GWO methodology validation and analyzing the proposed method's efficiency. In another detailed comparison of the performance of the models, the comparison of the three methods by the test data is denoted in Table I.

We obtained 100% sensitivity and a value of 100% specificity, 86% accuracy value for the proposed which is the best performance among the methods in the CNN/IGWO model. The lowest performance is achieved by the standard CNN with of 87% sensitivity value, 86% specificity value, and 86% specificity value accuracy. As a result, the CNN/IGWO method offers an advantage over the other two models in both the training and test phases. As can be observed, the highest level of accuracy belongs to the proposed CNN/IGWO method toward the other two aforesaid methods. The results show the effect of using the IGWO algorithm on the deep learning framework.

TABLE I. ANALYZING THE EFFICACY OF COVID-19 DETECTION USING PERFORMANCE METRICS

Method/Fold		Sensitivity	Specificity	PPV	NPV	Accuracy
CNN [18]	F1	0.87	0.86	0.87	0.86	0.86
	F2	0.90	0.91	0.88	0.87	0.89
	F3	0.85	0.83	0.84	0.83	0.85
	F4	0.92	0.93	0.90	0.92	0.89
	F5	0.86	0.85	0.86	0.88	0.87
	Mean	0.88	0.87	0.87	0.87	0.87
CNN/PSO	F1	0.88	0.87	0.86	0.87	0.87
	F2	0.92	0.93	0.89	0.88	0.89
	F3	0.87	0.84	0.86	0.84	0.86
	F4	0.92	0.94	0.92	0.93	0.89
	F5	0.85	0.84	0.87	0.89	0.88
	Mean	0.89	0.88	0.88	0.88	0.87
CNN/GWO	F1	0.94	0.90	0.91	0.94	0.92
	F2	0.95	0.93	0.92	0.95	0.94
	F3	0.90	0.87	0.84	0.83	0.88
	F4	0.96	0.94	0.93	0.95	0.95
	F5	0.93	0.89	0.88	0.86	0.90
	Mean	0.93	0.90	0.89	0.90	0.91
CNN/IGWO	F1	1.00	0.98	0.98	1.00	0.99
	F2	1.00	0.99	0.99	1.00	0.99
	F3	0.86	0.87	0.85	0.88	0.86
	F4	1.00	0.98	0.98	0.99	0.98
	F5	0.87	0.88	0.86	0.89	0.87
	Mean	0.94	0.94	0.93	0.95	0.93

V. CONCLUSION

The new coronavirus (Covid-19) is an infectious agent that causes severe respiratory illness in humans. Initially identified in Wuhan, China, in late 2019, the virus has since spread worldwide. Common indications of Covid-19 infection are fever, cough, dyspnea, muscle pain, malaise, and impaired olfaction or gustation. Diagnosis can be confirmed through laboratory testing for the virus or through medical imaging techniques such as sample chest radiography and calculated tomography (CT) scans. Generally, supportive care, hydration, rest, and symptom observation are the treatments for Covid-19. Computer-aided detection (CAD) is a method employed to identify Covid-19 in clinical imaging. This entails using artificial intelligence algorithms to discover infection in X-ray, computed tomography (CT) scans, and ultrasounds. The algorithm examines the image and locates any patterns correlated with the disorder. If a pattern is observed, it is flagged as a potential suggestion of Covid-19. This approach has been beneficial for the early detection of the virus and has improved the precision of diagnosis. This paper introduces a modified convolutional optimal neural network by an Improved Gray Wolf version (IGWO) Algorithm as a new technique for the optimal analysis of COVID-19 in medical imaging. The proposed method was tested on the Joseph Cohen dataset, and its performance was compared with that of other methods, including CNN and CNN/GWO, to demonstrate its effectiveness.

One potential future direction for further research in the field of medical imaging and disease detection is the development of a versatile and adaptable framework that can detect not only COVID-19 but also other respiratory diseases or conditions. While the focus of the current research is on COVID-19, expanding the framework to encompass a broader range of diseases would enhance its clinical utility and impact. To achieve this, researchers can explore the possibility of incorporating a wider variety of training data and expanding the dataset to include images of various respiratory diseases such as pneumonia, tuberculosis, lung cancer, and other pulmonary conditions. By training the model on a diverse dataset, it can learn to identify unique features and patterns associated with different diseases, enabling it to provide accurate and specific diagnoses.

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