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# **Advanced Imaging Techniques for the classification of Covid-19 by using Improved Chimp Optimization Algorithm based CNN- LSTM Model**

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**ABSTRACT:** Computer-aided diagnosis has become a vital tool for the precise and timely detection of COVID-19, which is required to lessen the strain on the healthcare system during the pandemic and keep the virus from spreading. Numerous studies have been published on the identification of COVID-19 using a limited collection of original X-ray images. Nonetheless, there is no literature on the influence of lung segmentation and image enhancement on COVID-19 detection over a large dataset. The data were acquired from the Kaggle Dataset. Adaptive optimum weighted mean filter (AOWMF) methods are initially used for image preparation. The pre-processed images are then segmented using the Modified region based semantic segmentation (MRSS) method. Feature extraction is applied to the extracted segments. The Equilibrium Optimizer (EO) and VGG-19 (EO+VGG-19) is used to extract the feature data. The proposed research classifies as either "NORMAL" or "COVID 19" using the CNN-LSTM architecture based on the Improved Chimp Optimization Algorithm (IChOA-CNN-LSTM). The suggested IChOA-CNN-LSTM model improves precision and identifies brain tumors more accurately.

**KEYWORDS:** COVID-19; image enhancement; CNN-LSTM; AOWMF; X-ray images.

## **I. INTRODUCTION**

COVID-19 is an infectious disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) coronavirus strain. The World Health Organization (WHO) declared the current epidemic a pandemic on March 11, 2020. Early diagnosis of COVID-19 could help with disease control and treatment options. This study uses images from X- to demonstrate whether COVID-19 can be detected using pre-trained deep learning algorithms [1]. The multiobjective genetic algorithm is considered to modify the hyperparameters of the proposed COVID-19 detection in chest X-ray images [2]. An important function in detecting COVID-19. Using deep learning and computer vision methods, chest X-ray images can be used to detect COVID-19 infection [3]. The most current virus that is endangering the lives of many people worldwide is COVID-19, which is brought on by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [4]. In each class, 70% of the photographs are authorized for training, 15% are used for validation, and the remaining percentage are used for testing to assess how well the proposed algorithm performs. The maximum classification accuracy of 89.3% is attained by the VGG19, which also has average precision, recall, and F1 score of 0.90, 0.89, and 0.90, respectively [5].

### **Contribution of this Work**

The following are the essential phases of the proposed approach; for further information:

1. A high-performing Initial and accurate Covid 19 classification using a IChOA-CNN-LSTM architecture based Deep learning system.



2. The pre-processing stage is done through a AOWMF, to improve the quality of image.
3. Then applied a MRSS segmentation for segmenting the chest X rays.
4. The feature will be extracted using EO+VGG-19 model.
5. A Deep learning based IChOA-CNN-LSTM architecture is used and optimized for classification of Covid 19 and normal is proposed. Precision, sensitivity, and specificity are used to evaluate how well the suggested strategy performs.

The following explains how the document is created. Section 1 contains the introduction. Section 2 discusses the relevant works. Section 3 describes the recommended methodology, Section 4 highlights the experiment's results, and Section 5 concludes and suggests future research.

## **II. LITERATURE REVIEW**

Mahajan et al. (2022) [6] have explained using improved deep learning algorithms, this research suggests a reliable and effective way for the early diagnosis of COVID-19 from chest X-ray scans. According to this research, the model trained for this task may perform better when the SSD design is combined with the Prediction and Deconvolutional Modules. The detection model with task-specific pre-processing and roughly 80:20 split using an openly available CXR picture dataset. For this problem, the suggested methodology unquestionably outperforms the majority of the current ones. The strength of the chest X-ray or chest CT pictures determines the severity of these types of infections, as was previously addressed and demonstrated by several medical research.

Ahishali et al. (2021) [7] have evaluated, the ability of advanced Machine Learning techniques to detect COVID-19 in chest X-ray images. This study considers both deep learning approaches and compact classifiers. This explains why we aim to investigate the viability of building an accurate, robust, and fully automated COVID-19 advance warning approach based on chest X-ray pictures. The Early-QaTa-COV19 dataset was created to capture as many COVID-19 patients as possible in their early stages. The results have conclusively demonstrated that it is possible to detect COVID-19 infestation early from X-ray images with extraordinarily high sensitivity and specificity.

Rahman et al. (2021) [8] have proposed, A new UNet model for lung segmentation was created and tested against the standard UNet model. The plain and segmented lung CXR images were used to evaluate a shallow CNN model and six different pretrained CNNs. In plain and segmented lung CXR images, the gamma correction-based enhancement methodology performs better than current techniques for detecting COVID-19. The visualization method showed that the segmented lung CXR images had significantly higher network performance dependability, even though they perform slightly better in classification than plain CXR images.

Çallı et al. (2021) [9] explained among the goals achieved by applying deep learning to chest radiographs are picture-level prediction, segmentation, localization, image synthesis, and domain adaptability.

Arias-Garzón et al. (2021) [10] have examined, in order to process and categorize images from chest X- of COVID-19 as either positive or negative, the research uses two deep learning models that are currently in use: VGG19 and U-Net. The proposed system incorporates a preprocessing stage that comprises lung segmentation, which removes background information that is irrelevant to the task and may result in biased findings. The classification model is trained using the transfer learning scheme, and the results are examined and explained using heat maps. The best models detected COVID-19 with an accuracy of about 97%. This method proves the utility of current models for a range of tasks, especially when the improved U-Net models are considered to perform no better. Visual noise is also used to highlight how bias can be introduced into models.

Kalane et al. (2021) [11] the U-Net architecture, a new deep learning model, is trained using signals from Computer Tomography (CT) images in an automated Covid-19 identification system. To evaluate the efficacy of the proposed method, a total of 1,000 chest CT scans were performed. The U-Net architecture for analyzing Chest CT images has proven useful. The proposed approach could be used as an additional tool for physicians to conduct primary screenings of COVID-19 patients.

Shelke et al. (2021) [12] proposed an algorithm for categorizing chest X-rays that can help with accurate COVID-19 diagnosis. Our approach classifies chest X-rays into four categories: normal, COVID-19, pneumonia, and

tuberculosis. COVID-19-related X-rays are classified as moderate, medium, or severe according to severity. VGG-16 is the deep learning model used to categorize pneumonia, tuberculosis, and normal, and it performs better on tests. DenseNet-161 was used to distinguish normal pneumonia from COVID-19, while ResNet-18 outperformed it for severity classification, resulting in greater test accuracy.

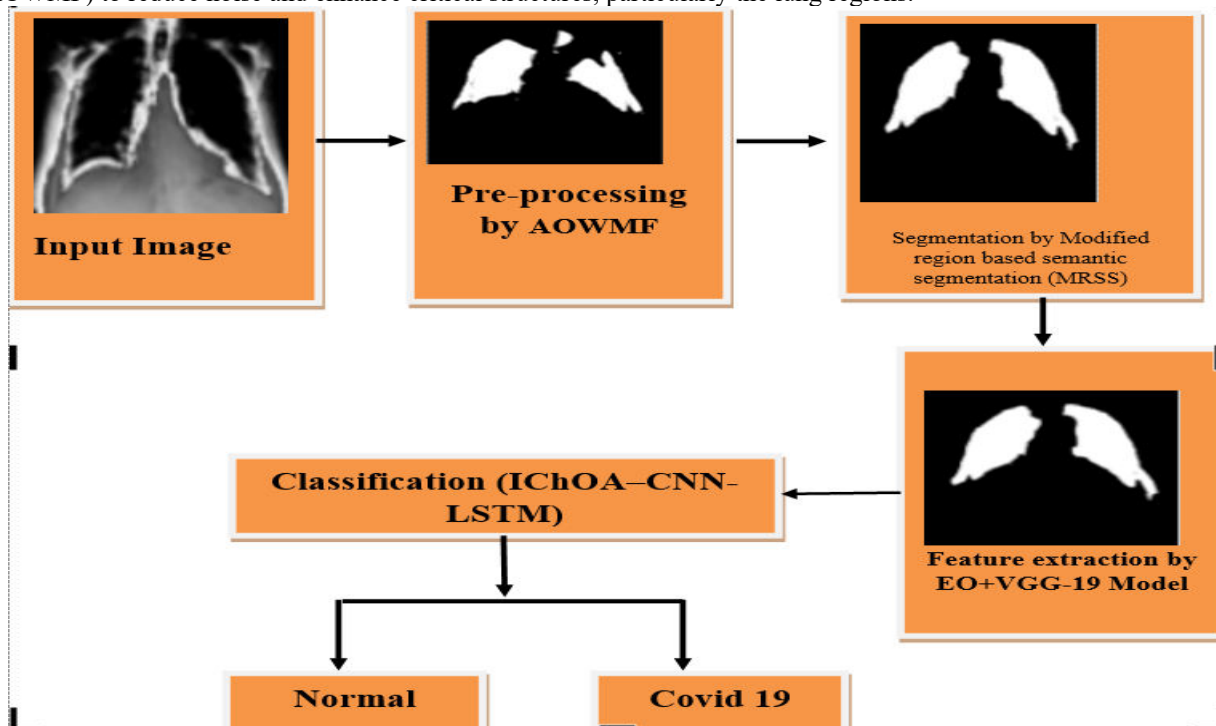
Johri et al.(2021) [13] have investigated Chest X-ray (CXR) pictures of probable patients are used to detect COVID-19 using a novel machine learning (ML)-based analytical framework. The framework has been created, trained, and validated to identify four types of CXR images: healthy, bacterial, viral, and COVID-19. According to the experimental results, the proposed framework may be a good choice for COVID-19 illness diagnosis utilizing CXR pictures because it has training, validation, and testing accuracy in four-class categorization.

Vinod et al.(2021)[14] have demonstrated an innovative framework by utilizing the Deep Covix-Net model to analyze chest X-rays and CT scan pictures in order to swiftly and successfully detect new patients infected with the coronavirus. The precision score slice is analyzed using performance indicators such as accuracy, confusion matrix, and receiver operating characteristic curve. The results are based on a database available in the GitHub and Kaggle sources that correlates to approved chest X-ray and CT images. Several approaches' categorization performance was examined using an 1800-photo test set. While preserving the rigor of the machine learning process, the proposed method yields fast results for training and testing datasets

López-Cabrera et al.(2021) [15] have discussed addressing some of the concerns now brought up in the scientific literature by the automatic classification of COVID-19 using artificial intelligence techniques. Many research on chest X-ray pictures have employed artificial intelligence approaches to automatically classify this condition. It is clear that in the majority of the evaluated papers, an inappropriate assessment technique is used, resulting in overestimating the outcomes.

### III. PROPOSED SYSTEM

The figure 1 illustrating a COVID-19 detection framework from medical images, likely CT or X-ray scans. The process begins with the input image, which undergoes pre-processing using Adaptive Optimum Weighted Mean Filter (AOWMF) to reduce noise and enhance critical structures, particularly the lung regions.



**Figure 1. Flowchart for the proposed Model of Covid 19 classification**

The pre-processed image is then passed to a Modified Region-Based Semantic Segmentation (MRSS) method to isolate relevant lung areas. Once segmented, the region of interest is fed into a feature extraction module that combines the Equilibrium Optimizer (EO) and the VGG-19 deep learning model to extract strong and relevant characteristics from the segmented lungs. Following that, these features are fed into the IChOA–CNN-LSTM classification model, a combination of the Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and ICChOA. The input is divided into two groups by this model: COVID-19 and Normal. This integrated pipeline ensures accurate detection of COVID-19 by leveraging both traditional image processing and advanced deep learning techniques.

### 3.1 Preprocessing using Adaptive optimum weighted mean filter (AOWMF)

The noise removal flow diagram for the AOWMF approach is shown in Figure 2. The adaptive weighted mean filter uses a variable window size to decrease excessive noise, which significantly reduces the clarity of MR images, in contrast to the conventional mean filter, which removes insufficient amounts of rician noise with a set window size. The adaptive weighted average filter progressively expands the window size to match the highest and lowest values of pixels of two consecutive windows. If the value of the window's center pixel is either the smallest or the highest, the window's average weighted value is restored. If the central pixel's value is neither and it was lowest nor the highest, the intensity value remains constant. For the original image of size, the center pixel intensity value  $M \times N(x, y)$  of the coordinate system is denoted by  $x_{i,j}$ . The dynamic range (DR) is defined as  $DR_{\min} \leq x_{i,j} \leq DR_{\max}$ . The letter "dr" represents a distorted image. Use the dynamic ranges  $DR_{\min}$  and  $DR_{\max}$  found in equation (1) to swap out an invalid pixel in an image.

$$dr_{i,j} = \begin{cases} DR_{\min} & \text{with } P_a \\ DR_{\max} & \text{with } P_b \\ x_{i,j} & \text{with } P_{1-a-b} \end{cases} \quad (1)$$

In the formula noise = a + b, a and b represent the likelihood that a particular pixel would be twisted due to the interference of P greatest (speckle) and P lowest (Rician) noise.

### 3.2 Segmentation using MRSS model

The portions of semantic-based classification as well as region-based extradition are segregated through MRSS. To perform this type of segmentation, the algorithm generates a separate area of leaf disease [16]. To ensure that each pixel can be detected by object recognition, the segmented disease regions are processed into observations together at pixel level. This MRSS was completed by using CNN architecture. Lifting characteristics from each of these several locations, the algorithm traverses the CNN.

The probability of the pixel value is given by:

$$P(Z_0) = P_1 \cdot P_1(Z_0) + P_2 \cdot P_2(z_0) \Rightarrow P_1 + P_2 = 1 \quad (2)$$

Where,  $P_1(Z_0)$  denotes the PDF of background pixels and  $P_2(z_0)$  represents PDF of object pixels.

If indeed the determined pixel's value is T or less, it belongs to the background; otherwise, it corresponds toward an object.

$$f(x_0, y_0) \geq T \rightarrow (x_0, y_0) \in \text{object} \quad (3)$$

$$(x_0, y_0) < T \rightarrow (x_0, y_0) \in \text{background} \quad (4)$$

$$E'_1(T) = \int_{-\infty}^{\infty} P_1(Z_0) DZ_0 \quad (5)$$

$$E'_2(T) = \int_{-\infty}^{\infty} P_2(z_0) DZ_0 \quad (6)$$

Where,  $E'_1$  represents the inaccuracy whenever an image pixel is mistakenly categorised therefore as background pixel and  $E'_2(T)$  denotes the error that occurs when a background pixel is misread for an object pixel.

Then, the total classification of pixels as background or object is calculated as,

$$E'(T) = P_2 E'_1(T) + P_1 E'_2(T) \quad (7)$$

When segmenting an input image, this method appears for special regions of any size. Perhaps the adjoining pixels that have been connected to as well as similar towards the initial pixel are automatically included in the modified region-based semantic segmentation (MRSS) of the regions.

### 3.3 Feature Extraction using EO+VGG-19 Model

After segmenting the images, the VGG19 method is applied to generate a set of feature vectors. It is mostly based on the CNN model, is straightforward, and features three convolution layers at the top to increase depth (3×3). The VGG-19 model uses the max-pooling layer as a handler to minimize the volume size.

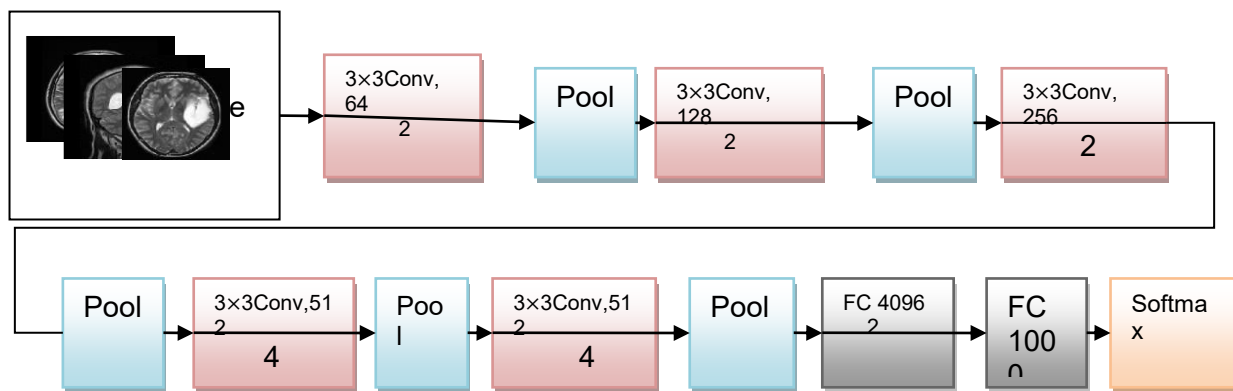


Figure 2: Structure of VGG-19 model for feature extraction

The VGG-19 model's structure is shown in Figure 2. In the next three steps, the EO technique's mathematical methodology was demonstrated.

#### Step 1: Initiation

In order to optimize the problem, EO uses a set of particles in this stage, each of which represents a concentration vector. Using the following equation, the principal concentration vector is generated arbitrarily from the search space.

$$\vec{v} = c_{min} + (c_{min} - c_{min}) * r \quad i = 0, 1, 2, \dots, n, \quad (8)$$

#### Step 2: Equilibrium pool and candidate solutions ( $\vec{p}$ )

When EO is tasked with achieving the equilibrium state, near-optimal solutions are obtained for optimized issues.

#### Step 3: update the concentration

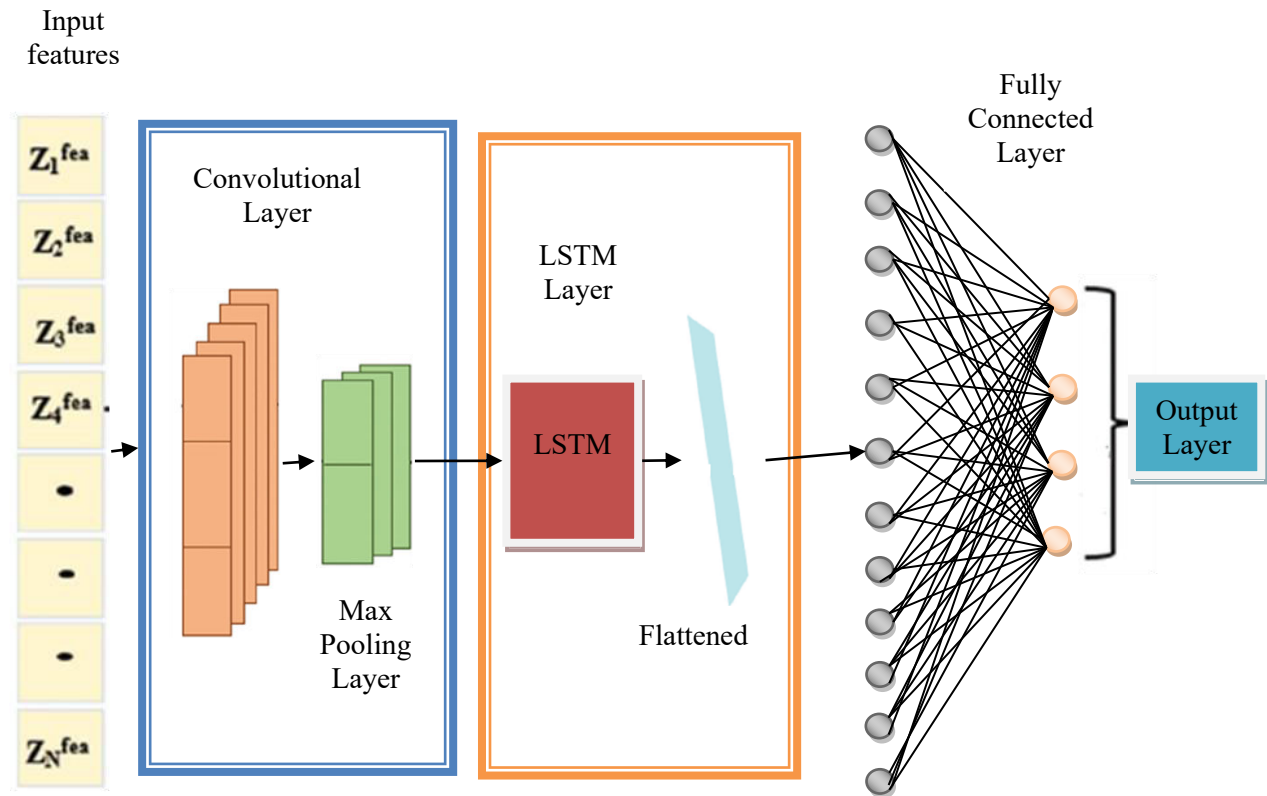
The EO with a tenable balance between intensity and diversity is supported by the following term. Since the turnover rate varies over time in actual control volumes, it is presumed that  $\vec{\lambda}$

$$\vec{F} = e^{-\lambda(t-t_0)} \quad (9)$$

Where, t reduces with increment from the iteration (it) utilizing the equation given below.

### 3.4 Proposed IChOA–CNN-LSTM algorithm using covid 19 classification

COVID-19 classification is being carried out using the IChOA-CNN-LSTM approach. CNN-LSTM combines long short-term memory (LSTM) and convolutional neural networks (CNN). Because the weight values in the CNN-LSTM model are chosen at random, the loss function grows, making it harder to anticipate the expected output. The CNN-LSTM and IChOA combine to improve the weight values generated in the convolution layer and raise the model's classification accuracy. Using the Basin chaotic map, the current ChOA enhances the chimpanzees' foraging strategies. Figure 3 depicts the suggested detecting system's construction.



**Figure 3.** Establishment of IChOA-CNN-LSTM classification model

#### Input Layer

The input layer is the first layer of nodes in an artificial neural network (ANN). This layer receives input from the external world.

#### Convolution Layer

The convolution between the input features and the convolution layer's kernels [20] is expressed as follows:

$$C_l(f_{m(i)}) = CD_n^{fea} * h_n(\varphi(f_{m(i)})) \quad (10)$$

Where,  $C_l(f_{m(i)})$  represents the feature map discovered using kernels  $\varphi$ , and  $h_n$  stands for the nonlinear activation function.

#### Pooling Layer:

Pooling is the stage that comes after convolution and reduces the size of the features map by removing unnecessary features. The network does this by utilizing the max-pooling function, which is expressed as

$$P_l(f_{m(i)}) = \zeta_{mP_n}(C_l(f_{m(i)})) \quad (11)$$

Where,  $\zeta_{mP_n}$  demonstrates how the dimensionality of the feature map was decreased using the max-pooling algorithm, and  $P_l(f_{m(i)})$  demonstrates the feature map's pooling.

#### Fully Connected Layer



At each layer, the entirely linked layer is found using the formula below:

$$f_{cl} = h_n(\Omega_{fc} O_g(m) + v_{fc}) \quad (12)$$

Where,  $h_n$  represents the activation function, the bias value is  $v_{fc}$ , and the completely connected layer, the weight matrix is  $\Omega_{fc}$ .

### Output layer

In a neural network, the output layer is the final layer that produces the network's classifications or predictions. It turns the data into a usable format after obtaining it from previous levels.

### 3.5 Evaluation matrix - COVID classification

Six performance criteria were used to assess the various CNNs' classification ability: weighted F1 score using Equations, weighted specificity, weighted precision, weighted sensitivity or recall, and total accuracy. The precision and recall weighted average is called the F1-score. Numbers 13, 14, 15, 16, 17, and 18 show the mathematical expressions for these metrics.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (13)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (14)$$

$$\text{Yenden's index} = \frac{TP \times TN - FN \times FP}{(FP+FN) \times (TN+FP)} \quad (16)$$

$$\text{sensitivity(recall)} = \frac{TP}{TP+FN} \quad (17)$$

$$\text{F1 - Score} = 2 \times \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}} \quad (18)$$

## IV. RESULT AND DISCUSSION

This section explains the investigative findings achieved using the recommended technique. The IChOA-CNN-LSTM classifier is used to categorize Covid 19. MATLAB is used to accomplish the suggested approach. This particular computer has an Intel Core i5 processor, Windows 11, 5GB of RAM, and 124GB of RAM.

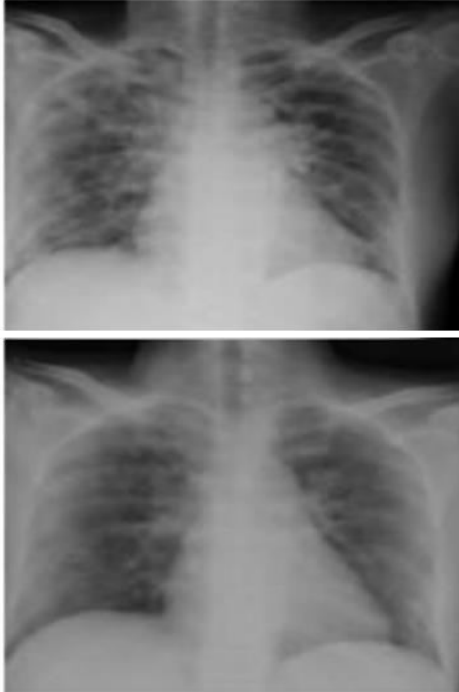
### 4.1Dataset

The Chest X-ray image dataset utilized in this study was sourced from <https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia/>. The dataset is divided into two folders: train and test, each with two subfolders (COVID19 and NORMAL). There are 6432 x-ray images in the collection, of which 20% are test images. The COVID 19 identification findings of the IChOA-CNN-LSTM technique are validated against the 7500-case database given in Table 1.

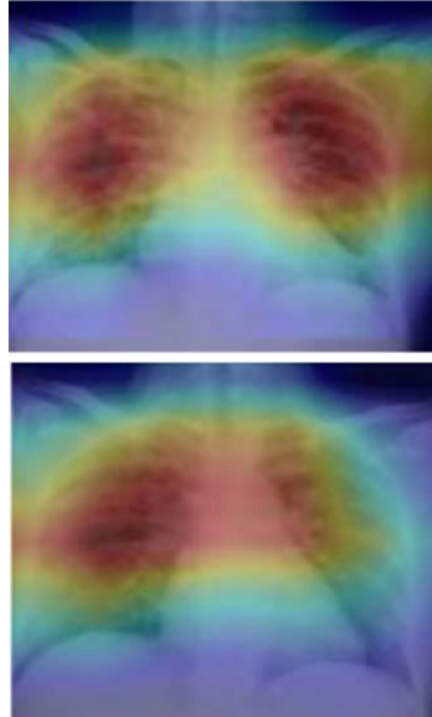
**Table 1.** Details about the database

Classes	No.of instances
Normal	5000
Covid 19	2500
Total Instances	7500





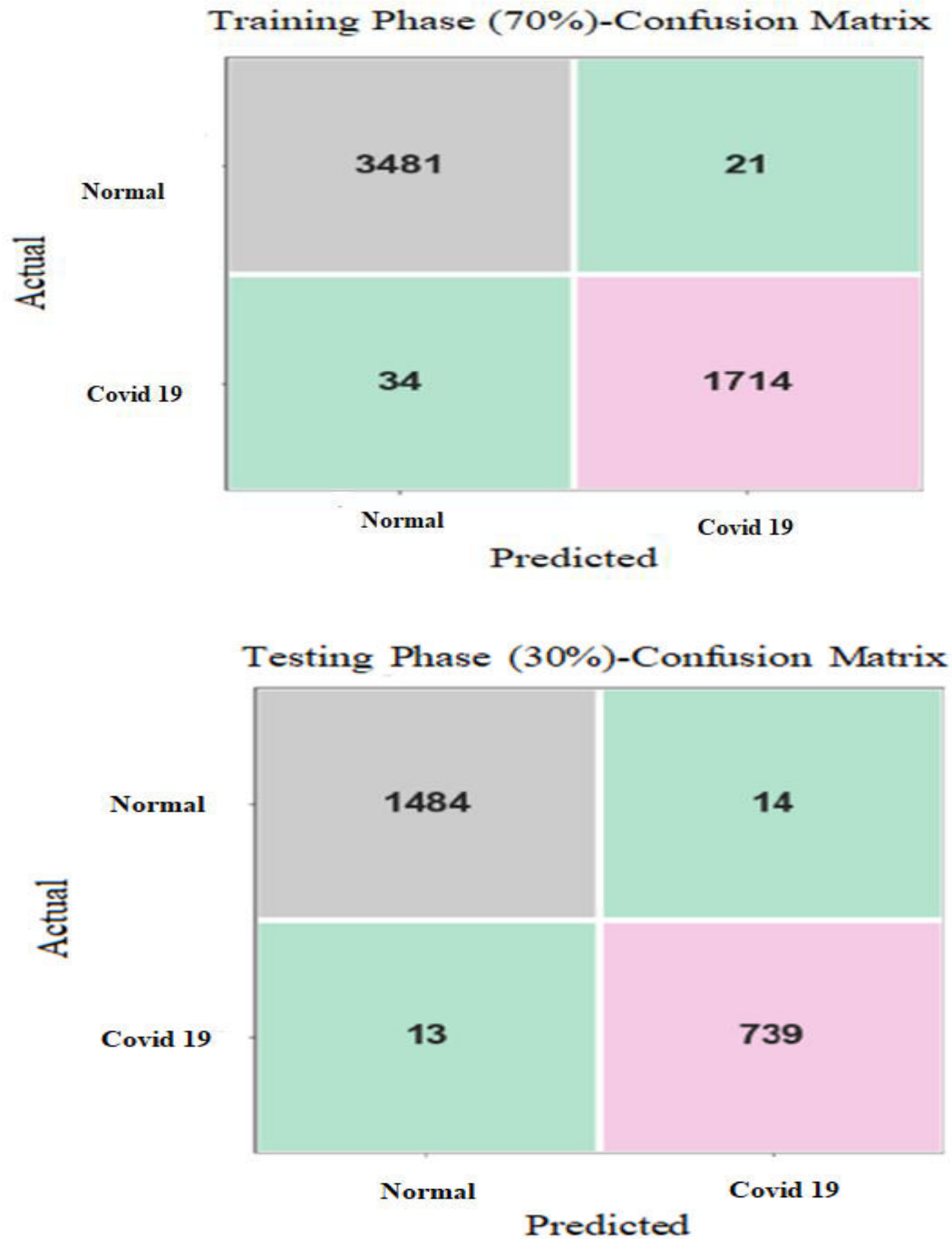
Chest X ray of diagnosed  
Covid-19 positive patient



IChOA-CNN-LSTM  
output

**Figure 4 .** IChOA-CNN-LSTM visualization of some of the CT scan and chest X-ray test cases of COVID-19 positive patients

The IChOA-CNN-LSTM visualization of a few CT scan and chest X-ray test cases of patients with COVID-19 is displayed in Figure 4. The IChOA-CNN-LSTM model's confusion matrices at a 70:30 ratio between the training and testing stages (LSTM and TRAP) are shown in Figure 5. The findings show that IChOA-CNN-LSTM can accurately identify both normal and Covid 19 samples across all classes.



**Figure 5.** Confusion matrix for IChOA-CNN-LSTM-based Covid 19 classification

Figure 6 shows the TRA and TES accuracy curves used to test the performance of the IChOA-CNN-LSTM strategy. The IChOA-CNN-LSTM system's solution over a lengthy period of time is shown by the TRA and TES accuracy curves [20]. The graphic illustrates important aspects about the IChOA-CNN-LSTM model's general capabilities and learning tasks. The TRA and TES accuracy curves grew with the epoch number. The IChOA-CNN-LSTM methodology has been proven to improve testing accuracy, allowing designs to be categorized from TRA and TES data.

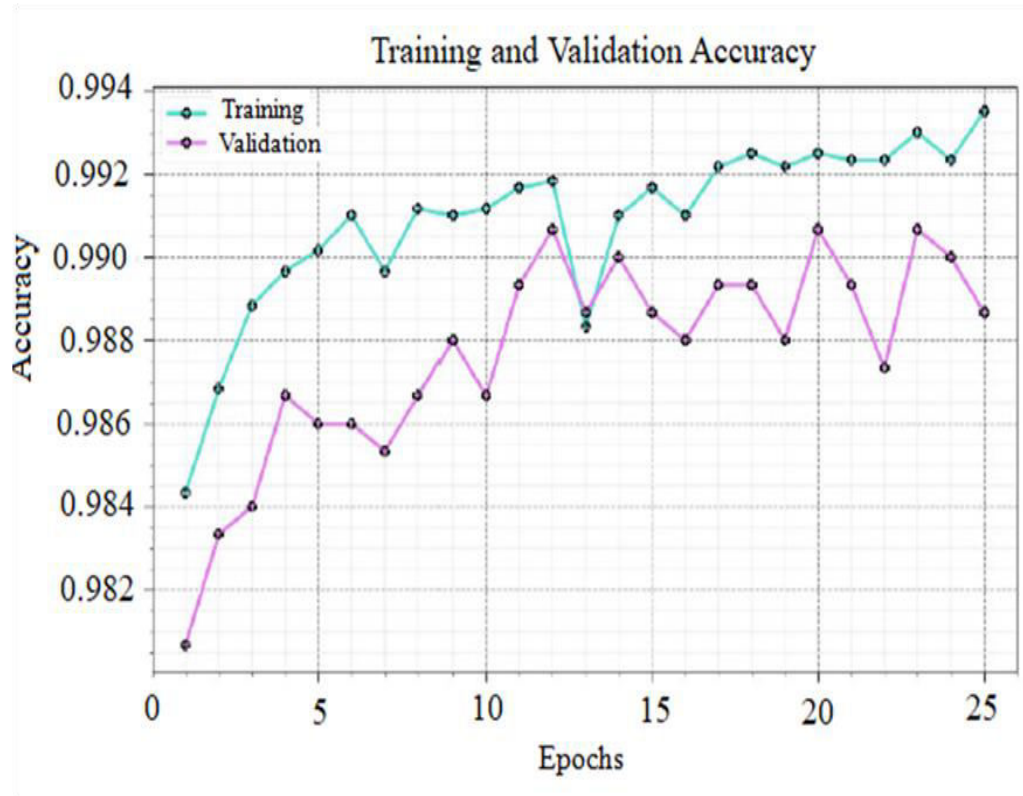


Figure 6. Accuracy curve of IChOA-CNN-LSTM methodology

Figure 7 shows the overall TRA and TES loss values at the TRAP/TESP across epochs for the IChOA-CNN-LSTM approach. The model loss decreases with each epoch as the TRA loss does. As the system adjusts the weight to lower the predicted error, the TRA and TES data reveal that the loss values drop [21]. The loss curves show how well the technique fits the TRA data. The IChOA-CNN-LSTM model is successfully identifying the patterns in the TRA and TES data, as seen by the TRA and TES loss that is gradually declining.

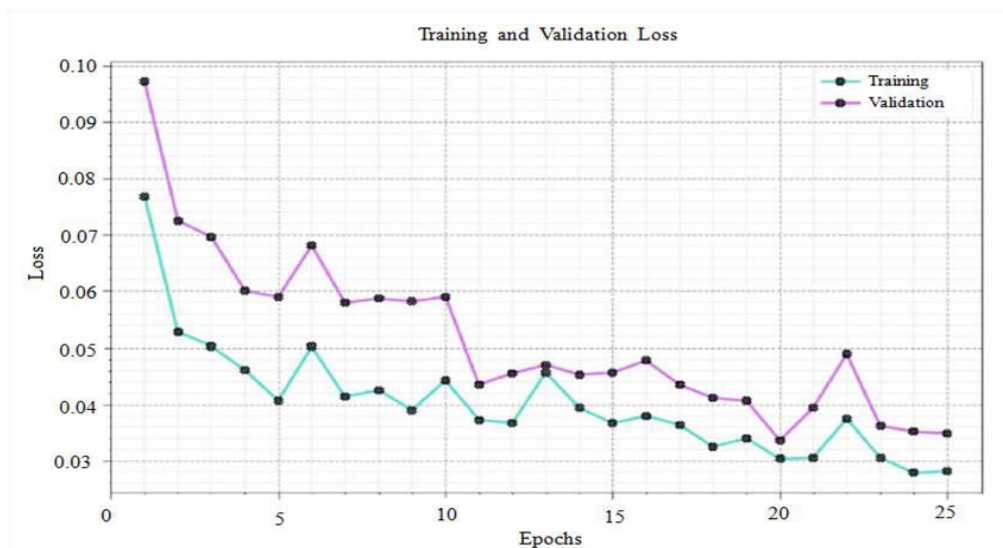
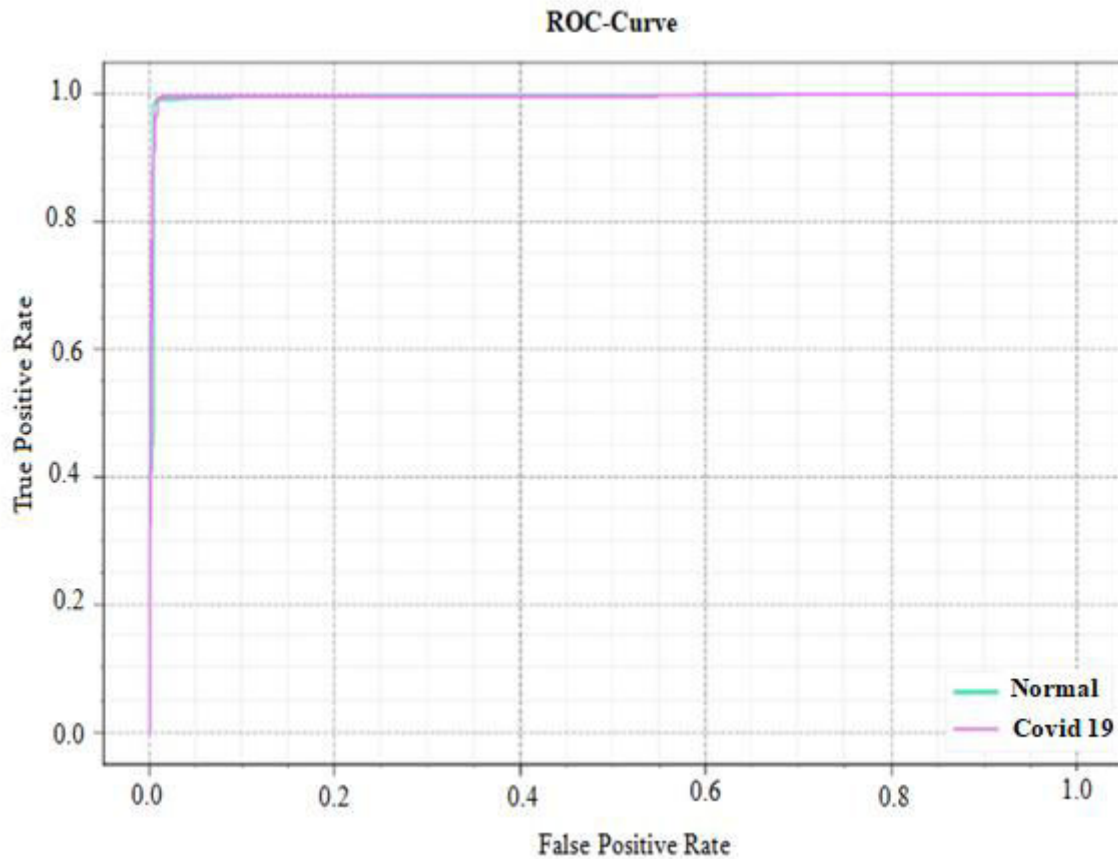


Figure 7. Loss curve of IChOA-CNN-LSTM methodology

Figure 8 shows the ROC curves obtained by the IChOA-CNN-LSTM model for data classification. The graph illustrates the trade-off between TPR and FPR rates under various categorization criteria and epoch counts. The exact prediction performance of the IChOA-CNN-LSTM approach for identifying all two class labels is described.



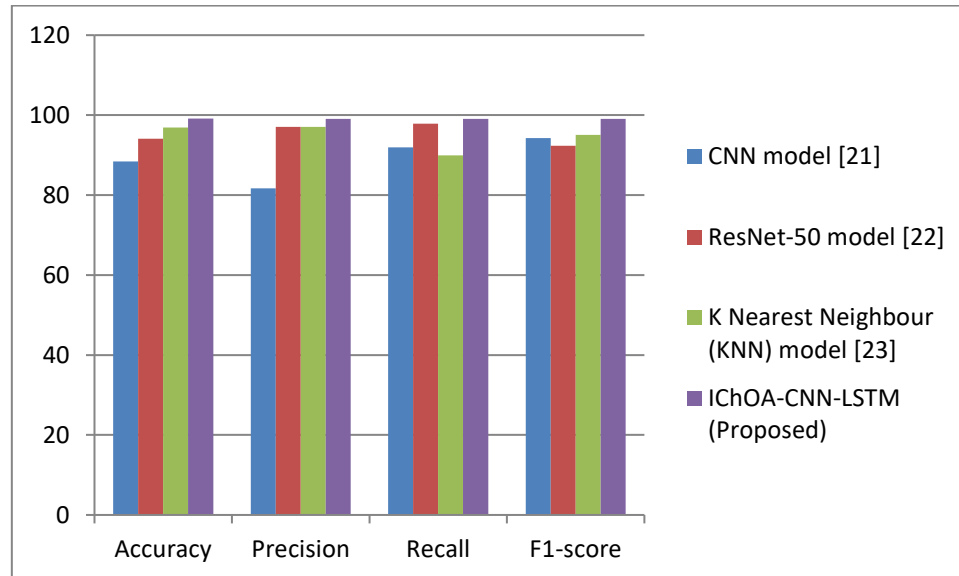
**Figure 8.** ROC curve of IChOA-CNN-LSTM methodology

**Table 2.** Comparative results of IChOA-CNN-LSTM approach with existing systems

Algorithm	Accuracy	Precision	Recall	F1-score
CNN model [21]	88.40	81.70	91.93	94.25
ResNet-50 model [22]	94.10	97.10	97.90	92.35
K Nearest Neighbour (KNN) model [23]	96.93	97.05	89.93	95.04
<b>IChOA-CNN-LSTM (Proposed)</b>	<b>99.18</b>	<b>99.10</b>	<b>99.04</b>	<b>99.07</b>

Figure 9 and Table 2 show the outcomes of the proposed and present models. Meanwhile, the IChOA-CNN-LSTM technique increases precision by 99.10%, while the CNN model, ResNet-50 model, and KNN techniques reduce precision by 81.70%, 97.10%, and 99.05%, respectively. The accuracy of the MLP, AdaBoostMI, and AAMD-OELAC techniques drops by 88.40%, 98.10%, and 98.93%, respectively, whilst the IChOA-CNN-LSTM strategy increases precision by 99.18%.





**Figure 9.** Performance comparison between the proposed and existing models

The CNN model, ResNet-50 model, and KNN techniques have accuracy values of 94.25%, 98.35%, and 99.04%, respectively, whereas the IChOA-CNN-LSTM strategy has a higher F1-score of 99.07%. Last but not least, the MLP, AdaBoostMI, and AAMDOELAC models obtain lower recall values of 91.93%, 97.90%, and 98.93%, respectively, compared to the greater recall value of 99.04% obtained by the IPREODL technique. Thus, the IChOA-CNN-LSTM method outperformed the other models.

## V. CONCLUSION

Healthcare professionals can detect COVID-19 with a deep learning technique that requires little processing of chest X-ray pictures. According to the study's findings, detection models constructed using CNNs and the transfer learning technique may effectively complete binary classification tasks using photos of pneumonia and COVID-19. COVID-19 and normal CXR images share characteristics that radiologists find difficult to interpret. However, the CNN model can quickly learn the properties and correctly label the photos after just a few training epochs. The high accuracies discovered show that the deep networks could correctly distinguish between the CXR images since the deep learning models could identify anything unique in the photos. The IChOA-CNN-LSTM architecture that has been suggested will categorize COVID as either "NORMAL" or "COVID 19". The suggested IChOA-CNN-LSTM model has 99.18% accuracy, 99.10% precision, 99.04% recall, and a 99.07 F-score. The effort of medical personnel can be effectively reduced by these trained models, while also increasing the accuracy and efficacy of COVID-19 diagnosis.

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