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# Artificial intelligence CNN-WCA model and Weiner filtered FRFCM image segmentation technique for extraction and classification COVID-19 Virus

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**Abstract**

The COVID-19 disease started during the period December 2019 in China, and spreads rapidly throughout the world caused death of more than million peoples as per the WHO. Diagnosis of COVID-19 diseases is a very important part in its treatment. A prime reason behind an increase in the number of COVID-19 patients worldwide is the ignorance of people towards treatment in its early stages. This research work proposes a novel Weiner filter based fast and robust Fuzzy C Means (FRFCM) segmentation technique for detection of tissues from COVID-19 image and Deep CNN-WCA model for classification of diseases. As the COVID-19 images are X-Ray images, from which it is difficult to extract the COVID-19 tissues, to avoid such situation we are motivated to apply the proposed FRFCM technique. The segmented images are applied to the, proposed AI based Deep CNN-WCA (Convolutional neural network with water cycle algorithm) for classification of the type of diseased tissues for visual localization by the radiologists. Further, a future central IoT based monitoring system, we are proposing through the proposed artificial intelligence Deep CNN-WCA model to serve the patients affected by COVID-19 which will help doctors to identify and classify the covid-19 diseases with automated system.

*Keywords:* Fuzzy C Means (FCM); Convolutional Neural Network (CNN); Artificial Intelligence (AI); Water Cycle Algorithm (WCA)

## 1. Introduction

Due to the COVID-19, the world economy, education system are drastically affected. Corona viruses are categorized as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) and SARS-CoV. Research evidence suggests that SARS-CoV-2(COVID 19) is the severe stage of infections in chest and lungs. The COVID-2019 epidemic is a member of the family of Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2). It is difficult for the doctors to identify the presence of virus from the X-Ray image due to its slow growth. The COVID-19 disease started during the period December 2019 in China, and spreads rapidly throughout the world caused death of more than million peoples as per the WHO [1]. According to the report all countries followed lock down to save their peoples from the virus affect. COVID-19 affects drastically in the countries such as Italy, Spain and Iran, US, Germany [2-5] directly. Ethiopia also affected by CORONA-19, but

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the cases registered as per the source is much less as compared to other country cases. The patients are admitted to hospitals has to go through the process of CT-Scan image of chest to identify about the virus, but it is difficult for the doctors to get information from the images of chest.

The field of medical imaging is gaining importance in determining automated, reliable, fast and efficient diagnosis. Artificial Intelligence (AI) based on a combination of deep-learning algorithms can be utilized to examine corona tissues and detect the region of tissues from the chest images. The imaging method and deep convolutional neural networks (CNNs) are to predict the tissues in an automated fashion due to its fast computational time. The method can also be useful in other surgical procedures, where doctors need to analyse other tissues while operating, including neck, breast, skin and gynecologic surgery. This recent AI technique can be a game-changer in intra-operative COVID-19 diagnostics. The method can help address the shortage of doctors and radiologists, which sometimes leads to delay in the detection and treatment. Expert doctors often tend to rely on more extensive methods of examination that can be done completed quickly.

The proposed new AI tool can help fill the gap in specialization and can help examine and detect signs of COVID tissues much faster than the traditional method which can reduce casualties with timely treatment. Another major benefit of the AI method is that it does not destroy the tissue. The same sample can be used again. The driving force of this research is to create a transparent environment which will help the medical staff to handle the situation in a calm order. As conventional clustering image segmentation is based on FCM(Fuzzy c means) which is efficient for images with simple texture and background, Chen and Zhang [6] employed average filtering and median filtering to obtain the spatial neighborhood as FCM S1 and FCM S2, segmentation. Cai et al. [7] proposed the fast generalized FCM algorithm (FGFCM) which introduced a new factor as a local similarity which performs clustering on gray level histograms. Gong et al. [8] utilized a variable local coefficient instead of the fixed spatial distance, and proposed a variant of the FLICM algorithm (FLICM) which is able to exploit more local context information in images. Guo et al. [8] proposed an adaptive FCM algorithm based on noise detection (NDFCM), where the trade-off parameter is tuned automatically by measuring local variance of grey levels. Despite the fact that NDFCM employs more parameters, it is fast since image filtering is executed before the start of iterations. Motivated by this, in this research work, we improve FCM algorithm, and propose a significantly fast and robust algorithm for image segmentation.

The proposed algorithm can achieve good segmentation results for a variety of images with a low computational cost, yet achieve a high segmentation precision. The proposed Weiner- FRFCM employs morphological reconstruction (MR) to smooth images in order to improve the noise-immunity and image detail preservation simultaneously, which removed the difficulty of having to choose different filters suitable for different types of noise in existing improved FCM algorithms. Therefore, the proposed Weiner-FRFCM is more robust than these algorithms for images corrupted by different types of noise. The proposed Weiner-FRFCM modifies membership partition by using a faster membership filtering instead of the slower distance computation between pixels within local spatial neighbors and their clustering centers, which leads to a low computational complexity. Therefore, the proposed Weiner- FRFCM is faster than other FCM based segmentation algorithms.

The classification and detection of the brain tumor's have been presented by the researchers through different classifiers such as SVM,PNN,RBFNN, LLRBFNN[9]etc and found classification results in terms of accuracy and computational time for the cancerous and noncancerous brain tumors. Deepa and Arunadevi [10] have proposed a technique of extreme learning machine for classification of brain tumor from 3D MR images. This method obtained an accuracy of 93.2%, the sensitivity of 91.6%, and specificity of 97.8%. Chaddad [11] has used Gaussian mixture model (GMM) for feature extraction and PCA for the enhancement of the GMM feature extraction process and obtained an accuracy of 97.05% for the T1-weighted and T2-weighted and 94.11% for FLAIR-weighted MR images. Nilesh Bhaskarrao Bahadure et al [12] has presented dice similarity index, which is one of the important parameters to judge the accuracy of any brain tumor segmentation and support vector machine for classification and achieved 96.51% accuracy,94.2% specificity, and 97.72% sensitivity. Mohamed et al [13] proposed CNN (Convolutional neural network) for classification, Wu et al [14] presented the application of deep neural network (DNN) with 20,000 screening mammograms. Kallenberg et al [15] proposed an unsupervised deep learning technique, Geras et al. [16] used deep convolutional neural network for prediction of tissues from MR images, and Zhu et al [17] proposed a deep structural network with end-to-end learning for the segmentation of masses. Further, Wang et al [18] presented a semi-automated detection using DL (Deep learning) to distinguish the micro calcifications and masses. Riddli et al [19] used transfer learning to implement the Faster R-CNN model to classify these lesions into benign and malignant utilizing the MR images. Shen et al [20] presented a deep architecture to pledge weights of full image in an end-to-end fashion. Huynh et al [21] proposed a hybrid method that used both CNN and features of SVM classifier with 5-fold cross-validations for classification. The above CNN based classification involves complex mathematical calculations. Further, it is found form the literature that the CNN too larger computational time for classification for magnetic resonance images. To get rid of such situation, we are motivated to propose a novel Deep CNN-WCA model for classification of COVID-19 diseases to improve the performance of conventional CNN classification. Researchers [22,23] presented AI-based techniques for data acquisition, segmentation, and diagnosis for COVID-19. We considered Kaggle and Github for data-sets containing Chest X-rays. We divide the data sets into two main categories, i.e., (a) SARS-CoV-2 (Covid-19)(b) Non-covid.

The rest of the article is organized as follows. Section 2 presents the implementation of research flow diagram, brief details of Covid related images, details of proposed FRFCM segmentation and proposed Deep CNN-WCA model. Section 3 presents the details of segmentation and classification results, In section 4, the discussions of the research are presented, Section 5 provides the concluding remarks for the article followed by references.

## 2. Materials and Methods

### *2.1 Implementation*

The research flow diagram shown in Fig.1 indicates the step by step accomplishment of the research work. Further the block diagram shows the flow of algorithm application for detection and classification of brain tumor.

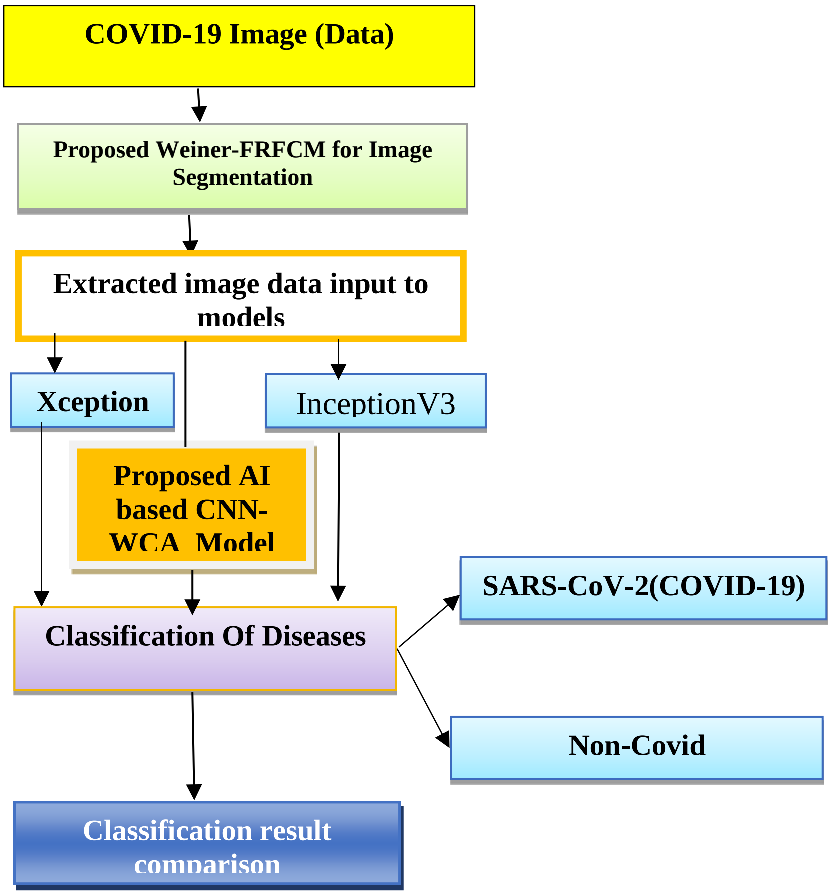



Fig.1: Research flow diagram

*2.2 Details of COVID-19 diseases related to patients*

Coronaviruses are a large family of viruses that are known to cause illness ranging from the common cold to more severe diseases such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). Infection with SARS coronavirus (SARS-CoV) can cause a severe viral respiratory illness. Since 2004, there have been no reported SARS cases. Research evidence suggests that SARS-CoV spreaded from infected civets to people. The case studies of the COVID-19, we have identified the properties of the COVID-19 virus, associated disease symptoms taken from various sources, to classify the COVID-19 diseases for images. The COVID-19 dataset[24] collected from Kaggle website. We emphasized the statistical significance of these measures for the purpose of detection and classification of COVID-19 diseases also. Fig.2 and Fig.3 shows the images of covid (Pneumonia**)** and non –covid.

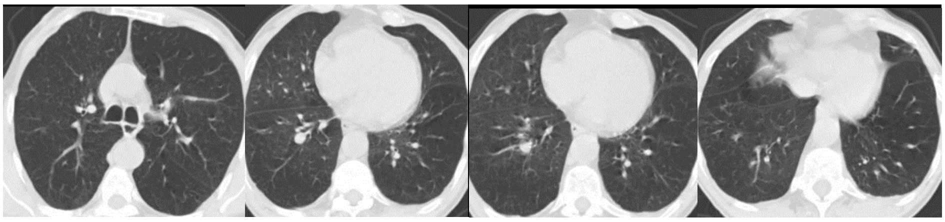


Fig.2 Normal Chest images of four cases (Patients)

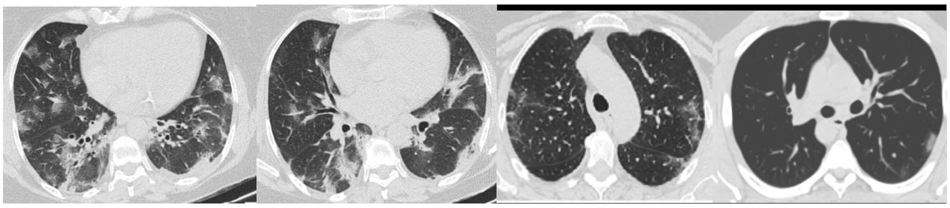


Fig.3 Pneumonia COVID-19 images of four cases (Patients)

*2.3 Proposed FRFCM Image Segmentation:*

There are different promising images segmentation methods such as V-Net, U-Net based on convolutional neural networks, which has been applied for 3D Brain tumor image dataset and Breast cancer mammogram datasets. As the available COVID-19 image datasets are X-Ray images, we are motivated to apply the fuzzy factor based FRFCM segmentation algorithm for the purpose of extraction of corona affected tissues form the images. Further, the member partition matrix of FRFCM has been modified to improve the performance of the segmentation algorithm. The improved Weiner-FRFCM technique has shown better segmentation result for covid-19 images. As the FRFCM algorithm is based on morphological reconstruction, it will best suit for COVID-19 X-Ray images to extract the tissues. In this research work, proposed modified FRFCM algorithm distinguishes the performance of segmentation than the other FCM based segmentation. From literature survey, it is observed that, some preliminary segmentation technique have been applied for brain tumor, breast cancer dataset, but FRFCM segmentation techniques yet not applied for COVID-19 image segmentation by the researchers till date. The advantage of FRFCM algorithm is to detect the tissues and at the same time the noise also removed from the COVID-19 images to improve the performance of the segmentation.

The proposed improved fast and robust FCM segmentation uses a Weiner filter to the modified membership partition matrix of the objective function of FCM algorithm with local information [9]. The objective function of the fuzzy c means algorithm with local information is given by

$$J_s = \sum_{v=1}^{N}\sum_{k=1}^{c} u_{kv}^{m}\|x_v - v_k\|^2 + \sum_{v=1}^{N}\sum_{k=1}^{c} G_{kv} \quad (1)$$

Where the fuzzy factor is given by

$$G_{kv} = \sum_{\substack{r\in N_v \\ v\neq r}} \frac{1}{d_{vr}+1}(1-u_{kr})^m \|x_r - v_k\|^2 \quad (2)$$

Where the spatial Euclidean distance between pixels $x_v$ and $x_r$ is denoted by $d_{vr}$, $N_v$ is the set of neighbours within a window around $x_v$ and $x_r$ represents the neighbours of $x_v$ and $u_{kr}$ is the neighbours of $u_{kv}$. With respect to cluster $k$, $x_v$ is the gray value of the $k^{th}$ pixel, $u_{kv}$ represents the fuzzy membership value of the $v^{th}$ pixel and $N$ is the total number of pixels in the gray scale image $f = [x_1, x_2.....x_N]$, $x_v$ is the gray value of $v^{th}$ pixel, $c$ denotes the cluster centre and $m$ determines the fuzziness of the consequential partition.

To reduce the computational complexity, the membership partition matrix is modified as

$$G_{kv}^{'} = \sum_{\substack{r\in N_v \\ v\neq r}} \frac{\log(\xi^{\tau})}{\exp(d_{vr})+1} u_{kr}^{m}\|x_r - v_k\|^2 \quad (3)$$

Where $u_{kr}$ is the neighbours of $u_{kv}$, $\xi$ is gray value of image and $\tau$ is the smoothness parameter between 0 and 1. Further, considering the morphological reconstruction operations such as dilation and erosion, the reconstruction of the image is considered as $\xi_p$, which is given by

$$\xi_p = R_e^C(f) \quad (4)$$

Where $R_e^C$ represents the morphological closing reconstruction which is efficient for noise removal and $f$ denotes an original image and reconstruction operators considering morphological closing reconstruction is given by

$$R_e^C(f) = R^{\chi}_{R_f^{\beta}(\chi(f))}\left(\beta\left(R_f^{\beta}(\chi(f))\right)\right) \quad (5)$$

Where $\chi$ is the erosion operation, $\beta$ is the dilation operation, $c$ is the closing operation and $f$ represents original image.

Further, considering convergence speed of the algorithms and the performance of the partition matrix $U$ we employ a wiener filter**.** The new membership partition matrix is given by

$$U^l = wiener[U] \quad (6)$$

Update $U^l$ according to equation (6) until convergence of objective function in programming.

### *2.4 Proposed Deep CNN-WCA Model*

A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. Though the layers are colloquially referred to as convolutions, this is only by convention.

Mathematically, it is technically a sliding dot product or cross-correlation. This has significance for the indices in the matrix, in that it affects how weight is determined at a specific index point.

The deep CNN-WCA is proposed to reduce the computational time of conventional CNN. We are proposing the WCA(Water cycle algorithm) to optimize the weights of CNN due to the robustness of the optimization capability as compared to accelerated particle swarm optimization, genetic algorithm etc. The water cycle algorithm is a complex mathematical calculation free algorithm based on the process of water cycle in rivers and streams flow in the ocean which permits a search agent to be transposed around the desired solution. Understanding the metaheuristic nature of the algorithms, we are motivated to hybrid the WCA algorithm with CNN to improve the performance of CNN and considered to apply for COVID-19 images for classification. Basically the Deep CNN is modelled with back propagation algorithm for weight optimization. Due to complex mathematical calculation and backward propagation from last layer to first layer during weight optimization consume larger time for classification. To avoid such situation, we are motivated to hybrid WCA with CNN model for weight optimization.

The figure below shown is the part of the proposed AI based CNN-WCA model. In this model the weights of the fully connected layer is optimized with a novel water cycle algorithm (WCA) model to improve the performance of Deep CNN.

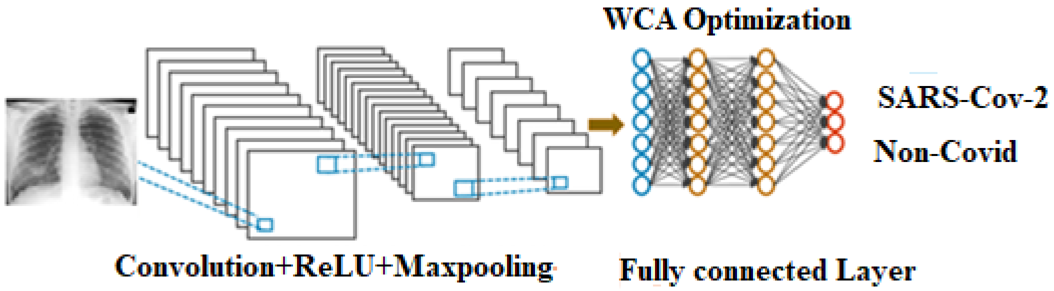



Fig.4 Deep CNN-WCA model for COVID-19 Classification

The classification model will classify the different categories of diseases such as pneumonia (SARS-CoV-2), and Non-Covid.

*2.5 Water Cycle Algorithm (WCA)*

WCA is a population based stochastic optimization technique inspired by river, sea and stream flow. WCA uses a population of individuals, to search feasible region of the function space. the “water cycle algorithm (WCA)” clones the flow of streams and rivers in the direction of the sea and imitative by the view of process of water cycle. The WCA [27-28] has not been used previously by the researchers for COVID-19 images. In this research work, we are proposing to apply the WCA in the fully connected layer to improve performance of conventional CNN model.

The algorithm needs the “generation” of an “initial population” in the form of a matrix of watercourses of size. $N_{Population} \times D$ ,where “ $D$ ”is the “dimension”. Therefore, the matrix is formulated which is given as

$$Total\ \ population = \begin{bmatrix} Sea \\ River1 \\ River2 \\ River3 \\ \vdots \\ StreamN_{sr+1} \\ StreamN_{sr+2} \\ StreamN_{sr+3} \\ \vdots \\ StreamN_{pop} \end{bmatrix} = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_D^1 \\ y_2^1 & y_2^2 & \cdots & y_D^2 \\ \vdots & \vdots & \cdots & \vdots \\ y_1^{N_{pop}} & y_2^{N_{pop}} & \cdots & y_D^{N_{pop}} \end{bmatrix} \tag{7}$$

The rows of Eqn.(7) represent the size of population as ( $N_{Population}$ ) and the columns of Eqn.(7) represents the design variables $D$. At the beginning, the $N_{Population}$ streams are createdand in the second phase $N_{sr}$ which is the addition of the number of rivers (good individuals or minimum values) are designated as a "sea" and "rivers".

Then, the other remaining population is considered using the subsequent equation:

$$N_{sr} = No.of\ rivers + 1(sea) \tag{8}$$

$$N_{Stream} = N_{population} - N_{sr} \tag{9}$$

$$NS_n = round\left\{ \left| \frac{f(River_n)}{\sum_{i=1}^{N_{sr}} f(River_i)} \right| \times N_{Stream} \right\}, \quad n = 1,2,3 \ldots N_{sr} \tag{10}$$

Where, $NS_n$ represents stream numbers which streams into the definite rivers and sea, and $f$ is the evaluation function in the algorithm.

New "positions" for "streams" and "rivers" of WCA have been modified as follows for the weights of fully connected layer as.

$$\begin{aligned} W_{Stream}(l+1) &= \lambda W_{Stream}(l) + Rand \times \chi \times (\beta W_{River}(l) - W_{Stream}(l)) \\ W_{Stream}(l+1) &= \lambda W_{Stream}(l) + Rand \times \chi \times (\beta W_{Sea}(l) - W_{Stream}(l)) \\ W_{River}(l+1) &= \lambda W_{River}(l) + Rand \times \chi \times (\beta W_{Sea}(t) - W_{River}(l)) \end{aligned} \tag{11}$$

With this update equation the algorithm continues till convergence achieved.

### *2.6 COVID-19 Medical image data-sets*

Medical images in the form of Chest CT scans and X-rays[25,26] are essential for automated COVID-19 diagnosis. This research followed the article for data [25,26] where COVID-Net, a deep convolutional network for COVID-19 diagnosis based on Chest X-ray images are presented**.**

## 3. Results

### *3.1 Preprocessing Results*

Data augmentation in machine learning refers to the techniques that synthetically create new examples from a data set by applying possibly stochastic transformations on the existing examples. In the image domain, these transformations can be, for instance, slight translations or rotations, which preserve the perceptual appearance of the original images, but significantly alter the actual pixel values. We performed the experiments on the Chest X-ray image data sets. We resized the 1.3 M images into 227 x 227 pixels, as a compromise between keeping a high resolution and speeding up the training. The pre-processing involves Random Rotations, Random Shifts and Random Flips.

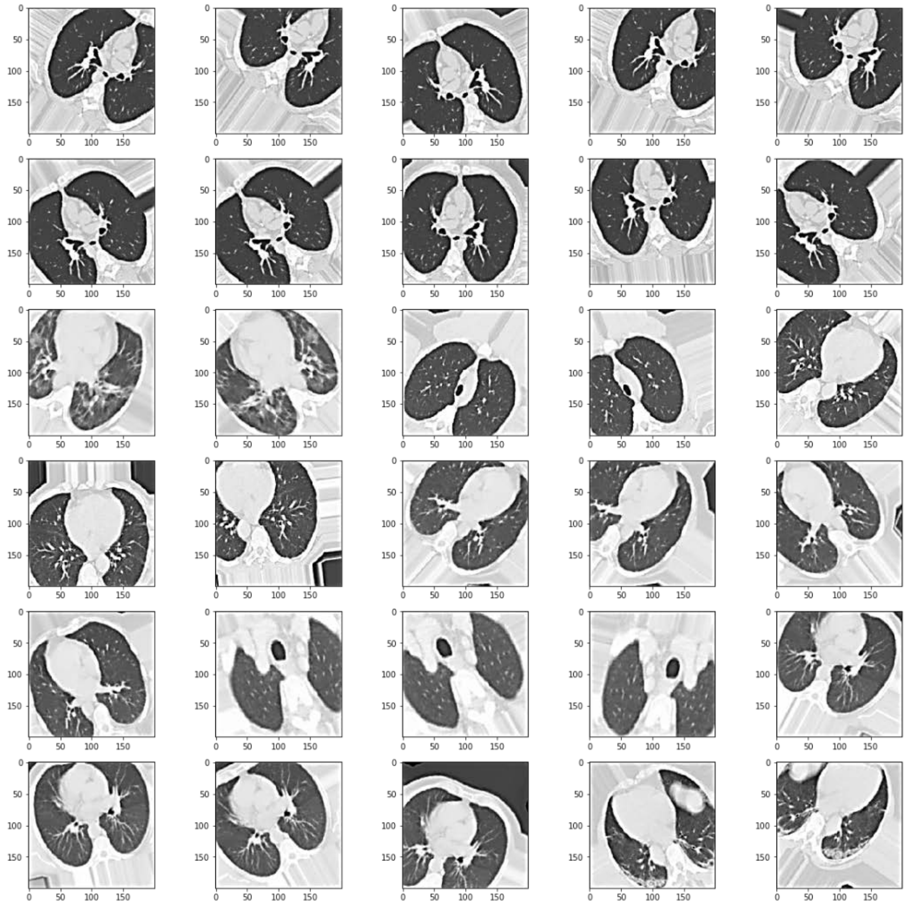


Fig.5 Output images of Image data augmentation techniques rotation, shifts and flips.

A higher number of images were needed to train a deep learning algorithm. The data augmentation technique was used to increase the number of samples in the dataset. After the data augmentation, we obtained 15,216 samples.

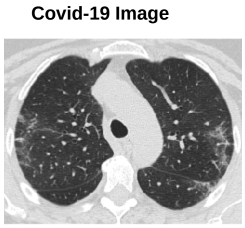
**Table-1:** Original Images

| COVID | | | Non-COVID | | |
|---|---|---|---|---|---|
| **Training** | **Validation** | **testing** | **Training** | **Validation** | **testing** |
| 1252 | 250 | 126 | 1230 | 250 | 124 |
| **Total: 1628** | | | **Total: 1604** | | |

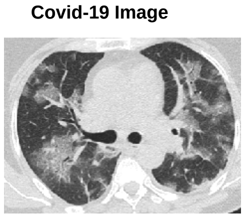
**Table-2:** Data Augmentation

| Training | Validation | testing |
|---|---|---|
| 159,472 | 160 | 79,799 |
| | **Total: 239,431** | |

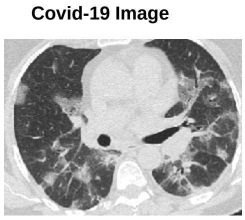
### *3.2 Segmentation Results*



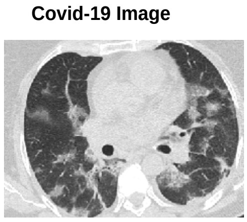

**(a)**



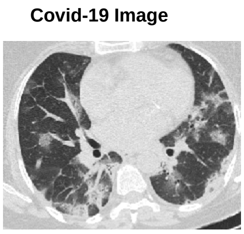

**(b)**




**(c)**




**(d)**




**(e)**

Fig6. Covid-19 Segmentation results of modified FRFCM segmentation

### 3.3 Classification Results

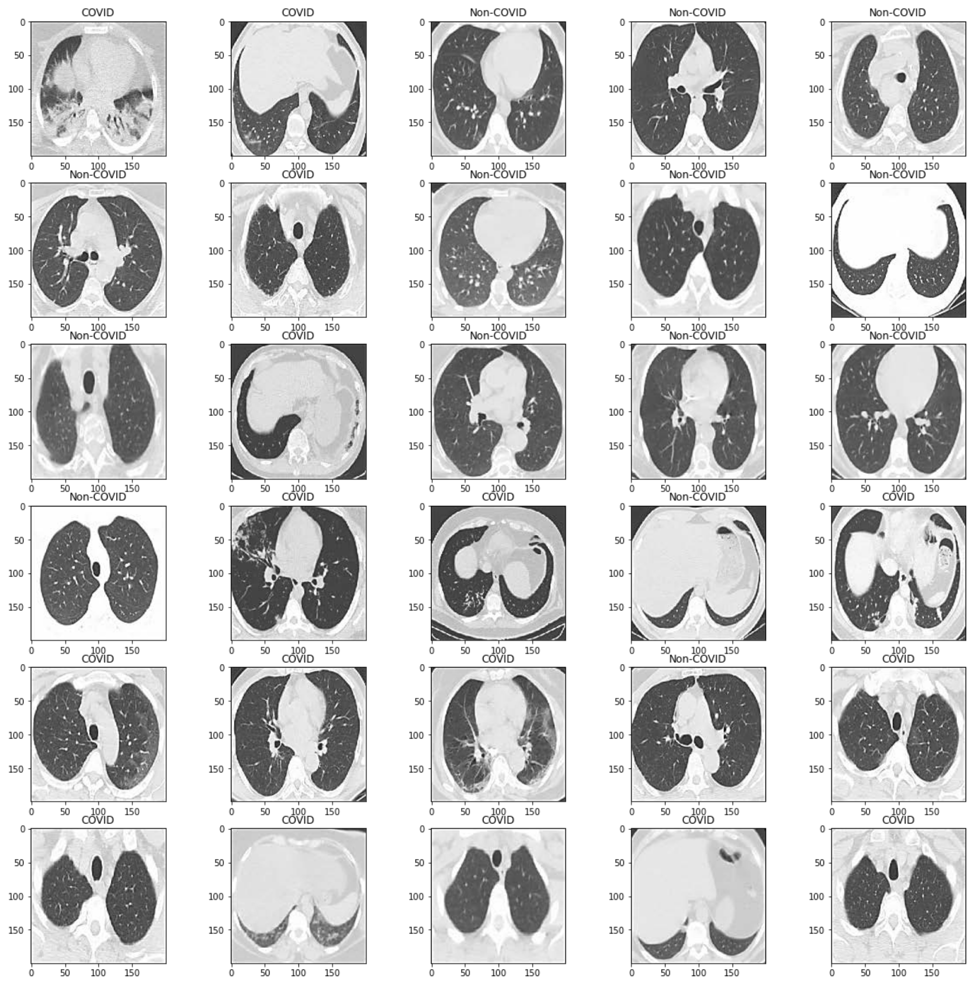



Fig7. Classification Covid-19 and Non-Covid results

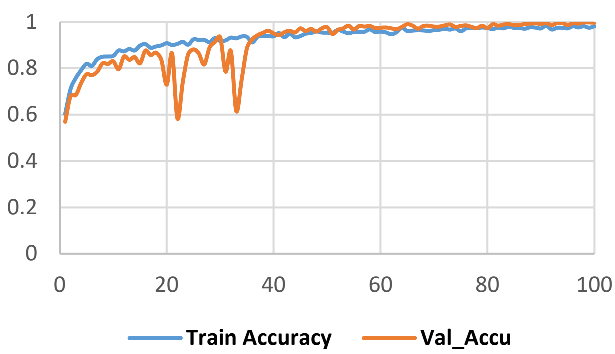



Fig.8 InceptionV3Model accuracy results

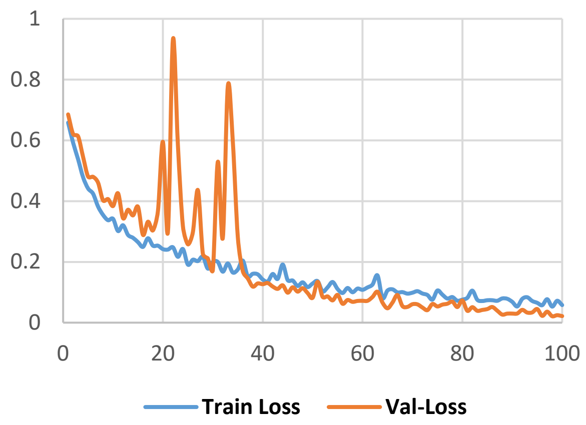



Fig.9 InceptionV3Model loss results

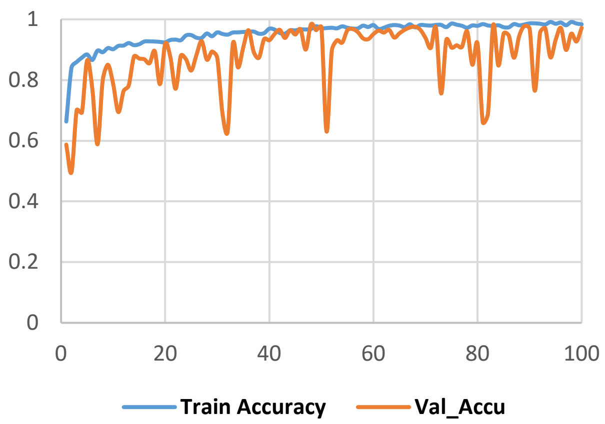



Fig.10 XceptionModel accuracy results

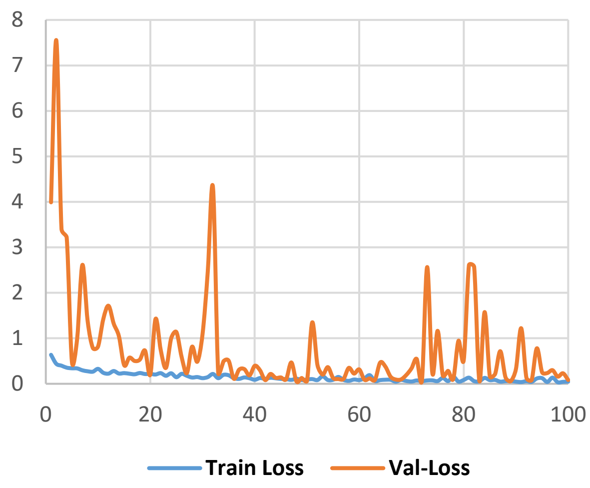



Fig.11 Xception Model loss results

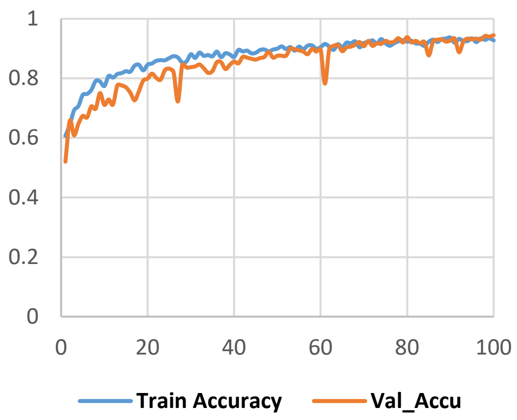



Fig.12 Deep CNN-WCA Model accuracy results

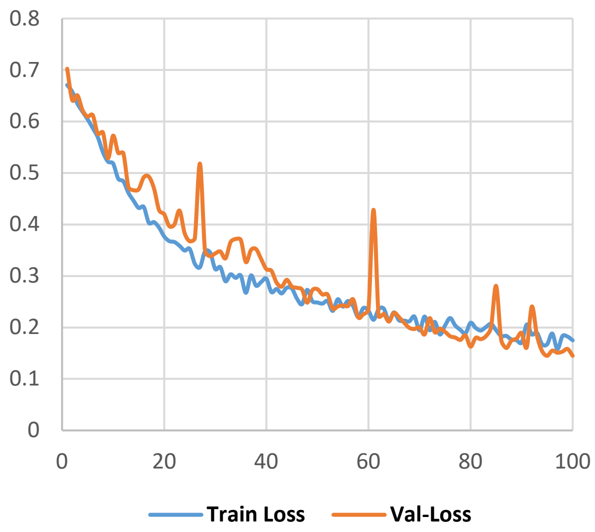



Fig.13 Deep CNN-WCA Model loss results

Table-3 Classification accuracy results

| Model | Training accuracy | Validation accuracy | Training Loss | Validation Loss | Computational Time in sec |
|---|---|---|---|---|---|
| InceptionV3 | 93.0986 | 91.5259 | 9.9014 | 8.4741 | 4033 |
| Xception | 95.2347 | 92.3879 | 4.7653 | 7.6121 | 3905 |
| Deep CNN-WCA | 99.6243 | 94.1523 | 0.3757 | 5.8477 | 3216 |

All the values are the average values of 100 epochs

## 4 Discussion

Fig.5 shows Image data augmentation techniques which includes rotation, shifts and flips. Fig.6 shows the image segmentation by utilizing the proposed modified FRFCM algorithm. The segmentation has been utilized to remove rician noise from the images and the images are fed as input to the Deep CNN-WCA model for classification. Fig.7 shows the classification results of the proposed Deep CNN-WCA model. The Deep CNN-WCA model classifies the images into Covid and non-covid categories. Fig.8 to Fig.13 presents the training accuracy, validation accuracy, training loss and validation loss for inceptionV3 model, Xception model and proposed Deep CNN-WCA model. The computational time and accuracy of classification results are presented in Table-3.

*4.1 Proposed Web Based Application*

1. The project can be implemented through IoT system, where the server with software will be taken care by Innovation and Technology support center.
2. Hospitals of all over Africa or state wise will be connected through the server.
3. Hospitals can be connected to the server with an identification number and password provided by the support center.
4. The Deep CNN-WCA model will support the detection and classification task and deliver the report.
5. The customers can access the reports from the hospitals by using there ID and password from the respective hospitals server system.

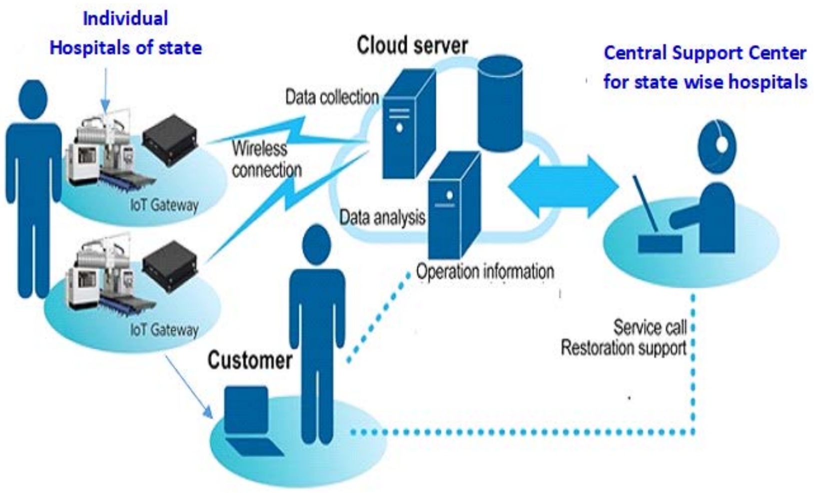



Fig.14 Web application diagram

## 4.2 Process of implementation

1. At the first step, we will develop a compact data acquisition system along with the software model design with power backup.
2. Further, the proposed CNN-WCA model and segmentation techniques needs to be tested by the team of doctors and radiologists for patients through the software system as test basis after scan of patients.
3. Finally with real data acquisition and positive results of testing of patients will be taken as reference point, and can be approached for the commercialization as testing kit for COVID related diseases.
4. The kit to be connected to digital scan machine to acquire the images to the system for analysis.

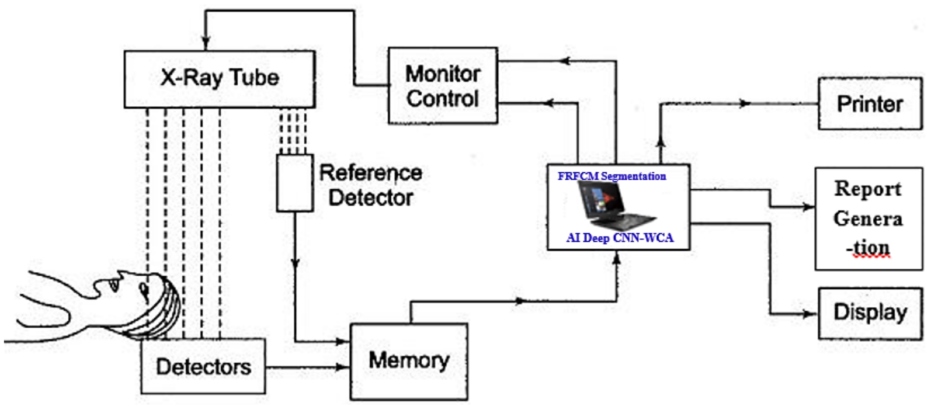



Fig.15 details of data acquisition and report generation

## 5. Conclusion

This paper presents a modified FRFCM segmentation to identify the region of tissues and removal of rician noise from the images. The preprocessed images are then fed to novel Deep CNN-WCA model for classification of Covid and Non-covid images. In the architecture of Deep CNN model, the fully connected layer in general plays an important role for classification. The back propagation algorithm generally utilized for weight optimization. In this research work, the meta-heuristic WCA algorithm has been employed for optimization of weights in the fully connected layer. The results of training and testing classification accuracy of the proposed Deep CNN–WCA model outperforms than the inception V3 and Xception model. Also the computational time requirement is less in the proposed Deep CNN model in comparison to the other mentioned models which is presented in Table-3. The simulations for the models are performed using python platform with GPU system.

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