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Artificial Intelligence Defogging Algorithm for Chest CT Scan Images for Post-Covid-19 Patients Infected with H3N2 Virus

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Abstract: On the verge of Covid-19 pandemic, new Influenza a H3N2 variant virus is immerging throughout India. It is crucial to identify the impact of post-covid-19 patients and H3N2 infected patients. As all comes to the lung health, the primary element for diagnosis is the CT scan image and MRI of patient regardless of type of the virus. The medicinal strategy is similar due to similar indications of lung infection status in CT images of lungs. The additional and painful symptom of H3N2 infected post-covid-19 patient is the blood in the cough. Doctors need to know the level of infection of lungs in a clear way by defogging the blood clots in the cough present in the lungs or respiratory track. Hence, this paper presents the research to identify with defogging of lung CT image analysis by capturing the more prominent area of lung CT images more clear vision. The proposed research presents the new algorithm named 'AI-Defogging' using artificial intelligence to automatically regenerate the augmented pixels out of lung CT images.

Keywords: *Artificial Intelligence, Human Machine Interface, CNN, deep learning, covid-19,H3N2*

1. Introduction

Early in the year 2020, the Corona virus Disease 2019 (COVID-19) became widespread over the planet, putting the world's health in an existential state of emergency. The automated detection of lung infections using computed tomography (CT) images presents a significant potential to supplement the conventional healthcare strategy for dealing with COVID-19 [1]. Since influenza viruses only circulated at very low levels during the start of the COVID-19 pandemic, the population's resistance to them is insufficient. [2] The H3N2 strain that is currently predominating has a hemagglutinin (HA) that contains many substitutions in comparison to the H3N2 vaccination strain that will be used in 2021–22. Establishing a clinical diagnosis might be difficult when secondary reactions or illnesses show with symptoms that are similar to those of the first condition being investigated. At the moment, the reverse transcription polymerase chain reaction, often known as RT- PCR, is the approach that is considered to be the gold standard for determining which patients have COVID-19 infection. (9). CT has also been frequently employed in other countries, in addition to the RT-PCR test, to give other ways of COVID-19 diagnosis and treatment-response monitoring. (5).

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Despite this, CT imaging is not recommended as a general diagnostic imaging technique for patients who have COVID-19 by a number of professional organizations in the health care industry (12–14). This is because of concerns regarding contamination of CT facilities and exposure of health care workers. The use of artificial intelligence is rapidly expanding across the board in the medical industry, particularly in the field of diagnostic radiology. Artificial intelligence has been crucial in the early detection and diagnosis of Covid-19 patients during the current pandemic.

Additionally, it has helped with the creation of new medications and a vaccine for the virus, as well as the monitoring of the offered therapy and the prediction of mortality rates. Finally, it has helped with the reduction of the total workload on medical staff. When it comes to the Covid-19 pandemic, the most significant obstacle that the healthcare systems must overcome is the prompt establishment of a diagnosis and the monitoring of the evolution of the disease.2,8 During the pandemic, around twenty percent of chest radiographs that were evaluated by general radiologists were deemed to be normal; however, a second peer reading revealed that these chest radiographs were actually abnormal.

The development of vaccines and helping in the fight against the Covid-19 global pandemic are just two examples of how artificial intelligence (AI) will play a significant role in the future development of all areas of healthcare. Clinical assistance to physicians through accurate diagnosis, prognosis, and treatment are other examples. This includes helping doctors clinically by offering precise diagnoses, prognoses, and treatments, as well as the creation of vaccines. AI plays a vital part in diagnostic radiology since the algorithms used in this field may be trained using big datasets to reliably and quickly deliver a diagnosis of the radiological images that are being provided. As a result of this, various artificial intelligence algorithms have been developed, and they are now in a position to be utilized in areas where there is a shortage of radiologists during the present pandemic. These algorithms are able to simply denote the presence or absence of Covid-19 pneumonia in PCR-positive patients on plain chest radiographs. The most common type of radiological examination performed in the setting of an emergency room is the plain chest radiography. There have been a number of studies that have been done comparing numerous AI algorithms to the work of expert thoracic radiologists in plain chest radiograph reports, with the aim of determining which method is more accurate for Covid-19 patients. Artificial intelligence, or AI, is described as the simulation of intelligent human behavior by computer programs. The development of such computerized algorithms has made it possible for it to complete jobs normally performed by humans, as well as given it the power to learn and to find solutions to issues. The application of machine learning, deep learning, artificial neural networks, and radiomics are all a part of this process. The application of machine learning utilizes aspects that call for the classification of the data that is provided. When additional data are made available, the performance of the algorithm that is being used improves.

When compared to other varieties of pneumonia, COVID-19 pneumonia can be distinguished from other types of pneumonia through the use of chest radiographs thanks to the specific benefits offered by machine learning approaches, in particular deep learning (15,16). The goals of our work were to:

(1) train and validate a deep learning system to discriminate COVID-19 pneumonia from other causes of abnormalities during chest radiography; and (2) test the method's performance in comparison to thoracic radiologists' performance.

The "AI-Defogging" technique developed in this research has been evaluated on CT scans of the lungs from patients infected with Covid-19 and H3N2. To make it easier for radiologists, surgeons, and other medical practitioners to determine a course of treatment, algorithm developers are working to automate CT image detection using AI. The most recent literature is reviewed in Section 2, the proposed research approach and algorithm is addressed in Section 3, the results and analysis is presented in Section 4, and the study is concluded in Section 5.

2. Literature Review

According to the author, in spite of advances in medical technology, lung diseases continue to be a leading cause of death and significant morbidity around the world. This is due to the fact that lung diseases directly impact the respiratory systems and frequently result in the formation of a layer of lesions on the lungs. There is a vast variety of organisms that are known to cause a variety of lung infections, and there are also new organisms that are coming to light. Computer-aided diagnosis, often known as CAD, is an essential diagnostic tool for making an early diagnosis of a disease [9]. CAD is a diagnostic tool that is equipped by image processing and machine learning techniques.

The author performed the analysis using the decision tree algorithm. According to the findings of the research, in contrast to patients with influenza, COVID-19 patients continue to have a high rate of lung involvement more than 14 days following the diagnosis. The most prominent pattern in COVID-19 progresses from ground glass in the early stages of the disease to consolidation in its later stages. Consolidation occurs earlier in the course of influenza, and ground glass opacity is lower overall (p

$= 0.002$) [10].

The suggested system is capable of performing early patient classification based on gathered samples of chest X-ray images and Coswara cough (sound) samples from potentially sick individuals. Coughsamples that have been taken are pre-processed with speech signal processing techniques, and features such as Mel frequency cepstral coefficient are extracted with the use of deep convolutional neural networks. Lastly, the weighted sum-rule fusion approach [11] is used by the proposed system to combine previously derived characteristics in order to provide an early diagnostic accuracy of 98.70% and 82.7%, respectively, based on chest x-ray images and cough (audio) samples.

In the 2.5D segmentation method developed by the author, the cross-sections of the human chest serve as the inputs for the 2D U-nets. The masks of the blood vessels and airways are shown here in the form of unconnected sections because these photos are in cross-section. There is a wide range of variation in the size of these regions. For example, the cross-sections of aortas consist of hundreds of pixels, whilst the cross-sections of microscopic blood arteries consist of only a few pixels. A voxel- level balanced cross-entropy loss is what's known as a feature-enhanced loss. According to what the author described, it is the accumulation of all of the voxel loss. The loss is calculated as follows for each voxel:

$$\text{voxel loss} = \omega \times l_n(p) \times \ p' - l_n(1-p) \times (1-p') \quad (1)$$

p is the weight showing the penalty for the incorrect negative prediction of this voxel, and p′is theground truth probability (a binary value) that the voxel is positive. For false positives, the penalty weight is always 1. The focus of the model is quantified by a value called w, which is assigned to every voxel with a positive p′ (p′ = 1). However, conventional loss functions based on voxel-wise performance pay insufficient attention to small regions, leading to false positives for small structures because the total area of all small regions is smaller than that of large ones. Therefore, we developed the feature-enhanced loss [12] to aid the 2D U-nets in extracting features of fine-grained structures.

Patients with COVID-19 are easily identified by the asymmetric, diffuse opacity of their airways. The CT scans and indications both show evidence of lung involvement on both sides. Reports from non- ICU patients with severe symptoms resemble ground-glass patterns, while those from ICU patients with consolidative patterns [13]. Patients who have recovered from COVID-19, the author argues, remain at risk for a variety of chronic illnesses. However, due to a paucity of data and various unexamined behaviors of corona virus [14], it is not possible to grasp the detailed long-term impacts at this moment. Author suggests that AI-based techniques for the automatic detection and quantification of COVID-19 lesions in chest CT could be useful for disease monitoring and management [15].

3. Research Methodology

As any pandemic impacts the community health, it is crucial to present the fast treatment options out of the research. Pandemic is the once in hundred years occurrence and it has impact on overall economy, social wellness, human stability etc. Hence, it is important to conduct the research for all segments. The core health related segments are mental health and the physical health. If physical health is in good condition then mental health can be cured early. But, recent Covid-19 pandemic impacted both with fear, anxiety, depression and hospitalization. As time has been changed and due to globalization and internet many new computational research got the chance to work faster to solve problems, proposed research contributes to diagnose the impact on lung due to Covid-19/H3N2 infection.

Once of the hurdle in analysis of lung CT images are the human visual error which can affect the lineof treatment. As lung infections grow and impact fast due to the cytokines deflection caused by medicines and infection collectively, it affects kidneys too. Hence, to control the lung disease early is important for which radiologist needs continuous lung CT scanning report. The proposed research is useful for identification of lung patches by pixel extractions which can show the dimensions of patches. This can help radiologists and other monitoring professionals to identify the growth of patches. Following Fig. 1 shows the proposed methodology.

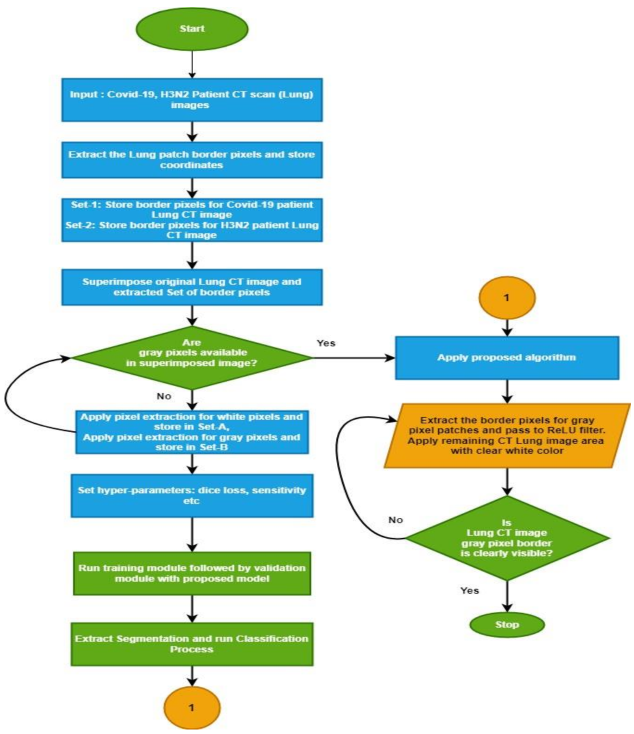


Fig 1: Proposed Methodology

Algorithm: AI-Defogging

Input: Lung CT images of Covid-19 and H3N2 patients
Output: Infective patch extracted defogged lung CT images

1. Create $Set1\_CTimage\_0$ (M, N): $Set1\_CTimage\_n$ $(M, N) + X_{ct}$

2. Create$Set2_CTimage_0$ (M, N): $Set2\_CTimage\_n$ $(M, N) + X_{ct}$

Where, $X_{ct} = 0$ *# Individual image set status for Covid-19 and H3N2 patients*

3. $Set1\_CTimage\_batch\_n = (ExtractedCovid - 19\_0\ (X, P) + ConcatLayer)$

4. $Set2\_CTimage\_batch\_n = (ExtractedH3N2\_0\ (X, P) + ConcatLayer)$

5. Mask BGColor = "white" # Masking of remaining CT image visibility as white color other than infected gray pixel borders

6. Create SubSet $SS = Set1\_CTimage\_batch_n + Set2\_CTimage\_batch\_n + ConcatLayer$*# Train using Concat Layer for identification of hyper parameters*

Where, $X_{ct}! = 0$

7. ***While*** *(*$X_{ct}! = 0$*)* ***do***

8. ***Go to*** Step-6

9. **Apply** ReLU filter # De-fogged patch extraction RF1=$ExtractedCovid - 19\_0\ (X, P)$ # Calculate hyper parameters RF1=$ExtractedH3N2\_0\ (X, P)$ # Calculate hyper parameters ***while*** *(*$X_{ct}! = 0$ && $Y! = 0$*)* ***do***

10. ***Go to*** *Step-9*

11. ***end while***

The above algorithm executes the convolutional neural network as a artificial intelligence module. The proposed deep learning algorithm can extract the pixel borders of gray patch out of lung CT image by masking the remaining area as an white. The reason of masking is to fetch the focus on infected area of lung CT image so, radiologist and medical experts can study the infection level of patients with Covid-19 and H3N2 infection. Many times in case of H3N2 infection, blood clots occur in lung which makes it difficult to identify exact border pixels of infected lung patch. Hence, masking provides opportunity to closely observe the status of gray pixel patch.

The artificial intelligence module provides fast algorithm training and validation. Hence, proposed deep learning algorithm can provide fast results of hyper parameters like accuracy, loss, sensitivity etc with the help of extraction of infected patch area which can be validated by superimposing the original image and extracted set of pixels. The results of proposed algorithm are discussed in next section of the paper.

The proposed method shown in Fig.1 is tested for CT Chest image processing. The convolutional Neural Network is used to detect the COVID in the lung.

4. Materials and Methods

Patient Overview

There were a total of 3507 people who fit the criterion and had pneumonia other than COVID- 19 (based on 5672 chest radiographs). Patients under the age of 18 made up 359 (out of a total of 372 chest radiographs). Twenty-eight hundred and six patients (6650 chest radiographs) with

COVID-19 pneumonia met the inclusion criteria, and three hundred and forty patients (845 radiographs) were omitted because they were taken at an inconvenient period for RT-PCR (5 days prior to and 14 days following a positive test result). The development (training, validation, and testing) stages made use of a total of 5300 chest radiographs with non-COVID-19 pneumonia from 3148 patients and 5805 chest radiographs with RT-PCT-confirmed COVID-19 pneumonia from 2060 patients (mean age: 62 years, 6 months, 16 days; 1059 men). (Men make up 1578 of the population; average age is 64 years, 6 months). Randomization and partitioning were applied to the data based on the chest x-ray machines used to collect the images. A total of 2654 chest radiographs from 1962 patients without RT-PCR-confirmed COVID-19 and 2582 chest radiographs from 1053patients with RT-PCR-confirmed COVID-19 were utilised for training and validation. For CV19- Net testing, a total of 5869 chest radiographs from 2193 patients were used, including 2646 from 1186 patients with pneumonia that was not caused by COVID-19 and 3223 from 1007 patients with RT-PCR-confirmed COVID-19.

Training and Testing

In 12 individuals, despite the absence of illness, a total of more than 350 slices were present. A total of over 1500 samples were obtained through the pre-processing and data augmentation processes. Following the application of the standard splitting method of 80%, the outcome was around 1200 slices for the train and the remaining for the test. The weights of the newly constructed deep convolutional neural network are trained using the data from the training set. In order to validate the model's capacity for generalization, a validation set must first be constructed. The system is being evaluated to determine the minimum and maximum values.

Table I: Analyzing the total CT scan images

Train	53	46	97
Test	51	53	100
Validation	54	56	100

Performance Evaluation Criteria

As the evaluation criteria becomes precision, recall, accuracy, AUC score and F1 score.

- **Accuracy:** The genuine or original values might be seen in a ratio of the measured value orfindings.

$$Accuracy = \frac{TN}{TN+FP+TP} \qquad \text{---------------- (2)}$$

- **Recall:** A ratio of cases that were correctly classified to actual instances.

$$Recall = \frac{TN+FP}{TN+FP+TP} \qquad \text{--------------- (3)}$$

- **Precision:** It measures how well COVID-19 is anticipated compared to all other pixels that are predicted to have a positive COVID-19 value.

$$Precision = \frac{TP}{TP+FP} \qquad \text{--------------- (4)}$$

- **F1 score:** The F1 score is the weighted average of recall and precision. Therefore, this score considers both false positive and false negative results.

$$F1\,Score = \frac{Precision+Recall}{Precision+Recall+Accuracy} \qquad \text{--------------- (5)}$$

The number of images used to analyze the CT chest image is 3150. This contains 1891 with tumor and 1259 without tumor. The system is trained with 2657 and tested for 493 numbers of images.

Imaging Evaluation

All CRs were digitally recorded, and they were carried out in accordance with the statutory requirements that were applicable to their respective regions. Only the very first CR that was performed at admission was taken into consideration for this study. We used every single one of the projections that we had. Both the radiologist's retrospective analysis of the radiographs and the analysis performed by the AI algorithm were conducted independently of one another and apart fromone another. Consensus was reached about the evaluation of the images by a senior resident and an experienced senior radiologist. Both of the evaluators were unaware of the subsequent patient treatment, the status of the pathogen detection, or the COVID-19 status. It was established that there were pacifications or consolidations present, both of which are consistent with pneumonia.

Additionally, the imaging pattern was categorized into one of the following groups: typical for a COVID-19 infection was the presence of predominantly peripherally located pacifications or consolidations on both sides; almost typical for a COVID-19 infection was the presence of predominantly peripherally located pacifications or consolidations on one side with no or minimal infection on the contra lateral side.

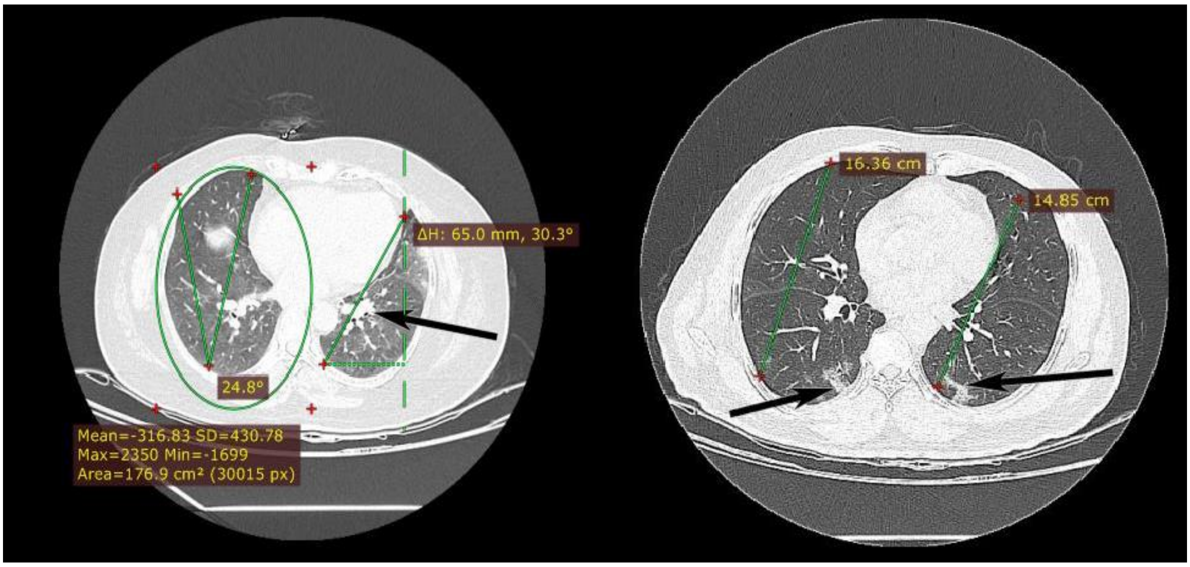


Fig 2: Radiography of the chest that show the distinct distribution patterns that indicate the likelihood of COVID-19 infection.

Data from Radient DICOM that have been processed using the Defogging technique. Take note that this tool can only evaluate projections from the anterior to the posterior or the posterior to the anterior.The scores range from 0 to 100, and a threshold of 15 is used to differentiate normal (more than or equal to 15) from pathological (less than or equal to 15) visual patterns. The findings of the AI-basedevaluations were contrasted with the interpretation provided by the radiologists, who served as the standard of comparison. We looked at the AUROC, along with the sensitivity and the specificity.

Overall Performance of Cv19-Net

In terms of its overall performance, the CV19-Net was able to attain an AUC of 0.92 (95% confidence interval: 0.91, 0.93) for the test data set. This approach demonstrated a sensitivity of 88% (95% confidence interval: 87, 89) and a specificity of 79% (95% confidence interval: 77, 80); but, when applied to a high-specificity operating threshold, it demonstrated a sensitivity of 78% (95% confidence interval: 77, 79) and a specificity of 89% (95% confidence interval: 88, 90). It is provided the performance of CV19-Net for four main vendors and five large hospitals.

The results of the three radiologists' interpretations of the subset of 600 test photos showed sensitivities that ranged from 52% to 72% to 90%, and their specificities ranged from 96% to 85% to 55%, respectively. An averaged receiver operating characteristic curve for the radiologists was created by using the interpretation findings of the same picture from each of the three readers. This curve had an AUC of 0.85 and a 95% confidence interval that ranged from 0.81 to 0.88. Applying the CV19-Net to the same set of tests resulted in an area under the curve (AUC) of 0.94, sensitivities of 71%, 87%, and 98%, and specificities of 96%, 85%, and 55%, respectively. This was done by selecting specificity that was in line with each radiologist's performance.

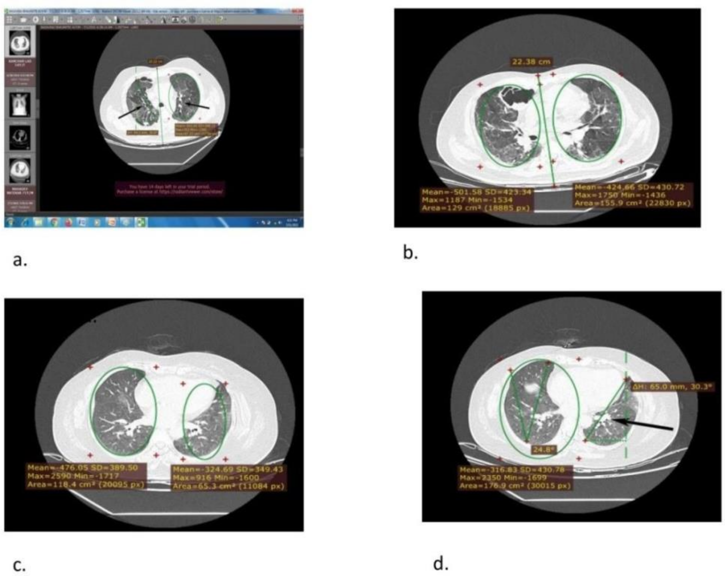
5. Results of Analyzing Images

Given that the appearance of COVID-19 pneumonia on chest radiographs can be highly variable, from peripheral opacifications only to diffuse opacifications, which makes differentiation from other diseases challenging, the results obtained by the AI system compared with radiologist readings are noteworthy. Initial chest x-rays may be benign or may reveal minor illness. Wong et al.

(20) found that 69% of patients hospitalized for COVID-19 had abnormal chest radiograph results upon admission. Eighty percent of those admitted had abnormalities on chest x-rays, with the severityincreasing over the course of a week after symptoms first appeared (21). Common COVID-19-related radiological abnormalities include bilateral lower lobe consolidations, ground glass opacities, widespread air space illness, and peripheral air space opacities.

To improve the AI system's ability to detect COVID-19, a larger training set of chest radiographs is needed. Combining the results of a chest x-ray with those of clinical and laboratory tests may also yield beneficial results. Analyzing The accuracy of the trained model for predicting infection from CT scans of the lung was approximately 0.92, whereas the accuracy for segmenting the lung was approximately 0.90. Infection and lung segmentation losses were respectively 0.03 and 0.04.

The below Fig a. and Fig b. shows the chest CT for both COVID 19 image extraction System Using Different analysis for COVID-19.



a. b. c. d.

Fig 3: Images (a to d) shows representative cases that the majority of radiologists classifieds.

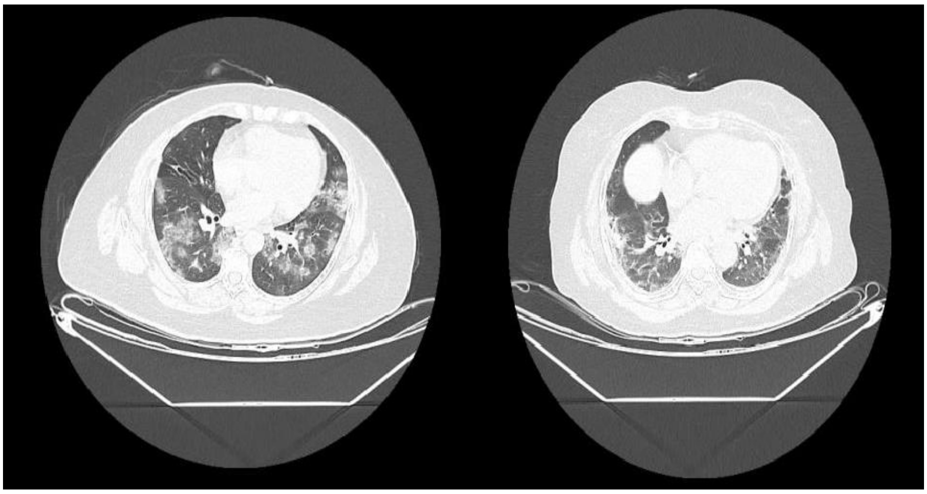
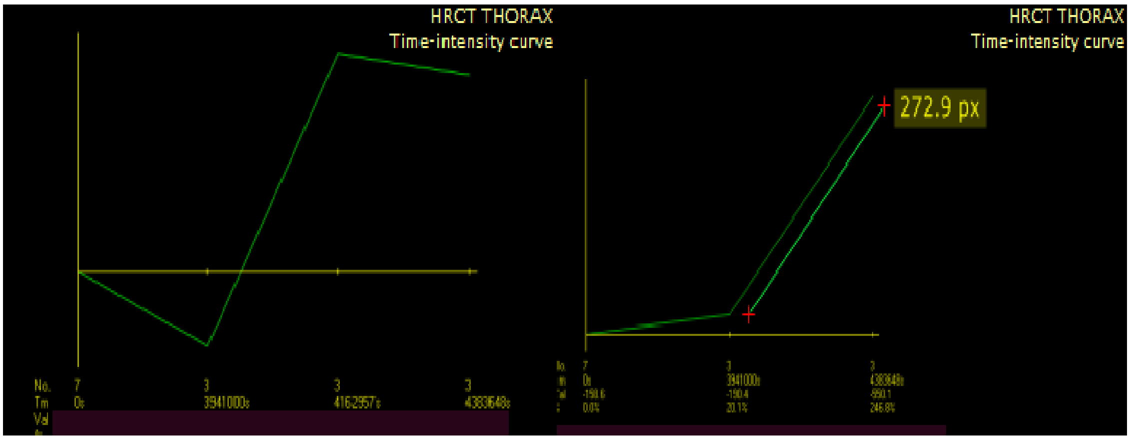


Fig. 4(a): CT Normal chest image. **Fig. 4(b):** CT COVID-19 image.

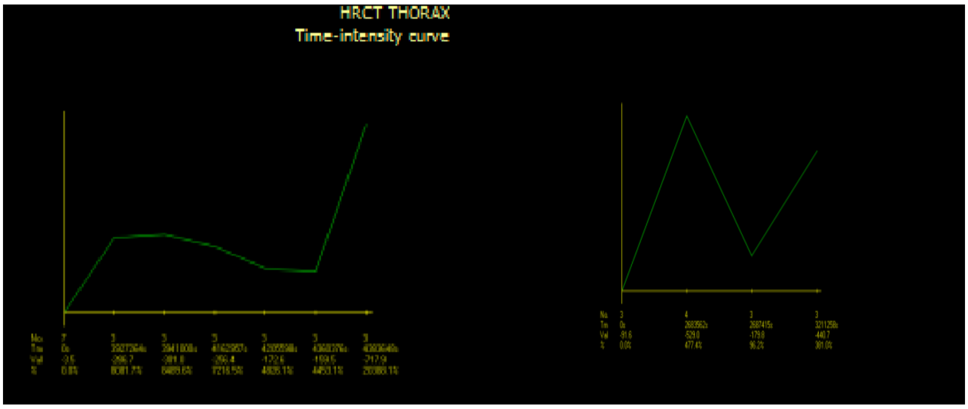
The outcomes of the new algorithms and those from earlier methods are simulated on a range of images, and their enhancement potential is contrasted in the following fig. The average brightness has increased rather than the contrast, as shown in this CE and HE image. In comparison to the original image, the various concentric circles are more distinct and wider.

Table II. Distortion (PSNR value of Enhanced Images)

Compression Ratio	CT chest image-1		CT chest image-2	
	MSE	PSNR(dB)	MSE	PSNR(dB)
10.1	0.5	54	0.3	59
20.1	1.5	57	0.8	54
30.1	2.5	50	1.7	45
40.1	3.4	48	1.9	49
50.1	4.2	51	2.1	43



a. **b.**



c. d.

Fig 5: CV19-Net performance as measured by the Time intensity curve. (a) The whole test data set's receiver operating characteristic curve (left) with 156 chest radiographs and the probability score distribution (right). (b) The performance of the three chest radiologists was compared to CV19-Net for the 223 test cases. (c) The test data set's CV19-Net receiver operating characteristic curves for a number of vendors (V1-V4) and hospitals (H01-H05). (d) The performance of the three chest radiologists was evaluated against CV19-Net for the 352 test cases.

- By showing time-intensity curves, the RadiAnt DICOM Viewer gives users the ability to visualize the enhancing behavior of lesions (for example, in the lung in CT).
- By showing time-intensity curves, the RadiAnt DICOM Viewer gives users the ability to visualize the enhancing behavior of lesions.
- Following the training, the model had an accuracy of approximately 0.92 for infection and 0.90 for lung segmentation in its predictions. Infection and lung segmentation led to a loss of around 0.03 and 0.04, respectively.
- The infection zones were sometimes segmented inadequately by the contrasted approaches, while other times they were segmented excessively.
- We are calculating the length, eclipse, and angle for the photos in the locations affected by the virus.
- Taking the second illustration as an example, our technique is able to appropriately segment the bulk of the huge infection zones. Integrated into the various regions (indicated by blue arrows).
- During the training phase and the data collection, the following characteristics were selected as potential performance measures: Testing Accuracy, Precision, Recall, and F1 Score. During training, we trained the data collection using five different models that had alreadybeen pre-trained. The results of the analysis of the complete CT scan pictures and the measurement data are presented in tables III and IV respectively.

Table III. Analyzing the total CT scan images

TRAINDATA	ACCURACY (%)	F1- SCORE (%)	AUC (%)
COVID-CT-349	79.5	76	90.1
COVID-CT-349 with lungmask	85	85.9	92.8

Table IV. Performances of measurement data.

<table>
<tr><td>Length</td><td colspan="2">11.85cm</td></tr>
<tr><td rowspan="3">Eclipse</td><td>Mean</td><td>357.34</td></tr>
<tr><td>Max</td><td>769</td></tr>
<tr><td>Min</td><td>24.88cm</td></tr>
<tr><td>Angle</td><td colspan="2">50.0º</td></tr>
</table>

The trained model predicted an accuracy of 0.90 for lung segmentation and 0.92 for infection.

For the segmentation of the lungs and the infection, losses of 0.03 and 0.04 were noted.

Comparison Results Classification Methods

With the help of the Inception Resnet-V2 and Inception-V3 methodologies, we compared our findings to theirs. Table V presents the findings.

Table V. Comparison of accuracy classification method

Model	Accuracy	Recall	Precision	F1 score
Inception ResNet-V2	87	84	91	86
Inception-V3	97	94	100	96
Propose Approach	98	96	98	97

As may be seen in Table: V above, we disclosed the results as well as any additional approaches. Theaccuracy, recall, precision, and F1 scores of the model that we have proposed are superior to those of the other models. We obtain an accuracy of approximately 98%. The accuracy achieved by Inception- ResNetV2 is approximately 87% at its worst. The establishment of an effective machine learning system includes the performance evaluation of the suggested approach, which is considered to be a basic component of the process. There are a total of 2568 photos captured, 932 of which are not COVID-19 (negative cases), and 1636 of which are COVID-19. (positive cases). These pictures areseparated into training and testing datasets in order to do experimental research on them. Displaying medical pictures (CT lung scans) in DICOM format is examined with RadiAnt Digital Imaging and Communications in Medicine (DICOM) Viewer as part of the proposed research.

6. Conclusion

As a modern medical computations becoming more prominent for human machine interfacing medical devices and artificial intelligence is back bone for such robotic systems, proposed research can be an intelligent solution for Lung CT image analysis. This paper presented the core difficulty in manual analysis of Lung CT, MR images and proposed methodology. The proposed algorithm “AI- Defogging” has been discussed and proved that the infected gray pixel extraction for covid-19 and H3N2 infected patients can be retrieved with more accuracy and less losses. The training and validation execution with proposed algorithm proves the better visibility of infected lung patches with recursive run to achieve higher accuracy. Hence, as a future development the proposed algorithm can be used as a interface between CT machine and digital analysis portal of hospitals for quick visibilityand higher accuracy.

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