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Automated COVID-19 Detection with Ensemble Deep Convolution Neural Networks using Computed Tomography Images

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Abstract: The recently identified presence of the novel coronavirus (COVID-19) has had disastrous effects, and the World Health Organization (WHO) has declared it a serious worldwide pandemic. A person's contact with the virus must be discovered as soon as possible to begin treatment and quarantine (if necessary) and prevent the virus from spreading to others in good health. This is equally as crucial as identifying the disease's root cause. In this study, we will investigate the use of various models based on Deep Learning (DL) techniques for the purpose of screening COVID-19, as well as the advantages and drawbacks of these methods in contrast with others. We will look into the potential value of this imaging method for the management and early treatment of COVID-19 patients and review recent research studies that examined the accuracy and reliability of various pre-processing methods and models on chest CT scans for COVID-19 diagnosis.

Keywords: *Convolutional Neural Network, Computed Tomography, COVID-19, Deep Learning, Machine Learning*

1. Introduction

COVID-19, also known as the novel coronavirus, is a disease that has afflicted us since 2019. Early detection of the virus, leading to early-stage treatments, has proven to be effective in saving lives. COVID-19 has wide-ranging effects, notably on the respiratory system, cardiovascular system, brain, and neurological system. The motivation behind this research paper is to explore COVID-19 detection using chest CT scans via Deep Learning models. Detecting COVID-19 in its early stages accurately can lead to timely treatment and isolation, helping to limit the spread of the virus among healthy individuals and ultimately saving lives. Chest CT scans have shown potential as a screening tool for COVID-19, and the use of deep learning models can enhance the accuracy and efficiency of this screening process.

This research study seeks to contribute to the expanding body of knowledge in the area of medical imaging analysis and ML models with respect to the COVID-19 pandemic by evaluating existing works and analyzing the advantages and limits of deep learning approaches for COVID-19 identification. The use of artificial intelligence (AI) models for chest X-ray image analysis in the context of COVID-19 detection is a promising approach, but there are several limitations and challenges that need to be addressed.

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One major research gap is the limited patient numbers and small sample size in some studies, which may affect the robustness and generalization of the model's performance. In addition, some AI algorithms are able to divide X-ray pictures into COVID-19 positive and COVID-19 negative categories, which could miss other significant illness patterns or severity levels. Moreover, the performance of the models may vary across datasets, indicating challenges in generalization due to differences in data quality, imaging protocols, and patient characteristics across hospitals or institutions. Data preprocessing challenges, such as limited prepared datasets requiring more data preprocessing, may also impact the model's performance. Furthermore, some studies may have a retrospective design and selection bias, which can introduce limitations in the accuracy and generalization of the model's performance. Lastly, low patient numbers for multi-class classification may affect the model's accuracy and reliability in identifying multiple disease categories. These limitations indicate the need for more research and improvements in data collecting, preprocessing, and model validation to increase the accuracy and reliability of artificial intelligence models for COVID-19 identification in real-world clinical settings utilizing images from chest X-rays.

1.1.1 Contribution

In RT-PCR, upper respiratory tract samples of sputum are used. Then, depending on how soon after the infected sample was collected, the COVID-19 virus's RNA is found in it, and its sensitivity varies. CXRs were introduced as an additional diagnosis but were hampered by a scarcity of qualified radiologists. Even in patients with deteriorating respiratory symptoms and those with negative results of RT-

PCR but infection within the differential, CT imaging offered a more accurate diagnosis.

In this paper, we aim to:

1. Summarize previous attempts' drawbacks at using Machine/Deep Learning techniques to detect COVID-19.
2. Use chest CT scan images as a screening tool to test, train, and validate an Ensemble model using a stacked classifier.
3. Test the model on 2 unique datasets to verify its performance with respect to previous works.
4. The research endeavors to create a robust framework for the automated detection of COVID-19 through the fusion of Ensemble Deep Convolutional Neural Networks (DCNNs) and advanced segmentation techniques applied to Computed Tomography (CT) images.

1.1.2 Literature Review

This comprehensive review delves into a chronological exploration of COVID-19 research, beginning from its emergence in 2019-20 up to the latest advancements in 2022-23. The focal points of this review encompass the interplay of COVID-19, machine learning (ML), and deep learning (DL), particularly in the context of their potential for COVID-19 detection.

The conventional testing methods for COVID-19, namely antibody testing and the widely used RT-PCR, are not devoid of limitations, exhibiting issues such as high false negatives and false positives. Consequently, alternative and automated detection techniques have been under scrutiny to ensure timely and precise detection of the virus. Notably, this has led to the exploration of imaging modalities such as Chest Radiography Images (CXRs) or X-rays and Computerized Tomography (CT) scans.

Machine learning and deep learning techniques applied to CT scan images have showcased promise in serving as effective screening tools prior to RT-PCR testing. Distinctive features observed in chest CT scans of COVID-19 patients, including ground glass opacity (GGO), consolidation, and pleural effusion, hold critical diagnostic value, particularly in progressive and advanced stages of the disease.

In the realm of deep learning models for chest CT scan image assessment, a structured approach involving image preprocessing and a feature-based classifier has proven fruitful. Techniques like cropping the Region of Interest (ROI) and resizing images, alongside the integration of Convolutional Neural Network (CNN) layers, have significantly enhanced prediction accuracy.

A novel approach involves employing a group of deep CNNs and implementing Ensemble hard voting to categorize COVID-19 and Non-COVID cases. This innovative method demonstrates potential for increased prediction accuracy while minimizing overall false prediction rates.

Furthermore, samples collected from the upper respiratory tract for RT-PCR testing, while essential, may vary in sensitivity based on the timing of sample collection relative to the infection onset. CT imaging, particularly in cases where RT-PCR results are inconclusive, has proven to offer a more accurate diagnosis, making it a valuable adjunctive diagnostic tool. Studies have showcased the potential of employing contrast enhancement techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the quality of lung CT images, consequently enhancing the performance of CNNs in classifying COVID-19-infected lungs.

In the pursuit of optimizing deep learning models, various studies have leveraged different architectures such as VGG16, DenseNet, Inception, Xception, and ResNet. The utilization of techniques like dropout, pooling, and dense layers, in conjunction with appropriate model selection, has led to notable achievements in terms of accuracy, specificity, sensitivity, and precision.

Additionally, transfer learning using architectures like Xception has been instrumental in developing robust CNN models capable of distinguishing normal, viral pneumonia, bacterial pneumonia, and COVID-19 chest X-ray images. These models have demonstrated impressive precision and recall rates for COVID-19 cases, underscoring their potential in accurate classification.

In summary, this comprehensive review underscores the pivotal role of ML and DL techniques in the accurate and timely detection of COVID-19, particularly through innovative approaches involving CT scan image analysis and classification. The continuous evolution of these techniques holds promise for enhancing diagnostic accuracy and ultimately aiding healthcare professionals in combatting the ongoing COVID-19 pandemic.

Table 2 shows a review of previous works and their limitations.

2. Datasets Used

The availability of diverse and comprehensive datasets is crucial for the success of medical research. With respect to deep learning, datasets are a fundamental component of training algorithms to perform tasks such as image recognition, natural language processing, and speech recognition. These datasets enable neural networks to recognize patterns and make accurate predictions. For this study, the publicly available COVIDxCT [11] and SARS-COV-2 CT-Scan [12] datasets were used. COVIDxCT is a

65GB dataset available publicly at https://www.kaggle.com/datasets/hgunraj/covidxct, which contains 425,024 CT scan images divided into 3 classes namely COVID, Pneumonia, and Normal. SARS-COV-2 CT-Scan is a 250MB dataset available publicly at https://www.kaggle.com/datasets/plameneduardo/sarscov2ctscan-dataset. It contains 2481 images divided into 2 classes - NON-COVID and COVID.

Table 1. Class Distribution of COVIDxCT

Type	Normal	Pneumonia	COVID
Train	35996	26790	294552
Val	17570	8008	8147
Train	17922	7965	7894

Table 2. Comparison of previous works on COVID-19 prediction via CXR/CT images

Ref	*Year*	*Classification Model*	*Limitations*
[1]	2020	Resnet50 + SVM	Number of patients. Additionally, this technique has a limitation if the patient has a serious ailment and cannot attend for CXR screening. From the provided chest scan images, the model can only differentiate between normal and COVID-19.
[2]	2021	EfficientNet	The model performed poorly on external sets than on the internal test set, suggesting that generalization may be impossible. This finding might be ascribed to a number of factors, including different data and picture acquisition among hospital systems. The model can distinguish only normal or COVID-19 from the given chest X-ray.
[3]	2020	Coronet	Small prepared datasets imply that the suggested model is capable of producing better results with lesser data pre-processing if given more data.
[4]	2020	2/3D DL Model	Low Patient Number
[5]	2021	GoogleNet Inception V3	Small Sample Size
[6]	2020	Resnet50	From the provided chest scan images, the model can only differentiate between normal and COVID-19.
[7]	2020	Coronet + Transfer Learning	From the provided chest scan images, the model can only differentiate between normal and COVID-19.
[8]	2021		Low Patient number for 3 classes classification
[9]	2021		The study's retrospective design, patient selection bias, and multi-institutional nature.
[10]	2020	3D DL Network	Low number of patients and selection bias

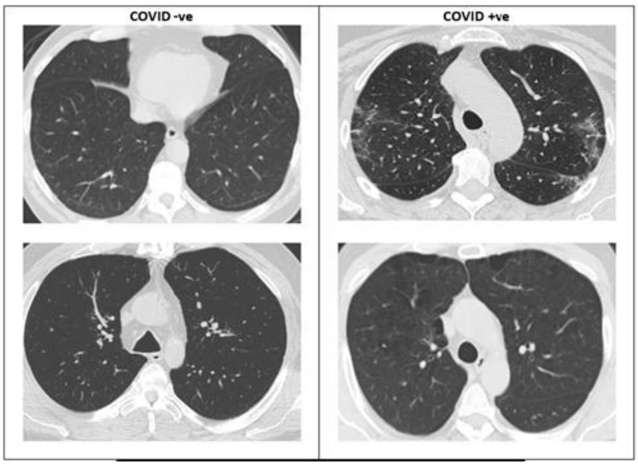

Fig 1. The figure shows some sample chest CT scan images of COVID-19 +ve and COVID-19 -ve patients from the used dataset.

Table 3. Pre-processing used on COVIDxCT

Rescaling	1/255
Resizing	512x512 to 256x256

Table 4. Pre-processing used on SARS-COV 2

Rescaling	1/255
Resizing	256x256 to 150x150
Rotation Range	360
Width Shift Range	0.2
Height Shift Range	0.2
Zoom Range	0.2
Data Augmentation	Horizontal Flip, Vertical Flip

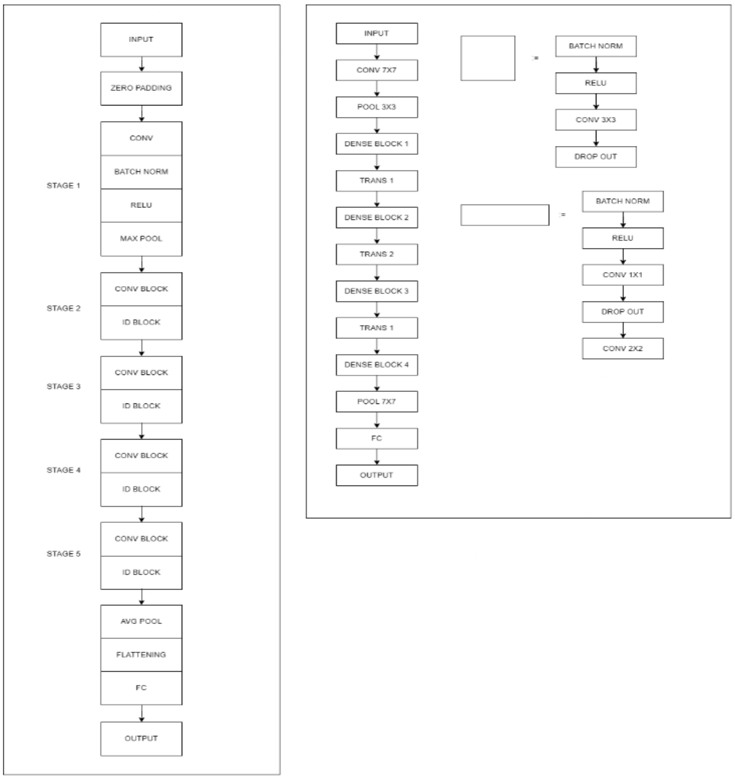

Fig 2. Steps involved in ResNet50 AND DenseNet121 architecture [13] [14]

3. Proposed Methodology

In this section, we outline the specific methods that we employed on our data as well as our model's construction. Overall, we believe that our methodology has allowed us to provide a fairly accurate solution to our research problem. Figure 4 shows our proposed methodology in a flowchart.

3.1. Pre-Processing Techniques

Figure 1 shows some sample images of the lungs of a normal person vs. a COVID +ve person. The affected lungs visibly display the ground glass opacity (GGO), consolidation, and pleural effusion—three distinctive features of COVID-19.

3.2. Model Construction and Specifics

Ensemble learning is a popular approach in deep learning that involves combining multiple models to improve predictive accuracy and reduce the risk of overfitting. We combine ResNet50 [13], which is a 50-layer deep CNN with DenseNet121 [14], a CNN that utilizes dense connections between layers. It has 1 7x7 Convolution, 58 3x3 Convolution, and 61 1x1 Convolution. The model was trained for COVIDxCT dataset for 10 epochs with a batch size of 8, whereas it was trained for 100 epochs on the SARS-COV-2 dataset with a batch size of 64. The experimental work was conducted on a 2.30GHz processor, 13-GB RAM, and an NVIDIA P100 GPU.

3.3. Segmentation

In the realm of Convolutional Neural Networks (CNNs), segmentation refers to the process of dividing an input image into distinct, meaningful regions or segments. Unlike classification tasks that assign a single label to an entire image, segmentation involves assigning a label to each pixel in the image, effectively outlining different objects or areas within the visual data. In medical imaging, such as CT scans in the context of COVID-19 detection, segmentation becomes crucial for isolating specific regions of interest, like infected lung tissue. Segmentation plays a pivotal role in isolating and delineating specific regions of interest within these intricate scans, allowing for a more nuanced analysis of affected areas.

Model Integration The ensemble model that was trained uses a pretrained model at its core, and its outputs are passed through another set of convolutional layers to get one of the three classes of the dataset. The learning rate used was 0.003, epsilon was 0.1, beta 1 was 0.9, and beta 2 was 0.99. The loss function used by the models was sparse categorical cross-entropy. The models used Adam as an optimizer because Adam combines the benefits of both SGD (Stochastic Gradient Descent) and momentum-based methods by adapting the learning rate of each parameter based on the historical gradients. This allows Adam to converge faster and with greater accuracy than SGD, especially for datasets with high variance or noisy gradients. The proposed ensemble model uses three different models based on two pre-trained models, DenseNet121 and ResNet50. Two of the three models have the same architecture but differ in the pre-trained model used, while the third model has one less each of dense, batch normalization, and dropout layer. The proposed ensemble model uses a stacked classifier to give us the ensemble result. The specifics of the ensemble model are outlined in Figure 3.

Diagrams

As shown in Figure 3 below, we are proposing the ensemble of 3 models. These three proposed models all add different layers on top of previously proven to be effective DL models.

- Proposed Model 1: This is the first model which adds layers on top of the base DenseNet121 model. It adds 9 layers - 1 input, 1 convolutional, 1 global average, 2 batch normalization, 2 dropout, 2 dense layers.
- Proposed Model 2: This is the second model which adds layers on top of the base ResNet50 model. It adds 9 layers - 1 input, 1 convolutional, 1 global average, 2 batch normalization, 2 dropout, 2 dense layers.
- Proposed Model 3: This is the third model which adds layers on top of the base DenseNet121 model. It adds 8 layers - 1 input, 1 convolutional, 1 global average, 2 batch normalization, 1 dropout, 2 dense layers.

Stacked Classifier

In deep learning, a stacked classifier, also known as a stacked ensemble, is a type of model that combines the predictions of multiple base models to make a final prediction. It involves training multiple base models on the same dataset and then using their predictions as inputs to another model, called the 'meta-model' or the 'aggregator,' to make the final prediction. In Figure 3, the 3 base models are passed through a stacked classifier, and the created 'meta-model'/'aggregator' is shown.

3.4. Proposed Flow

Figure 4 shows a visual representation of the system. It includes the dataset, how its images look, the process the model is employing, and the final classes for output division. Starting with 2 datasets, COVIDxCT and SARS-COV-2 with classes of images, followed by Feature Analysis, then passing through the ensemble model. The ensemble model uses 3 base models along with a stacked classifier. Finally, the input is segregated into one of three classes - COVID-ve, Pneumonia, or COVID+ve.

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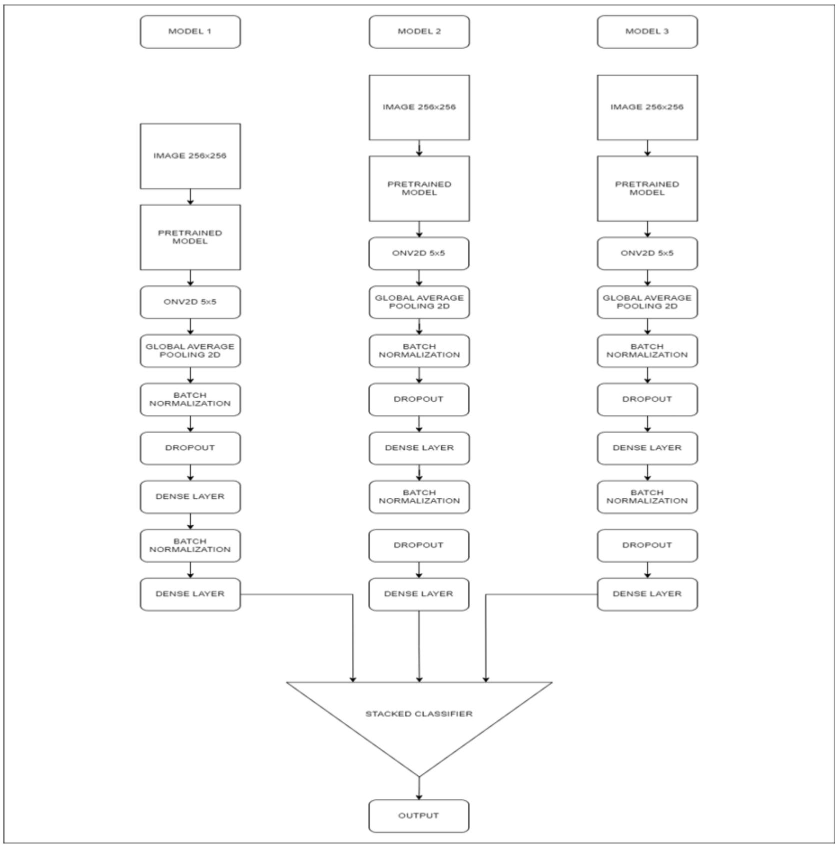

Figure 3. Proposed Integrated Model

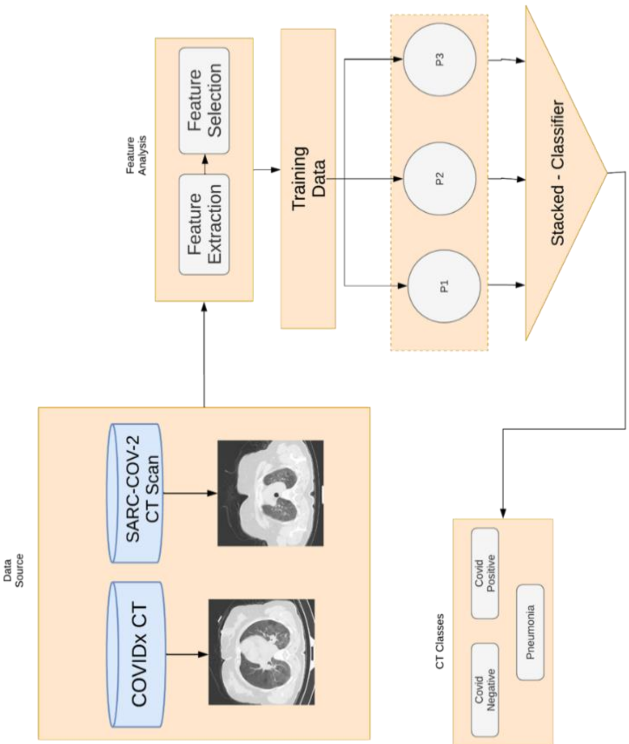

Fig 3. Flow Diagram

4. Result Analysis

Ensemble models leverage the strengths of multiple base models, combining their predictions to create a more reliable and accurate prediction. Through the process of stacking, ensemble models are able to reduce the impact of errors or biases that may exist in individual models, resulting in improved overall performance. Each of the models were trained and check-pointed was used to save the best trained outcome. Tables 5, 6 show the results of individual models and the ensemble model on the two datasets.

The ensemble version shows higher precision, recall and F1-scores than the individual models (on average) and it outperforms individual models in terms of predictive accuracy and robustness. In deep learning, ROC curves are used to evaluate the performance of binary classification models that are based on Deep learning models, such as CNNs for image classification.

Since our model is not a binary classification and has 3 classes, we are plotting 3 curves. 5 shows the plot of the normal class versus the others, 6 shows the plot of COVID-19 versus the others and 7 shows the plot for pneumonia versus others.

In the analysis of our ensemble model compared to other existing works Table 7, our findings demonstrate that our model performs better in terms of various performance metrics. Here are some key points from the result analysis:

Higher accuracy: 98%: Our model achieved higher accuracy compared to other works, indicating its superior predictive performance. This was evident through rigorous testing and evaluation on diverse datasets, showcasing the robustness of our model.

Higher precision: 98%: Our model achieved a higher precision compared to other works, indicating its ability to make accurate positive predictions and minimize false positives. This suggests that our model is more precise in identifying the true positive cases, reducing the chances of false alarms or incorrect predictions.

Graphs 8, 9 and 10 show the loss curves of the 3 base models per epoch. In general, loss curves show how the loss value changes as the model learns from the training data. They start with a relatively high loss value at the beginning of training and gradually decreases over time.

Table 6. Result analysis on SARS COV-2

Model	Class	Precision	F1	Accuracy
Proposed Model 1	Normal	0.99	0.97	
	Pneumonia	0.98	0.93	0.96
	Covid-19	0.83	0.90	
Proposed Model 2	Normal	0.98	0.98	
	Pneumonia	0.97	0.95	0.94
	Covid-19	0.89	0.92	
Proposed Model 3	Normal	0.98	0.96	
	Pneumonia	0.99	0.96	0.96
	Covid-19	0.84	0.90	

Table 5. Result analysis on COVIDxCT Dataset

Model	Class	Precision	F1	Accuracy
Proposed Model 1	Normal	0.99	0.97	
	Pneumonia	0.98	0.93	0.96
	Covid-19	0.83	0.90	
Proposed Model 2	Normal	0.98	0.98	
	Pneumonia	0.97	0.95	0.94
	Covid-19	0.89	0.92	
Proposed Model 3	Normal	0.98	0.96	
	Pneumonia	0.99	0.96	0.94
	Covid-19	0.84	0.90	

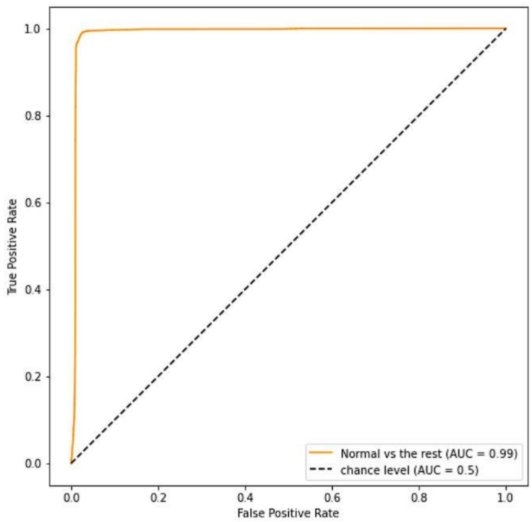

Fig 4. ROC Curve of normal class for COVID-19 classification

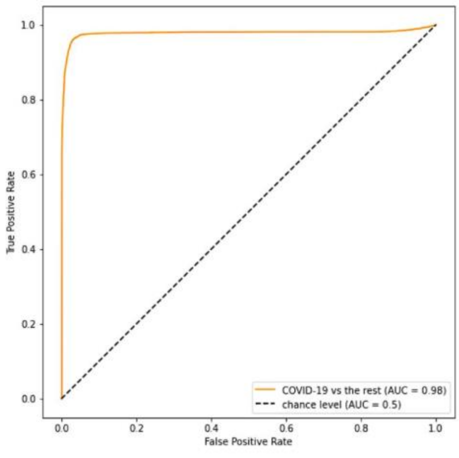

Fig 5. ROC Curve of COVID-19 class for COVID-19 classification

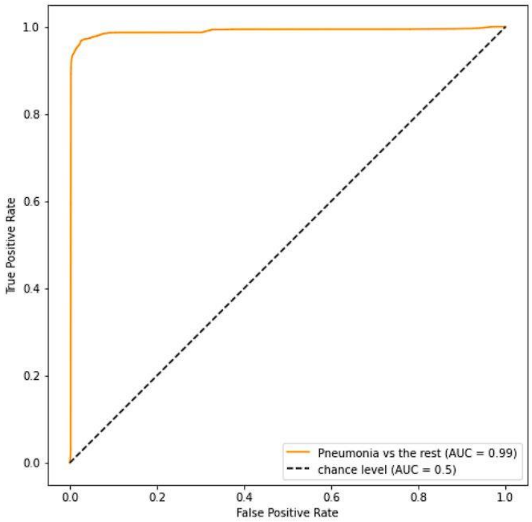

Fig 6. ROC Curve of Pneumonia class for COVID-19 classification

Fig 7. Loss curve for DenseNet121 based model-1

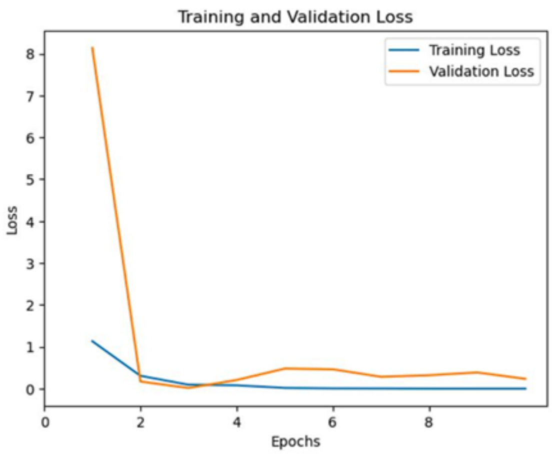

Fig 8. Loss curve for ResNet50 based model

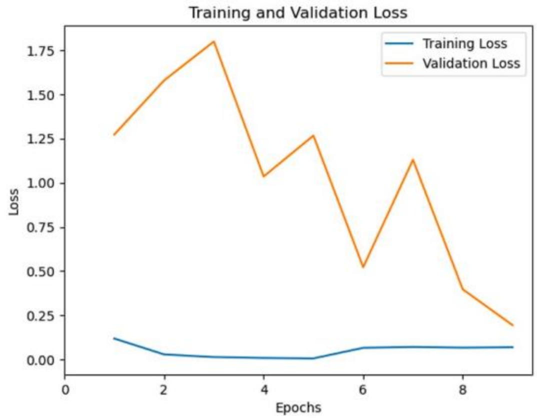

Fig 9. Loss curve for DenseNet121 based model-2

Table 7. Performance indicators of other work on the prediction of COVID - 19 based on CXR/CT images

Reference	Acc [%]	Spec [%]	Prec [%]	Area Under Roc Curve
[1]	95.38	-	-	-
[2]	-	-	-	0.85 on internal testing and 0.80 on external testing
[3]	89.6 95.0	-	-	-
[4]	-	-	-	0.948 on internal testing and 0.80 on external testing
[5]	89.5	88	-	-
[6]	-	90	-	0.96
[7]	99.87	100	-	-
[8]	97	-	-	0.99
[9]	78	-	80	-
[10]	86.7	-	-	-
[15]	88.52	-	97.32	-
[16]	93	-	-	-
[17]	94.52	-	-	-

5. Conclusion

The detection of COVID-19 in its early stages is of paramount importance for timely treatment and containment, ultimately saving lives and curbing the spread of the virus. The utilization of deep learning techniques, particularly ensemble CNNs, has shown promising results in accurate and efficient COVID-19 detection from CT scan images. When combined with RT-PCR confirmation, ensemble CNNs demonstrate significant potential in addressing the challenges posed. Notably, our model's novelty lies in the utilization of an ensemble approach, combining two diverse CNN architectures—ResNet and DenseNet. This combination, along with extensive hyperparameter tuning and creative data augmentation techniques, has resulted in an impressive accuracy rate of 98%. These innovations represent a substantial leap forward in the field of early COVID-19 detection and diagnosis, promising to have a positive impact on public health.

6. Future Scope

CT images show immense promise as a tool to detect COVID-19 before an RT-PCR. Along with CT scans, deep learning models have shown great promise in leveraging X-ray images to detect COVID-19, providing a rapid and efficient approach to aid in the identification of cases and help manage the spread of the virus. X-rays of the chest/lung region with the same ensemble model can also be used as data points. Usage of both types of images together and passing through the CNN is a promising avenue to further advance the accuracy of Automating COVID-19 Detection. One of the significant applications of deep learning models is in the detection of other lung diseases, specifically - lung cancers, pulmonary diseases, such as pneumonia, tuberculosis, and chronic obstructive pulmonary disease (COPD), interstitial lung diseases. The use of our ensemble CNN model in conjunction with X-ray imaging for the detection of lung diseases is also an avenue to explore further.

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