Deep Convolutional Neural Network based Solution for Detection `of COVID-19 from Chest X-Ray Images

Y.Rama Mohan[1],D.Satyanarayana[1*], R. Sudheer Babu[2], K. Ashfaq Ahmed [1] and M.Siva Satyanarayana [3]

[1]Department of Computer Science and Engineering(AIML) G. Pulla Reddy Engineering College(Autonomous) Kurnool-518007, India
[2] Department of Electronics and Communication Engineering, G. Pulla Reddy Engineering College(Autonomous)Kurnool-518007, India
[3] Department of Electrical and Electronics Engineering, G. Pulla Reddy Engineering College(Autonomous)Kurnool-518007, India
sathyaphd223@gmail.com

Abstract. A global health and healthcare catastrophe has been brought on by the ongoing COVID-19 pandemic, in addition to its substantial socioeconomic impacts. One of the primary issues in this pandemic situation is the timely identification and monitoring of COVID patients to make timely decisions regarding therapy, monitoring, and management. Research is underway to create less time-consuming methods to complement or replace RT-PCR-based techniques. In the current study, a deep convolutional neural network (DCNN) approach is proposed for identifying COVID-19+ patients from images of chest x-ray. To evaluate the effectiveness of this treatment, we examined publicly available chest x-ray scans of COVID+ patients.. The 538 images of positive detected patients and the 468 images of negative detected patients were divided into 771 images for training and 235 images for testing. The present work provided accuracy with 95.7% in classification and sensitivity around 98% in test setup.

Keywords: Covid-19, Ensemblemethods,CNN,DenseNet,ResNet, Inceptionv3.

1 Introduction

The coronavirus has claimed several thousand lives so far and has caused millions of confirmed cases worldwide. This disease has taken the form of a pandemic and had impact on the well-being and healthy world population. SARS-CoV is the Severe Acute Respiratory Syndrome which is the disease which was an acronym Covid-19.This is a member of the same family as other coronaviruses like MERS and SARS. It is a contibious disease that spreads rapidly through droplets infection from respiratory when compared with another common flu. Currently, the majority of diagnostic tests for coronavirus disease are genetic tests, like Reverse Transcriptase Polymerase Chain Reaction (RT-PCR).Even the less traces of virus in a patient sample can be measured and identified.

However, it should be mentioned that PCR testing is quite costly, time-consuming, and difficult. Because of this, not all hospitals are able to perform

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this test. In light of these drawbacks, radiography scanning might be utilized as an alternative technique for disease diagnosis, where chest x-rays can be Analyzing can identify the novel coronavirus's presence or symptoms. According to [8],[9],[11], [13] and [21], research, the family of viruses exhibits observable radiographic symptoms. To get the accurate and faster categorization, X-rays, such as chest X-rays (CXR) are used which are less expensive than PCR testing.

Furthermore, when compared to other radiological tests, X-ray of chestis the less expensive . The primary challenge in diagnosing COVID with chest X-rays is the possible shortage of skilled doctors, especially in rural areas. Due to their limited exposure to chest X-ray pictures of positive patients, many experts are also unfamiliar with the radiographic findings associated with the virus.

With the pictures of chest X-ray, we presented a simple and affordable deep learning technique to find the difference among positive and negative detected images. Within seconds, this technology makes it possible to quickly and accurately identify the people who have COVID-19. We included a tool in this study that can identify people who test positive for COVID-19. our deep learning technique consistently produces a diagnosis without intervention of a radiologist or in medical debate situations. In this paper, we used open source data to show how good the suggested tool is in terms of classification accuracy and sensitivity. Some other scholars have also compared it with previous comparative studies.

Furthermore, only few existing studies have employed individual methods in deep learning with CXR pictures to provide both positive and negative Covid-19 predictions [2, 26, 27]. A personalized network was attempted to be created in one paper [5]. On the other hand, our study focuses on merging multiple high-quality deep learning models to increase accuracy. The fundamental tenet is that a group of models performs better than a single model [4].

The remaining paper is organized as follows:

- SectionII explorestherelatedresearch that presentsoutline,theirapproachesandmethodology.
- Section III includes, the proposed technique that has discussed with some background on the currently advancedmodelsusedinthe research.
- Section IV includes , the setup that is used in experiment in the present research.
- SectionV includes,theexperimentalresultsarepresented withaccuracy of classification F1-Score and sensitivityoftherecommendedwork.
- Attheendofthepaper,theresultsaresummarized insectionVI.

2 Literature Work

CT, MRI, and chest X-rays (CT) are thought to improve the study of lung viruses. Pneumonia and other chest conditions have served as the basis for the development of a various methods based on deep learning concepts [10], [11],

[12], [13], [14], [15].Using comparatively straightforward structures, a few of them demonstrated encouraging outcomes. For instance, in [9], we diagnosed patients with COVID-19 using a CNN (Convex Convolutional Neural Network) model. [18] Employed a multitasking self-supervised AI model with the aid of CT scan images of corona virus that are used to identify patterns in lungs having 89 % of accuracy .

The lungs' measured and programmed division is eliminated [19]. shows a fully programmed system that can differentiate between lungs affected by the coronavirus and other lung diseases from chest CT scan images. [31] , [17] found that due to the promising results of CXR machines and their support they act as superior to other methods in detecting the virus.Several analyses using CXR images have been conducted by analysts in the Covid-19 understanding discovery region. The existing study explored that images of chest X-ray are classified as normal , pneumonia and Covid and using exchange learning and Inception-v3 model.

The study with DenseNet with the ChexNet architecture has differentiated viral pneumonia, bacterial affected patients and healthy people.ResNet50 v2 and Xception models were integrated in another investigation. ResNet was used in another study to recognize viral pneumonia affected patients and Covid affected patients. Many researchers in this field may face difficulties due to limited access to huge volumes of imaging data from individuals who tested positive for COVID-19. Enhancement of CovidGAN for the information age has been attempted [21], which will help with the advanced Covid-19 localization. apart from applying cutting-edge profound learning models.

3 The Proposed Approach

In real life, we are constantly inclined to make restorative decisions based on a variety of therapeutic master views. A more reliable judgment might be reached by combining the findings of the restorative professionals. Following the same reasoning, our suggested work has used a number of benchmark CNN models. They have been ready to develop their own expectations on their own. With contemporary weighted normal ensemble approachthe models are integratedto predict a class value which will strengthen the expectation. There are 3 pre-trained models based on CNN —DenseNet201 [28], Resnet50V2 [29], and Inceptionv3 [30]—make up our suggested work. The Thick Convolution Organize orDense-Net,appearedinFig.1requireslessparameters when compared with conventionalCNN.

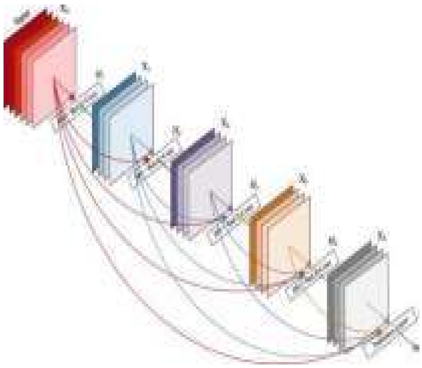

Fig1. DenseNetarchitecture[33]

All previous layers in highlight maps are inputs which are used in each layer in DenseNet.This has an impact on reinforcing, energizing, and highlighting reuse. ResNet50v2, shown in Fig. 3, is a possible contemporary convolutional architecture that is easier to set up than existing deep convolutional neural systems, produces more noticeable accuracy, and combines more quickly. By using "residual blocks" in the engineering, it also solves the vanishing or detonating angle issues. Many leftover squares were piled one on top of the other in a leftover arrange.

Fig. 2 shows Each remaining squarein shaped of short-cut associations that skips one or more layers.3-layerremainingpiecesareutilized inResNet50.Initially appearedinFig. 5

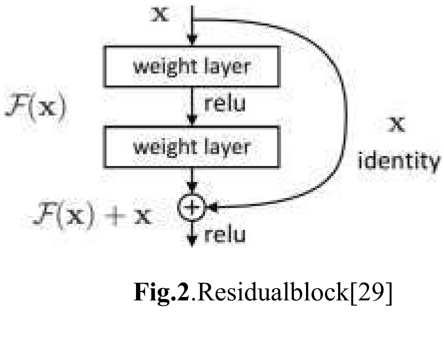

Fig.2.Residualblock[29]

This straightforward model efficiently extracts characteristics and uses those features to classify photos. The introduction's third version has 48 chapters, including an extensive archive of 11 chapters. As shown in Figure 4, each initial stage consists of a ReLU (Rectified Linear Unit) processing function, an adjustment unit, and a validation filter. Plus 0.6, this acts as a set mode before complete integration.

The fact that we ki = diD (3) employed a novel weighted average technique based on the CNN convolution method is one noteworthy aspect of our suggested methodology. In this sense, a model, like ResNet50v2, that outperforms the other two models—that is, the assigned less weight has a lower validation error, which increases its contribution to the cost value.

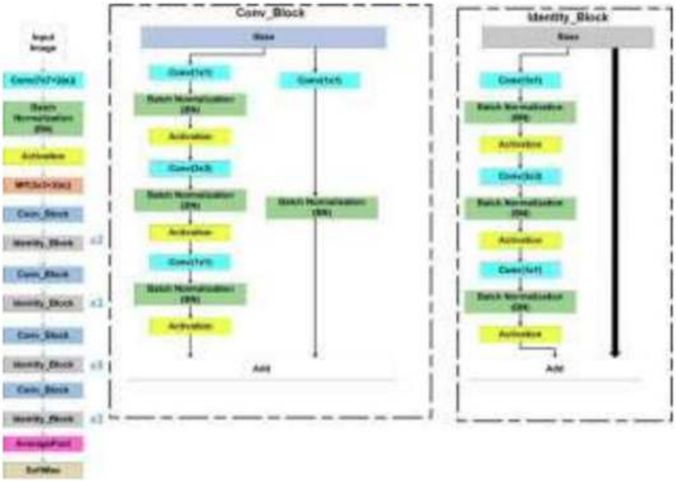

Fig 3. Architecture of ResNet [29]

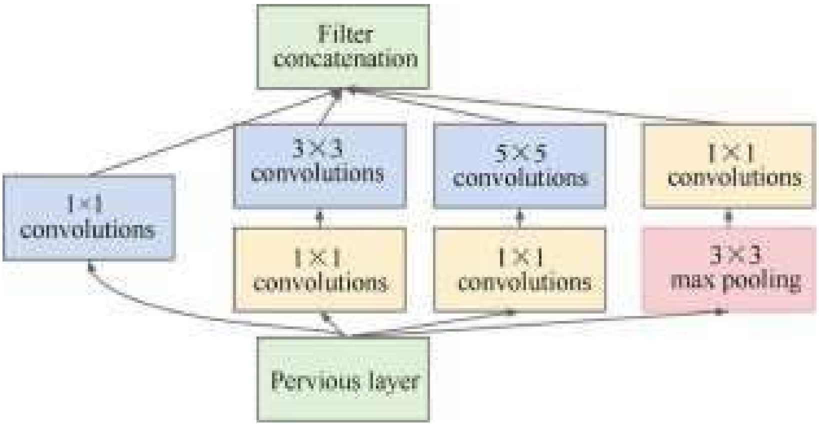

Fig. 4. Module of Inception [30]

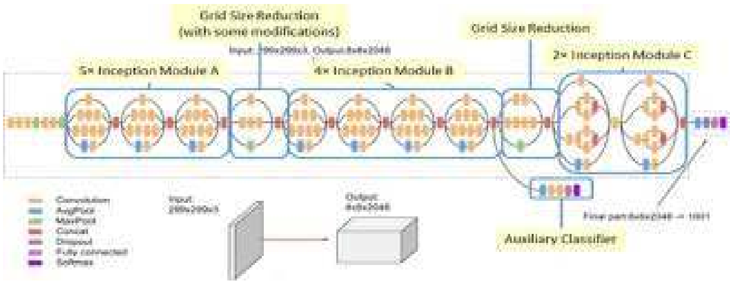

Fig. 5. Architecture of Inceptionv3[30]

Let us assume ,

i^{th}model accuracy percentage = ai

Validation error = (100 - ai)

We define a factor k_i as below:

$di = 100 - ai$ (1)

$D = \sum d_1^2$ (2)

$ki = diD$ (3)

i^{th} network Weight is derived as:

$$w_i = \frac{1/_{k^2}}{\sum 1/_{k^2}} \qquad (4)$$

Suppose that the neural systems' yields have the form [y0, y1], where y0 denotes the probability of Course and y1 is the probability of Course 1. Assume that the predictions for each of the three unique models fall into the following frames: [y01, y11], [y02, y12], and [y03, y13] for models 1, 2, and 3. Let [w1, w2, w3] be the weights determined for each model separately using the suggested approach stated in condition 4. At that point the weighted likelihood is calculated as:

$$Average = [\frac{w_1 \times y_{01} + w_2 \times y_{02} + w_3 \times y_{03}}{w_1 + w_2 + w_3}, \frac{w_1 \times y_{01} + w_2 \times y_{02} + w_3 \times y_{03}}{w_1 + w_2 + w_3}]$$

Thesummary of proposed approach is given inFig. 6 that comprises :

- CXR pictures are Consolidated for the subjects with the patientshaving bacterial infection , pneumonia or corona virus fromdiverse images.

- frontalCXRimages are retained
- Arranging the sizes of the pictures tothe size with uniformity.
- Segmenting the pictures into 2 parcels - first parcel toprepare the models and second parcel tests the viability ofthepreparedmodel.
- Whileseparatingthepicturesaspreparing modelsand models for testing thatguarantee no persistent cover is distinctive.
- Same understanding pictures isn't displayed datasets for preparationandtest.
- DenseNet201, ResNet50v2 and Inceptionv3 models are trained
- Onthetestpicturespreparedmodels are executedand based on weighted normal course name esteem is selected
- 3models are ensemble

4 Methods and Materials

4.1 Dataset Generation

Pictures from a variety of open sources ([24], [25], [27], [23], [24], [25]) that provide open-access datasets with chest X-ray (CXR) pictures of patients with infections, pnenumonia and Covid were collected for this investigation. European countries are the primary source of the data. This data includes CXR images of several patients, where sidelong images are eliminated and frontal views are taken into consideration. Our area of interest is usually the lungs, which are much easier to examine from the front than from the side.

COVID-19, Pneumonia, and Typical are the names of the first group of CXR images. In any event, we have separated the images for this project as two categories: course 1 has images of patients detected negative and course 0 has images of patients detected positive . There are 538 images for the course that are similar to those in Figure 7, and 468 Covid-negative patient's images for Course 1 that are identical with those in Figure 8.

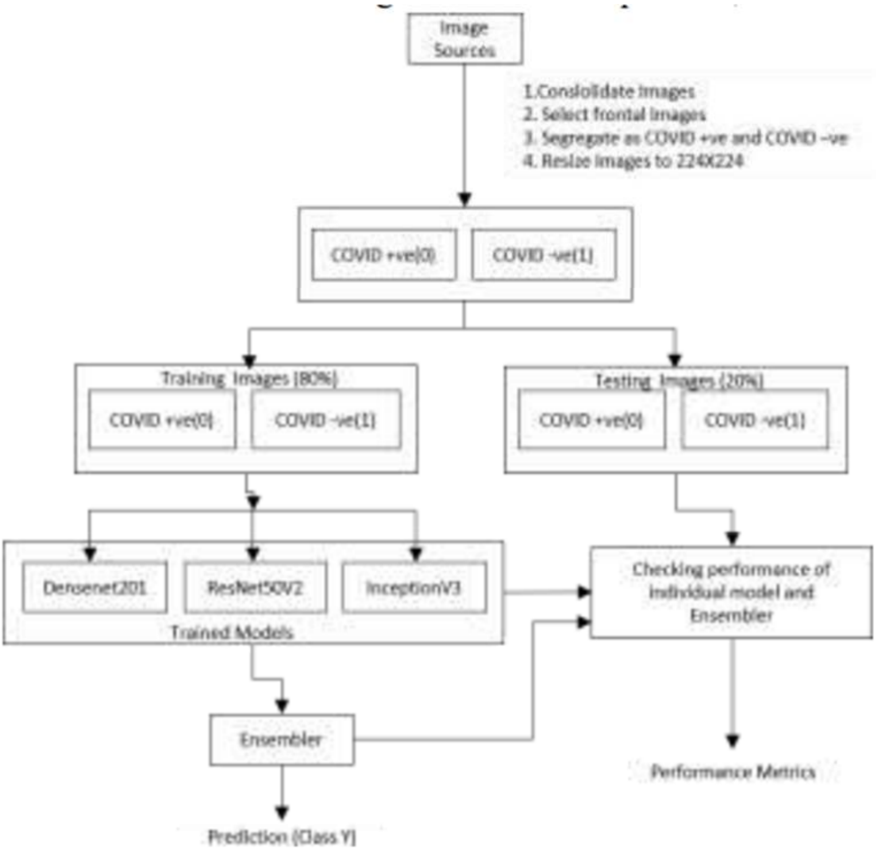

Fig. 6. Proposed approach

4.2 Pre-processing

The initial step is to normalize and resize the solidified images into 224 × 224 created images. These are then reorganized and divided as information for testing and preparation, with 20% going toward the test measure and the remaining portion going toward preparation. Thus, there are 771 images in the preparation materials, 438 of which are for the course and 333 of which are for lesson 1. There are 235 images in the testing materials, 100 of which are for the course and 135 of which are for lesson 1. In any event, if two or more images of the same persistent are present, it is certain that they are either marked as test information or as preparation information, but not both.

The results may be highly optimistic because of the silent cover if the photo of the same patient are retained for both preparation and test data. This allows the photo envelopes to be ready for the demonstration, which is then tested to ensure it is adequate.

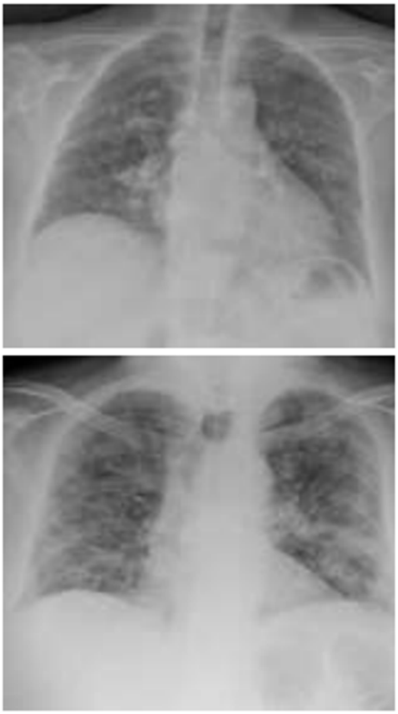

Fig 7. Subjects of Covid positive in CXR images [29]

Fig. 8. Subjects of Covid negative in CXR images [27]

4.3 Tools Used

We used TensorFlow 2.2.0, Python 3.7, and a Google Colab GPU with a Tesla K80 12GB GDDR5 VRAM. The Convolutional Neural Network (CNN) on Google Colab was developed and evaluated in large part using the deep learning framework TensorFlow 2.2.0

4.4 Performance Metrics

F1 score , Precision and Classification accuracy are the parameters used to evaluate the performance for the proposed method. They are measured as follows:

$$\text{Classification Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{F1 Score} = \frac{2 \times Sensitivity \times Precision}{Sensistivity+Precision}$$

Confusion matrix has,

- TP = True Positive, are the positive instances that are accurately grouped as patients diagnosed +ve
- FP = False Positive, are mistakenly negative identified patients
- FN = False Negative, are the cases accurately diagnosed as negative
- TN = True Negative, are the cases that are mistakenly grouped as positive

We have suggested an underutilized weighted normal-based outfit technique in this paper. In any event, we have also compared the results from the suggested calculation with the results from the other gathering calculations, close to the results from the person systems used within the gathering. We have contrasted our planned work with three widely used gathering methodologies.

Unweighted normal approach [33] which takes unweighted normal of yield score / likelihood for all beginners to produce the anticipated score / likelihood.Weights based on the accuracy are calculated by Weighted average approach[16] , shown as

$$W_i = \frac{A_i}{\sum A_i} \quad (5)$$

5 Experiments and Results

Every model is trained with early termination recall (patience = 10 epochs) across 60 epochs. For quicker access, RMSProp, SGD pulse, and Adam Optimizer are combined.parameters such as α = 0.0001, β1 = 0.9, and β2 = 0.999 for the learning rate. All three templates are saved as.h5 files after being optimized using the same optimizer. The DenseNet201 model takes 31 seconds per epoch to train, while the ResNet50v2 and Inceptionv3 models take 17 seconds per epoch. The stepwise change in loss (training and validation/testing) over epochs for each of the three models—DenseNet201, ResNet50, and Inceptionv3—is displayed in Figures 9, 10, and 11.

This shows that when training models there is the lowestloss with Inceptionv3.

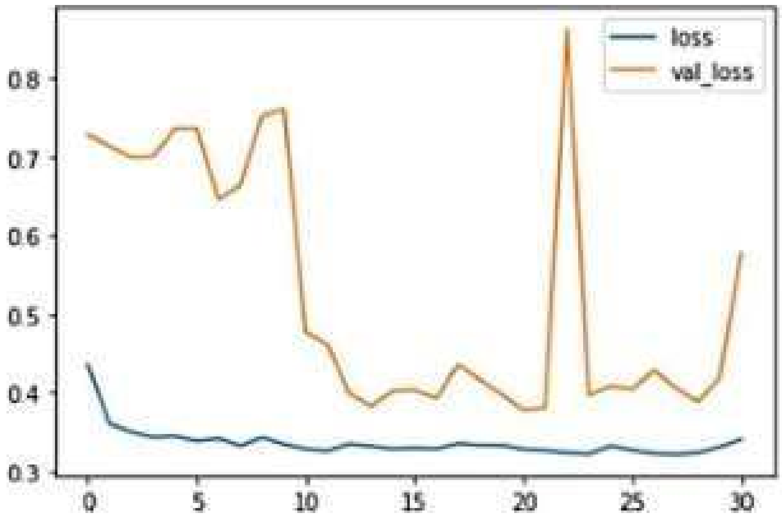

Fig. 9. DenseNet201Trainingand validation loss

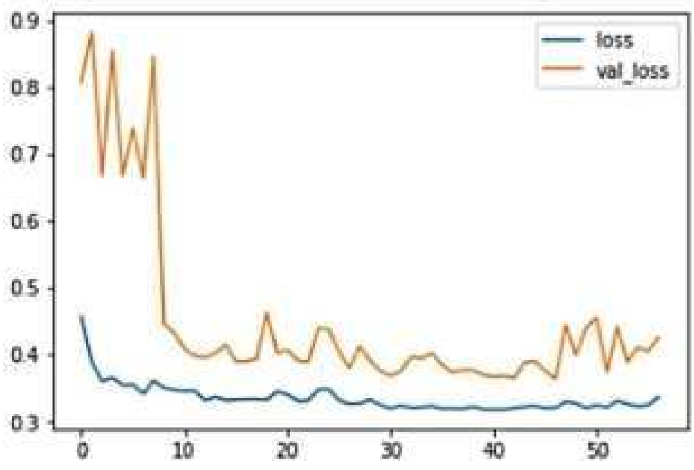

Fig. 10. ResNet50v2Trainingand validationloss

Out of 100 Covid positive patients, there are 98 that had their confusion matrix rectified, according to Fig. 12. Just two out of every 100 patients with COVID-19 have been mistakenly labeled as such. Similarly, the CXR pictures have accurately diagnosed 127 of the 135 Covid-ve patients. Just eight patients have been mistakenly classified as having COVID-19. F1-score sensitivity and accuracy of our suggested model and the developed CN are displayed in table 1. The summary demonstrates that our suggested method performs the individual models in terms of performance. ResNet50v2 has the closest performance.

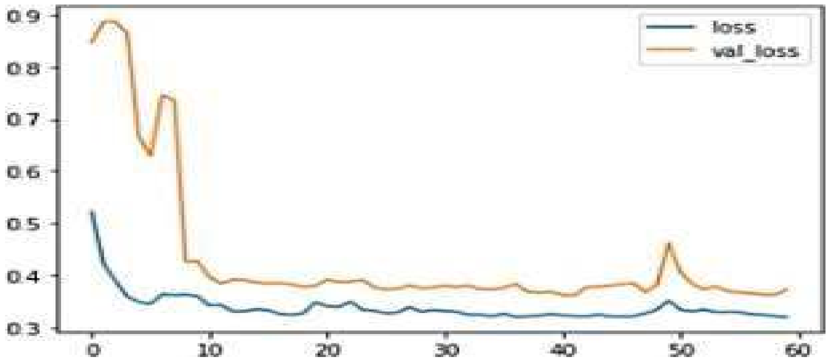

Fig. 11. Training and validation loss of Inceptionv3

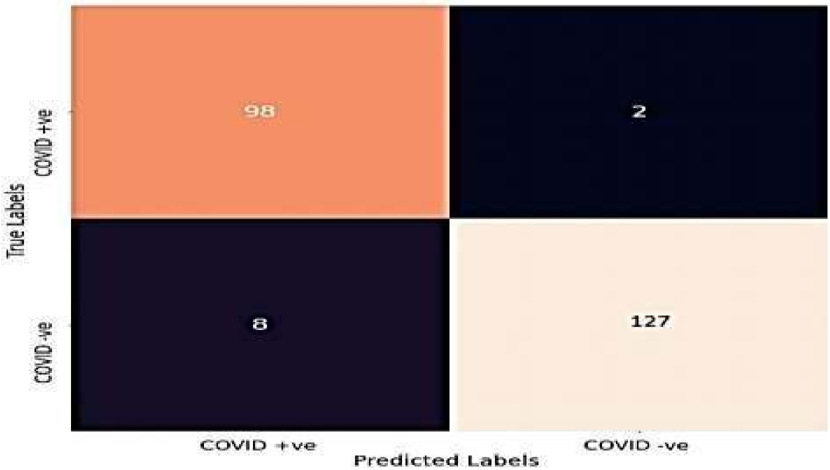

Fig.12. Ensembling with Confusionmatrix

Table 1. Performance Summary

Models	Parameters	ValidationAccura-cy(Rounded –Off)	Sensitivi-ty(Rounded –Off)	F1-Score(Rounded –Off)
Single networks				
DenseNet201	17,325,826	94%	92%	94%
ResNet50v2	23,568,900	95%	98%	96%
Inceptionv3	20,806,993	94%	93%	95%
Ensembled networks				
Unweighted average		95%	95%	95%
Weighted average(accuracy)[33]		95%	95%	95%
Weighted average(rank)[33]		95%	97%	96%
Currently Developed Approach		96%	98%	96%

6 Conclusion

It is crucial to identify Covid affected patients immediately to stop the disease's spread. This study aimed to identify patients with Covid +ve in a straightforward and less expensive using aX-ray of chest. Three new deep learning models were developed and merged with the work presented in this study. The suggested model's classification accuracy is 95.7%. It provided a sensitivity of 98% or 100, which is more significant.Our suggested approach can accurately diagnose 98 of the five Covid patients. We think that the medical field will greatly benefit from this study.

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Disclosure of Interests

The author(s) declare that there is no conflict of interest regarding the publication of this paper.

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