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Chest X-Ray Examination Using AI for COVID-19 Detection

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Abstract- In this paper, a proposition of CNN architecture is made which is trained to develop various convolutional patterns for different types of pneumonia. Among these layers, a specific set of convolution layers are trained to filter and respond only to a specific type of pneumonia. The proposed system in this paper uses 4 convolution forms- VGG, Inception, Resnet 50, and Xception, to conclude the presence of COVOD-19 in a patient. Hence, the CNN architecture further incorporates various convolution styles to improve the categorization and labeling of filters in the layer for better accuracy.

Keywords— *COVID, CNN architecture, X-ray, pneumonia, convolution pattern, chest scan*

I. INTRODUCTION

After the COVID-19 outbreak in December of 2019, the disease has taken the lives of nearly 30 lakh people worldwide, and the figure is still rising. COVID affects individuals differently, and the early effects vary based on a variety of factors such as climate, immunity, diet, and so on. However, lung pneumonia is used in all coronavirus cases, and COVID lung pneumonia can be distinguished from non-COVID lung pneumonia. As a result of this finding, doctors now focus on radiology detection as one of the methods for detecting COVID-positive patients. This method of diagnosis employs X-ray scanning, which can be performed in any facility without the need for any special equipment and is also cost-effective, rendering the technique an excellent alternative to antigen tests.

In this study, a custom CNN architecture was proposed to allow automatic learning of latent features. A convolutional neural network (or CNN) is a form of multilayer neural network or deep learning architecture[4]. The CNN is ideal for an assortment of machine vision and characteristic language handling applications. The essential accentuation is an in-depth assessment of a significant number of CNN's central components .[5]

For each kind of pneumonia, the proposed CNN learns a different convolutional filter sequence. This happens by restricting certain filters in a convolutional layer to react only to a specific type of COVID[3][8].

II. ARCHITECTURE

CNN models for image recognition are pre-trained on massive image databases and re-trained to learn COVID-19 positive vs negative scenarios[4]. Chest X-ray photographs that are diagnosed as COVID positive after clinical examination are pre-processed and only used to retrain current deep CNN image recognition models[5]. To satisfy the input criteria of each pre-trained deep CNN model, X-ray image preprocessing consists of image resizing and pixel value normalization. The CNN models are retrained as differential classifiers to distinguish between positive and negative COVID patients [9].

The re-trained deep CNN models were put to the test, obtaining new chest X-rays with unknown clinical diagnoses as feedback and automatically labeling them as positive or negative COVID-19 cases, i.e. making a binary decision per chest scan. Figures 3 and 4 show a block diagram of the assessed architecture for detecting COVID positive cases from chest X-ray images [3].

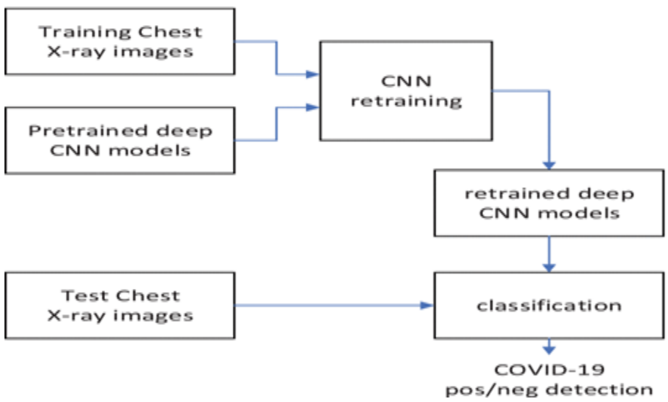

Fig 1. Architecture Diagram

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III. MATERIALS AND METHODOLOGY

CNN's generally perform much better when they are worked upon with a larger database than when they're worked upon with a smaller database. In this study, our objective is to classify the chest x-ray into Covid: positive or negative.

In this experiment, the procured database of X-ray images is first preprocessed and then augmented to maximize variance, making it easier for the AI model to classify the images. The classification model is a strong pre-trained network that is often used in computer vision. In the model, the concept of transfer learning is used. This model employs the principle of transfer learning, in which the weights of VGG, Resnet-50, Xception, and Inception have been already trained on Imagenet.

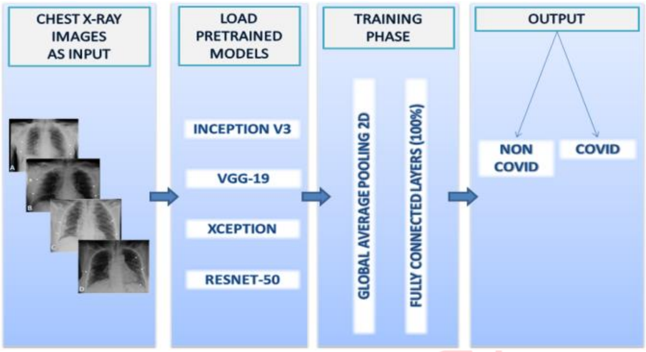
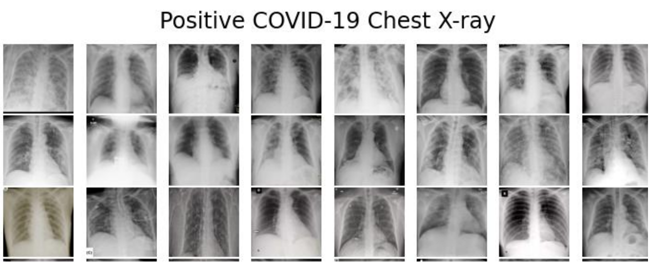


Fig 2. Sequence Diagram

A. Data Collection

The dataset for this study was obtained from Kaggle.com and it includes Chest X-Ray scans of Covid-19 positive and pneumonia patients. This collected dataset is not intended to assert any Deep Learning model's diagnostic performance, but rather to investigate numerous potential methods of efficiently detecting Coronavirus infections using machine vision techniques. The data was divided as follows: 80 percent of the photographs were used for teaching the models, while the remaining 20 percent were used for research[7]. The image format should be jpeg, png or, jpg else the model will show an error.

The total set number of chest X-ray samples in the collected dataset is 21k. This data collection is subdivided into normal and covid pneumonia, for training 80% of the collection is used, and for testing the remaining 20% set. To help in the speedy training of the model, the scans are scaled down to 224 × 224 sizes[8][9].



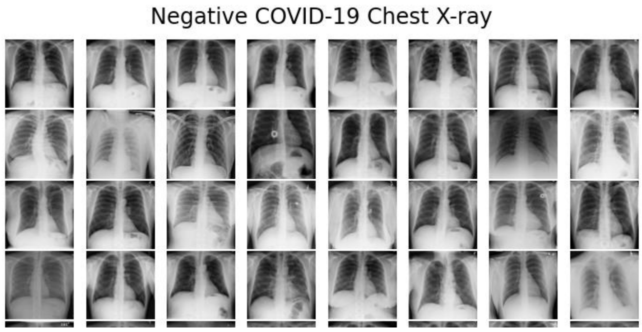


Fig 3. Data Collected as Positive and Negative COVID Chest X-ray

B. Data Preprocessing And Augmentation

Pre-processing is a technique for transforming raw data into a usable format. When data is obtained from various sources, it is collected in raw format, which makes interpretation impossible. Collecting medical-related data can be time-consuming and costly at times. Augmentation may be used to solve certain types of problems. Augmentation can help to solve the overfitting problem and improve the consistency of the proposed model.

Pre-processing the image is the first step in applying the proposed model. For this function, we used the Keras data generator. The color distortion is reduced by converting the chest x-ray image to grayscale. The grayscale image is then transformed into pixels. The picture is reshaped to 224 x 224 which means that the image has 224 vertical lines and 224 horizontal lines.[2] When multiplied we get a total of 50,176 pixels. This process is called binarization. The image was then rotated randomly by 10 degrees, with Horizontal Flip set to True and Zoom Range set to 0.5[9].

Table 1. The number of pictures utilized in the dataset for preparing and testing the CNN models

Classes	Training Dataset	Testing Data set	Total
Normal	8150	2042	10192
Covid-19	2532	1084	3616
Pneumonia	941	404	1345

For the prediction, the pre-processed image that has been turned into pixels, i.e. black and white region, is differentiated and compared

C. Prediction

Given a trained model, predict the mark of a new set of data. This method takes a single assertion, new data Z new (for eg. model. predict (Z new)), and returns the trained mark for each individual in the sequence[10].

IV. MODEL FORMULATION

All the preparation a model involves is learning (training) a good amount of values for the entirety of the loads and the inclination from marked examples so they can be prepared for

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the labeling part of the execution. The ML algorithm creates a supervised learning model dependent on the examination of numerous models and in the endeavor to track down a model that limits losses; this method is called analytical risk minimization[1].

The loss is a mathematical value that indicates how much the model's forecast was off on a single occurrence. On that occurrence, if the model's estimate is correct, then there is no loss in the instance; otherwise, the loss is noteworthy and decreases the accuracy of the system. The aim with which a model undergoes training for most of the experiment is to ultimately get results that have low overall loss examples[10].

The ML algorithm creates a paradigm based on the analysis of a large number of cases and the attempt to identify a model that limits failure. The proposed solution is made up of four CNN models that have been qualified for prediction[7]. The aim of training the models is to find a set of datasets with a range of heterogeneity that has a low overall failure rate. Furthermore, the stimulus models used in this paper provide effects that are consistent with a wide range of platforms. The pre-processed images are fed to the four models to visualize and normalize.

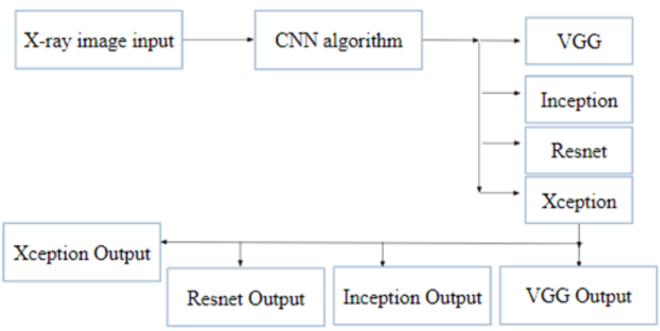

Fig 4. Model Diagram

A. Inception

Inception is one of the few early methods of CNN found, and it is still in use today. This network has 48 layers. A million images from the ImageNet archive can be used to train it. It will then identify and mark the input images into 1000 different pieces. It generates concatenations within the same network module, multiplying the structure for better categorization. As a result, the model will acquire representations for a vast variety of categorizations.

B. VGG

The VGG model was first proposed by K. Simonyan and A. Zisserman. This model, as suggested, can achieve the test accuracy of 92.7 percent in ImageNet, which contains a dataset of over 14 million images categorized into thousands of different groups. It uses thirteen convolutional layers along with three fully connected layers and employs 3×3 convolution layered stacks, which decreases the volume size of the module data and simplifies the dataset handling. The networks are often converged and used as initializations during pre-training. The default size of the input image used for VGG-16 modeling is 224×224.

C. Xception

Francois Chollet suggested the Xception Model. Xception is an inception architecture extension that substitutes regular inception modules with depth-wise Separable Convolutions. The model would have a more in-depth data filter. The proposed model uses a 71-layer deep CNN with the extraction base of the architecture using up 36 layers of the network.[6]

D. Resnet

ResNet-50 is, as the name suggests, a '50'-layer deep CNN model. ResNet, instead of the convolution method of stacking up more layers to get better accuracy, uses residual learning for the training of the ultra-deep networks. The architecture can be utilized for various computer vision assignments for instance image classification, object localization, object detection, etc. However, this structure can likewise be applied to non-computer vision undertakings to give them the advantage of depth for more precise outcomes.

V. EQUATIONS AND IMPLEMENTATION

A. Model Testing

In a generalized way, we can say that system testing is a type of testing in which the main aim is to make sure that the system performs efficiently and seamlessly. The process of testing is applied to a program with the main aim to discover an unprecedented error, an error that otherwise could have damaged the future of the software. Test cases that bring up a high possibility of discovering an error are considered successful. This successful test helps to answer the still unknown errors.

The remaining 20% of the data is used for the testing part of the model to determine the potentiality of our four models. The efficiency of the models namely, Inception-V3, VGG-16, Resnet-50, and xception can be determined using the following parameters, Accuracy, Precision, Sensitivity, and F1-score. The epoch value has taken 500 with the batch size is 32.

B. Evaluation

The experimental approach described in section II is used to evaluate architecture. The proposed model was tested using various parameters such as accuracy, precision, sensitivity or recall, specificity, and F1 score, as shown in Eqs. (1) to (5).

$$\text{Accuracy}(\%) = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Sensitivity/Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4)$$

$$\text{F1-score} = \frac{2\times Precision \times Recall}{Precision + Recall} \quad (5)$$

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Where, T.P. is True Positive, F.P. is False Positive, T.N. is True Negative and F.N. is False Negative.

The model's classification performance can be observed by the confusion matrices provided in Figure 5.

Here the confusion parameters i.e. the false positive and false negative depict the number of false predictions done by each model. These findings make us aware of the specific type of false predictions that are being made which can then be rectified.

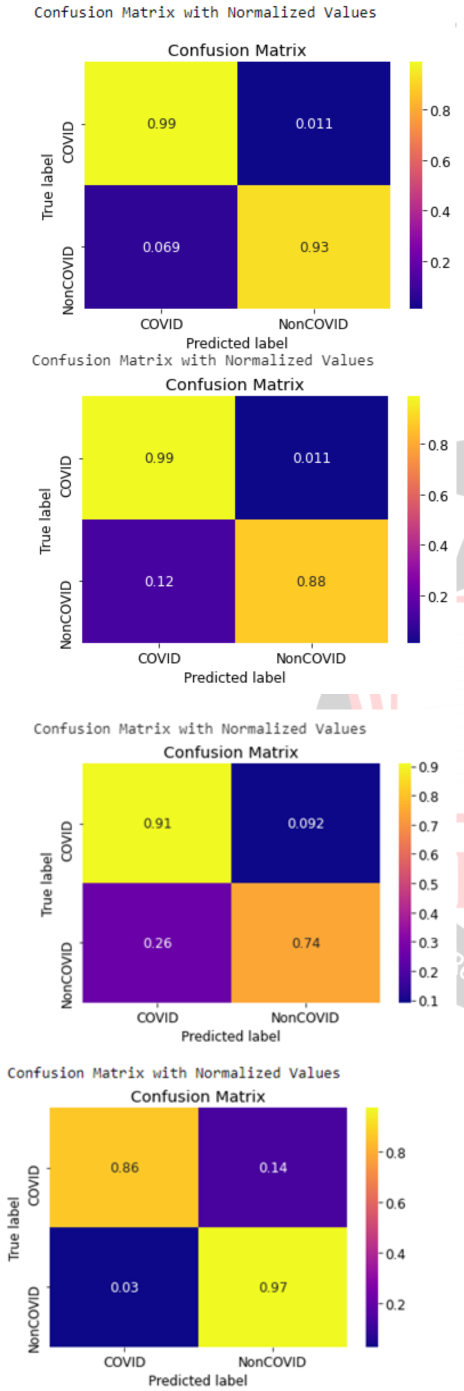

Fig 5. Confusion matrix for the 4 models in the order Inception-V3, VGG-16, ResNet-50, and Xception

VI. EXPERIMENTAL RESULT

The experimental result comprises the formulations that are used to evaluate the machine learning models. Here, precision is defined as T.P. / (T.P. + F.P.), which is described as the model's ability to avoid labeling a negative sample as positive. Similarly, recall is defined as T.P. / (T.P. + F.N.), it determines the model's capacity to locate all positive samples. The F-beta or F1-score, as labeled in this paper, is the weighted harmonic mean of precision (P) and sensitivity/recall. Here recall is used in the formula as R This expression can have the best value and the worst value as 1 and 0 respectively. These are derived during the testing of the model. Here the labeling is done with the numbers 1 and 0 where 1 stands for non-covid database and 0 stands for the covid database. These results are unique to the models and the user input. The final values for an experimental input are depicted in tables 2 to 5.

Table 2. The final result of Inception model

Classes	Precision	Sensitivity (Recall)	F1-Score	Accuracy
Non-Covid	0.82	0.73	0.77	80%
Covid	0.78	0.86	0.82	

Table 3. The final result of VGG model

Classes	Precision	Sensitivity (Recall)	F1-Score	Accuracy
Non-Covid	0.93	0.93	0.93	93%
Covid	0.94	0.94	0.94	

Table 4. The final result of Xception model

Classes	Precision	Sensitivity (Recall)	F1-Score	Accuracy
Non-Covid	0.88	0.97	0.93	93%
Covid	0.97	0.89	0.93	

Table 5. The final result of Resnet model

Classes	Precision	Sensitivity (Recall)	F1-Score	Accuracy
Non-Covid	0.92	0.97	0.94	95%
Covid	0.97	0.93	0.95	

Model accuracy is used to verify our training algorithm. The accuracy is plotted across epoch values. Here, during every

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epoch, the accuracy of all the data items is calculated and plotted. this process is repeated 500 times with a batch of 32 epochs to increase the effectiveness of the process. The saturation of the graph shows that the model is learning properly The model accuracies for an experimental input are depicted in fig. 6.

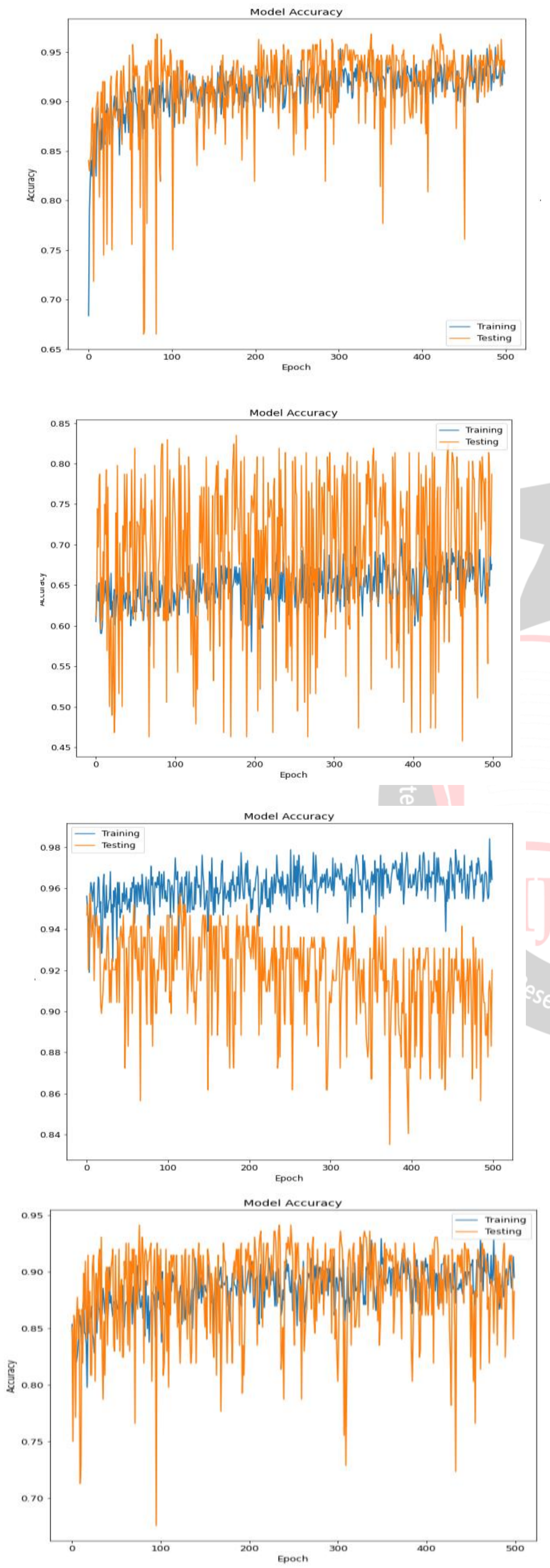

Fig 6. Model Accuracy graph for the models in the order Inception-V3, VGG-16, Resnet-50 and Xception

The model loss graph is calculated across epoch values of the dataset. This evaluation is used in debugging and optimizing the training algorithm. The model losses for an experimental input are depicted in Fig. 7.

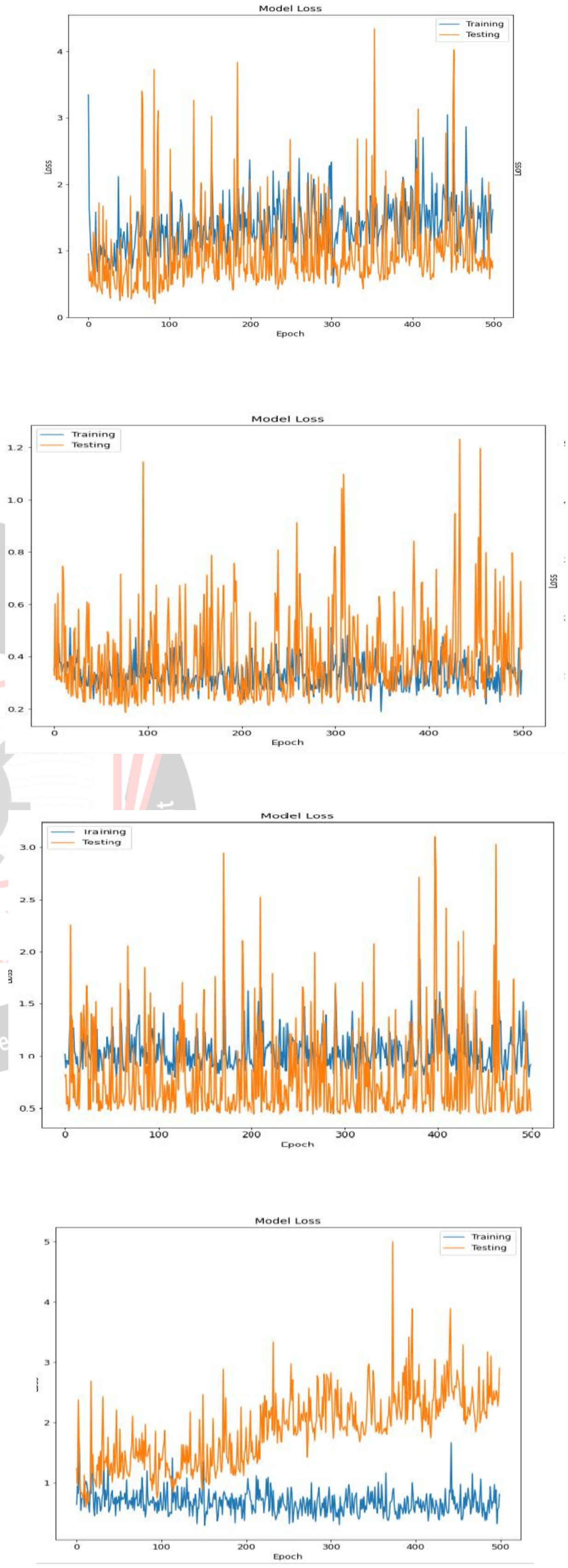

Fig 7. Model loss for the 4 models in the order Inception-V3, VGG-16, ResNet-50, and Xception

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These results are formulated for all the 4 CNN models and the ultimate result is shown on the website. This website result takes in input from the user in the form of .jpg or .jpge and after the whole process completes the cycle for all the models, the result is declared on the website where the user can compare and tally the predictions. the experiment is done on the website to make it easily accessible and easy to use for all. The program results can be surveyed on any platform with suitable internet access and proposed software.

Since the data input is vast and unlabelled, instead of relying on classification accuracy exclusively for the measurement of model efficiency, we carried on the evaluation using precision, F1-S, and specificity, to validate the applied model's superiority[12]. The model's efficiency is seen in Figures 6 to 9 show the graphical description of the model results and tables 2 to 5 show the formulated results

VII. Conclusion

We proposed a proof-of-concept hypothesis in this paper that COVID-19 contaminated patients can be diagnosed using X-Ray chest images. To address the issue of insufficient COVID-19-related data, we explored two approaches. To begin, train a custom CNN using a huge data collection of non-COVID-19 X-ray chest images (ChexPert). The model is then fine-tuned using the tiny COVID-19 results. This method yielded Model 1, which did not yield positive results in detecting COVID-19 contaminated patients. The second approach was to import pre-trained deep learning models and train them on COVID-19 results. In this section, we modeled and tuned certain models to effectively detect whether or not the patients are affected by the covid. We proposed a proof-of-concept theory based on X-Ray chest images that COVID-19 affected patients may be identified. In order to solve or accelerate the detection of COVID-19 using chest X-rays and CT scans, 4 CNN algorithms were used, namely, Inception V3, VGG-16, Xception, and ResNet 50. We educated the models and obtained high precision in predicting covid or non-covid events.

For identifying COVID-19 patients, the created model has an accuracy of 80-95 percent. Due to the presence of so many covid mutation variations, and with each variant having various symptoms, the procedure becomes more complicated hence, in turn, increasing the False-positive and False-negative parameters.

This model is a reliable solution that can work with a considerable compact dataset and has an accuracy that can be compared to or considered better than that of current CNN models. In comparison to existing deep learning algorithms, the suggested technique offers greater accuracy and takes much less time to train.To verify the efficacy of the suggested approach, a detailed comparison study is done between the Four improved CNN Models. The categorization of COVID-19 versus common pneumonia cases rather than normal (healthy) pneumonia patients is the key uniqueness of our proposed approach.

VIII. References

[1] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin,S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga,S. Moore, D. G. Murray, B. Steiner, P. Tucker, V. Vasudevan, P. Warden, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: A System for Large-Scale Machine Learning. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI), pp. 265–283. Savannah, GA, USA, Nov. 2016

[2] D. Shen, G. Wu, and H. Suk, "Deep learning in medical image analysis", Annu. Rev. Biomed. Eng., vol. 19, pp. 221-248, 2017.

[3] M. Anthimopoulos, S. Christodoulidis, L. Ebner et al., "Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network", IEEE Trans Med Imaging., vol. 35, no. 5, pp. 1207-1216, 2016.

[4] S. Albawi, T. A. Mohammed and S. Al-Zawi, "Understanding of a convolutional neural network", 2017 International Conference on Engineering and Technology (ICET), pp. 1-6, 2017.

[5] C. Szegedy, W. Liu, Y. Jia et al., "Going deeper with convolutions", 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1-9, 2015.

[6] F. Chollet, "Xception: Deep Learning with Depth Wise Separable Convolutions' ', 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1800-1807, 2017.

[7] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Liu, X. Wang, G. Wang, J. Cai, and T. Chen. Recent advances in convolutional neural networks. Pattern Recognition, 77:354–377, May 2018.

[8] M. Mishra, V. Parashar, and R. Shimpi, "Development and evaluation of an AI System for early detection of Covid-19 pneumonia using X-ray (Student Consortium)," 2020 IEEE Sixth International Conference on Multimedia Big Data (BigMM), 2020, pp. 292-296, doi: 10.1109/BigMM50055.2020.00051.

[9]Shen, Dinggang et al. "Deep Learning in Medical Image Analysis." *Annual review of biomedical engineering* vol. 19 (2017):221-248. doi:10.1146/annurev-bioeng-071516-044442

[10] S. Miroshnychenko, D. Radko, V. Yefimova and A. Nevgasymyy, "Effectiveness assessing of softwares with AI for chest area x-ray images post-processing," 2020 IEEE 40th International Conference on Electronics and Nanotechnology (ELNANO), 2020, pp. 580-583, doi: 10.1109/ELNANO50318.2020.9088882.]

[11]Henderi, M. Maulana, H. L. H. S. Warnars, D. Setiyadi, and T. Qurrohman, "Model Decision Support System For Diagnosis COVID-19 Using Forward Chaining: A Case in Indonesia," 2020 8th International Conference on Cyber and IT Service Management (CITSM), 2020, pp. 1-4, doi: 10.1109/CITSM50537.2020.9268853.

[12] N. Rochmawati et al., "Covid Symptom Severity Using Decision Tree," 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE), 2020, pp. 1-5, doi: 10.1109/ICVEE50212.2020.9243246.

 DOI : 10.35291/2454-9150.2021.0392