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DETECTION OF CLINICAL FEATURES OF COVID-19 PATIENTS BY DEEP LEARNING TRANSFER MODEL

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Abstract: The first signs of the COVID-19 pandemic were discovered in December of this year. COVID-19 was blamed for 1.4 million fatalities by the year 2020. A worldwide pandemic was declared by WHO because of the large number of fatalities because of COVID-19 or SARS-CoV-2. Fever, dry cough, exhaustion, and a diminished sense of smell and taste have been recorded in persons who have been exposed to COVID-19, and many have been admitted to critical care units for urgent intermittent required breathing (IMV). In order to mitigate the damages caused by this epidemic, immediate actions were necessary.

WHO recommends widespread usage of COVID-19 testing to combat spread of such disease. It's imperative that an automated detection method for COVID-19 detection be developed and used as an alternate diagnostic option due to the restricted quantity of COVID-19 testing supplies accessible in medical institutions. When it comes to the accurate finding of illness, chest Xray is often the first imaging tool used. With the use of computer vision & deep learning, it is possible to identify COVID-19 viruses in chest X-ray pictures. Utilising CNN for photo classification & prediction is being successful due to abundance of large-scale digital image database. COVID19 might be identified from a chest X-ray using an intelligent clinical decision support system (SADC) that is more accessible. That's why we've amassed 566 radiological pictures, all of which have been divided in 3 types: pneumonia-type, & healthy-type. As into experimental assessment, 70% of data were utilized for training and 30% for testing. In addition to the pre-processing, the image is augmented by rotating, flipping horizontally, shifting channels, and rescaling. f1 score of 98.60 percent and a sensitivity of 98.30 percent were reached by the final classifier, making it the most accurate and sensitive. Recognizing COVID-19 in x-ray pictures using the suggested method thus proves its efficacy.

***Index terms*- COVID-19, CNN, VGG19 architecture, MobileNet architecture, InceptionV3 architecture**

I. INTRODUCTION

However, PCR test, qtypical COVID-19 test, have several drawbacks like false negatives & false positives when looking for antibodies to a specific virus. For medical purposes The gold standard is pathogenic laboratory testing, although these are time consuming and provide many false negatives. Using aiAI and ML, as well as historical data, parallel diagnostic and testing methods will be incredibly beneficial. It may also aid into selecting procedure for who will be tested most.

Early-stage frosted glass opacification & pulmonary consolidation in advanced stages are common radiographic findings in the majority of COVID-19-related patients. Because the pictures of multiple viral pneumonias were comparable & combine with certain other common pathological lung illnesses, radiologists have a hard time distinguishing it by others. Use of deep learning algorithms in medical imaging and AI maybe able to deliver a rapid, low-cost, and exact diagnosis of COVID19. Tumor and inflammatory localisation in medical imaging, machine learning for diagnosis, and patient aid have all employed deep learning. When it comes to the early diagnosis of pediatric pneumonia using chest radiography pictures, Deep Learning is being utilized to identify the kind and location of nodules in the lungs, classify polyps automatically using colonoscopy movies, and extract cystoscopic picture identification from video.

Medical imaging characteristics have been used in clinical studies to help identify viral infections and describe COVID-19 as having an early onset of symmetrical dispersion of uneven shadow & blurriness of frosted glass that increases in severity as the illness advances. Due to their similarity to other viral pneumonias, radiologists have difficulty distinguishing them from one other. To propose an early detection method for COVID19 that can be implemented using a chest x-ray equipment.. Prior to the pathogen test, this technology provides clinical diagnosis, which saves vital time in stopping spreading of COVID 19.

II. LITERATURE SURVEY

[1] Relative Research upon Earlier Discovery of COVID-19 by Chest X-Ray Images

Mete Ahishali, Aysen Degerli, Mehmet Yamac, Khalid Hameed, Serkan Kiranyaz, Senior Member, IEEE.

As part of this investigation, the researchers are looking to see whether modern Machine Learning algorithms can identify COVID19 in plain chest X-ray pictures early enough. In this work, both deep learning & compacted classifiers are examined. The CSEN technique, a new compact classifier, is also suggested since it is well-suited to the classification of scant data. Fresh standard database termed Early-QaTa-COV19, that includes 175 earlier phase COVID-19 Pneumonia samples identified by medical professionals and 1579 samples for controllinf class, was introduced in this work. Extensive testing reveals that CSEN has a very high sensitivity (over 98.5%) & specific (over 96%). With 97.14 percent sensitivity & 99.49 percent specificity, our deep CheXNet-tuned transfer learning network outperforms all other deep networks.

[2] XCOVNet: Chest Xray Image Classifying inCOVID-19 Early Detecting Utilising CNN

Vishu Madaan, charu Gupta, Anand Sharma, Aditya Roy, Prateek Agrawal, Cristian Bologa, Radu Prodan © The Author(s) 2021.

A new approach dubbed XCOVNet, which employs intricacy of positive/negative COVID chest X-ray pictures to training network & identify virus in disease in its early phases, has been proposed by the authors. COVID+ and COVID-positive chest X-rays are identified using CNN. A CNN is used in their XCOVNet model, which has a learning rate of only 0.001. No feature selection approach is required, and a handmade seeding data for CNN global & regional characteristics is used, which includes 196 COVID+ and 196 COVID pictures from chest X-rays taken from patients. An accuracy of 98% for COVID-19 identification was obtained using 3 convolutional layer-based models with kernel sizes of 3 x 3 & the implementations. Also, the approach was compared to various cutting-edge works with an accuracy limit of up to 98 percent. In more than 98% of patients correctly classified as COVID+ and COVID, we still need to determine the severity of the illness, which is why the XCOVNet model has been developed. Future trials will be conducted using chest CT scan pictures for detecting COVID19 & integrating both models to determine the severity degree of the disease They also have ideas for early COVID19 infection diagnosis based on voice recognition and intelligent approaches in the future.

[3] Transferring Learning by Pneumonia to COVID-19

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An investigation into the use of pretrained models by an region to successfully alter an system for use into comparatively newer sector is presented in this research as a research of transfer learning in image classifying. They used COVID-19 X-ray pictures as a study case in the research. It is clear from the experiment results that suggested strategy and the models established by researchers are effective and efficient.

In order to build a system for quickly and accurately classifying COVID-19 photos, this study investigates the concept of transfer learning. An evaluation of 2 transferable deep learning models shows that the suggested strategy provides good results, despite a restricted data set and the high cost of computation. Work in future will concentrate on learning from fresh pictures to better transfer learning.

[4] Computerized Analysis of Chest X-Ray for Earlier Detecting of COVID-19 Disease

Ebrahim Mohammed Senan, Mohammed Y. Alzahrani, Nizar Alsharif, Ali Alzahrani, and Theyazn H.H.Aldhyani. King Faisal University.

ResNet50 & AlexNet deep learning models have been used to analyze X-ray data by various resources. Dataset with four classes (multiclass) and a dataset with two classes were each diagnosed by a network. Using image processing, the photos were cleaned up, and data augmentation techniques were used to balance the classes. CNN models were merged with classic GLCM & Local Binary Patterns (LBP) techniques into 1-D vector of every picture, that yielded detailed characteristics for each illness, as seen in the following figure. To provide the best possible performance, network settings were adjusted. Precision, certainty & AUC was 95 percent with multiclass and 99 percent by binary classes.

[5] DeepCOVIDExplainer: Explainable COVID-19 Diagnosis from Chest X-ray Images Till Do hmen, Md. Rezaul Karim, Oya Beyan, Michael Cochez, Dietrich Rebholz-Schuhmann, Germany Department of Computer Science, German National Library of Medicine, Vrije Universities Amsterdam, the Netherlands.

DeepCOVIDExplainer, a DNN-based approach for automatically detecting COVID-19 signs using chest radiographs (CXRs), is described in this research as a "explainable" deep neural network (DNN). 15,959 CXR pictures of 15,854 patients were utilized to cover normal, pneumonia and COVID-19 cases, correspondingly. Prior to categorizing CXR pictures using a neural ensemble technique, the images are thoroughly preprocessed and enhanced. Class-distinguishing areas are then highlighted utilising gradient-guided class activation mappings and LRP. In addition, we explain the diagnosis in terms that may be understood by the

average person. Considering normal, pneumonia, and COVID-19 cases, our technique has PPV of 91.6 percent, 92.45 percent, and 96.12 percent correspondingly. This outperforms current approaches. Their methodology has a PPV of 96.12 percent and a recall rate of 94.3 percent, which outperforms a previous method.

Radiologists will always be needed to interpret the results of the "Deep COVIDExplainer." However, it would be inaccurate to say that their models are free of overfitting because of a small number of CXR pictures utilized in training. In addition, radiologists were not capable of validating accuracy of diagnosis & localization. In the future, they want to use multimodal learning outcomes to circumvent these restrictions.

[6] The Deep Learning Approach for the Detection of COVID-19 from Chest X-Ray images using Convolutional Neural Networks.

Aditya Saxena*, Birla Institute of Technology and Science, Pilani, Dubai Campus E-mail: f20190089@dubai.bits-pilani.ac.in, Shamsheer Pal Singh, BITS, Vilas H Gaidhane, Pilani, UAE

A deep CNN trained using 5 open-access datasets having binary output: Normal & Covid, has been suggested in this research Pre-trained (i.e., four) CNN models are compared to the proposed model and the proposed model delivers superior precision upon valid dataset than remaining 4 pre-trained models (COVID-Net, ResNet, MobileNet, and ResNet18).

They also examined and used alternative model aspects for getting deep perceptions into Chest X-Ray characteristics crucial for distinguishing Covid & nonCovid patients, that may benefit physicians into improving monitoring and improving confidence and transparency in the medical system. However, the suggested concept is by no means a ready-to-go commercial product. Scientists & data analysts alike are hoping that the encouraging findings from this study may be used to help accelerate the growth of reasonably precise still applied deep learning systems for COVID-19 detection by Chest X-Ray pictures.

[7] The Deep learning based detecting & examination on COVID19 with chest x-ray images

Meenu Gupta, Rachna Jain, D.Jude Hemanth, Soham Taneja, Springer Science+Business Media, LLC, part of springer Nature 2020.

For both covid-19-infected and healthy patients, PA viewpoint of chest x-ray images was obtained. They employed deep learning-based CNN architectures & evaluated their efficiency following clearing up photos and performing data augmentation. There has been an evaluation of the correctness of the models Xception, Inception V3, ResNeXt, and Inception V3. The Kaggle collection contains 6432 chest x-ray images, of these 5467 was utilized for train & 965 were used for validation. Results analysis shows that the Xception model is more accurate in identifying Chest X-ray pictures than other models (i.e., 97% accuracy). This study does not pretend to be medically accurate; instead, it looks at several ways to categorize people who are infected with covid-19.

[8] Automatic Detecting of COVID-19 Infection Utilising Chest X-Ray Images by Transfer Learning.

Elene Firmeza Ohata, Aloísio Vieira Lira Neto, Adriano Bessa Albuquerque, IEEE.

The authors in this study suggest a technique predicated upon chest X-ray pictures for automated identification of COVID-19 infection. A total of 194 X-ray pictures of patients having corona viruses & 194 X-ray pictures of normal persons were used to create the datasets for this investigation. This is because there are just a few publicly accessible photos of patients with COVID-19. To extract the X-ray image's features, they train CNNs using ImageNet and then modify them to operate as feature extractors. k-Nearest Neighbor, MLP, Bayes, Random Forest, & SVM are some of the machine learning approaches used with CNNs (SVM). Results demonstrate that the best extractor-classifier combination is MobileNet design with SVM classifier employing a linear kernel, that yields 98.5 percent accuracy and an F1-score. MLP and DenseNet201 achieve 95.6 percent accuracy in the other dataset, making them the top duo.

[9]COVIDGR Database & COVID-SDNet Method to Predict COVID-19 depending upon Chest X-Ray Images

S. Tabik , A. Gómez-Ríos, J. L. Martín-Rodríguez, I. Sevillano-García, M. Rey-Area, D. Charte, E. Guirado, J. L. Suárez, J. Luengo, M. A. Valero-González, P. García-Villanova, E. Olmedo-Sánchez, and F. Herrera IEEE.

We constructed COVIDGR-1.0, homogenous & dataset which contains every severity level, including healthy to +RT-PCR. It covers 426 +ve & 426 -ve CXR pictures of the PA (PosteroAnterior) region, and they propose COVID-SDNet technique to enhance simplification power of COVID-classifying systems. ' In severe, moderate, and mild COVID-19 severities, our technique achieves accuracy values of 97, 86, and 61 percent respectively, which is constant across all three severity levels. Early identification of COVID-19 may be made easier using their technique.

[10] COVID-19 Detecting by AI

Fatima M. Salman1, Eman Alajrami2, Samy S. Abu-Naser1, Bassem S. Abu-Nasser1, University of Palestine, Gaza,

With the goal of alleviating the burden on radiologists and aiding in the containment of the pandemic, our study developed a deep learning model to identify COVID-19 pneumonia in higher-pixel X-rays. GitHub & Kaggle repositories provided 260 photos for testing and validation of the suggested model. Normal X-ray photos and COVID-19 pictures are included in Images collection. Findings: Its sensitivity, specificity, accuracy, and PPV and NPV were all 100 percent in the dataset,

according to the suggested model. The model's performance was similar with an proficient radiologist over course of 260 pictures. The scanning period of radiologists will be substantially reduced with the help of the model. Radiologists will benefit immensely from using the deep learning model, which performed as well as an experienced radiologist. It has the potential to alleviate the strain on radiologists, enhance early diagnosis, isolation, and treatment, and hence aid in epidemic management.

III. PROBLEM STATEMENT

On the basis of the previously reviewed literature for COVID-19 detection, we have identified following limitations.:

1. TB, lung cancer, and other lung disease datasets must be integrated with COVID-19 cases in order to better identify extent of illness.
2. When compared to other illnesses included in the gathered dataset, limited COVID-19 picture collection leads to an uneven issue of class.
3. When using pre-trained CNNs or custom-designed CNNs, it is necessary to use GPU resources. If other illnesses are evaluated, it's not really known how COVID-19's deeper traits are separated.

There's need for an effective COVID-19 detection system in light of all of these variables. There have been several cases of this terrible illness spreading around the globe, with many individuals losing their lives as a result. For diagnosing COVID-19, many physicians and practitioners still utilize the first approach they learned about: RT-PCR. However, this approach has the drawback of being quite time consuming, with effects taking anywhere from a few days to a few weeks to appear. This is a serious problem for smaller clinics and hospitals. Because they are readily accessible and inexpensive as comparing to PCR technologies, chest radiography imaging (CRI) has numerous benefits over these latter. Use of chest X-ray imaging devices is essential in locations where adequate testing kits are not readily accessible Reliability of electronic media is a determining factor in radiographic pictures. Like a features extraction method, the chest radiograph approach, which uses deep metric learning, plays a significant role. With the refinement of this model, a visual saliency-guided complex information extraction prototype may be used to get more clearly the picture patterns for management and treatment of COVID-19 patients. X-ray & CT scans are two of the CRI techniques that may be used. Because of CT's high values for lung homogeneity & ground-glass opacity, a limited number of tests have employed it to better assess & identify COVID-19 characteristics. Although CT machines are expensive, they may not be the best option owing to the lack of availability. COVID-19 may be detected with an X-ray test since it is more readily accessible and costs less. However, finding X-ray pictures to discriminate between CAP, COVID-19, as well as other lung illnesses might be a difficult challenge for a radiologist. Due to the increasing number of patients in hospital emergency rooms (ERs), accurate disclosure of radiography data is essential since it may save a significant amount of time. In this part, we'll take a look at the difficulty we described before and suggest a solution.

IV. MATERIALS AND METHODOLOGY

For the identification of COVID-19, an ensemble-based learning algorithm based on seven pre-trained architectures is presented. The area of AI ensemble learning, which incorporates ML and DL, is relatively young. Multi-classifier system, or ensemble system, is another name for this. In order to increase the overall system efficiency, these systems minimize system error. With the use of classifiers and grouping, multiple models are able to better forecast the future by taking into account different aspects of each other. Assembling is a two-way street. In the first stage, pre-trained architectures are used to extract the deep characteristics of a network. Using classifiers, the next step is accurately predicting the outcome. The ensemble network is always more accurate than a single model. These classifiers include decision trees, K-Nearest Neighbor (KNN), SVMs, Auto Encoders (AE), Boltzmann Machine (BM), and more. In order to produce a conclusive recommendation depending upon that clustering it employs several methods for training dataset, the classifier is used to identify deep characteristics from a picture. The voting approach was utilized and the voting group gathers the choices of several classifier & carries out a specific classification job; it enables flexibility in clustering tactics so that the highest potential classification accuracy may be achieved. Hard voting & soft voting are two types of voting methods. In the hard voting approach, the test sample class labels are unchangeable by majority vote. During the testing phase, each base classifier assigns a class label to a particular test sample. The final classification of a sample is based on how many times it has been allocated a certain class label. There are two different types of soft voting methods: those that use the average likelihood of all categories, and those that use just the class that has the greatest likelihood of winning. Ensemble models may benefit from the usage of these approaches since they do not rely on any algorithm to combine predictions from base classifiers, as needed by the stacking set.

Powerful CNN model (inception v3, inceptionres v2, dense v121, and xception) the suggested model is fine-tuned with higher number of trainable parameters, and simply extracts more detailed features. The detailed overview of the suggested technique is outlined in the next section.

STRUCTURE OF PROPOSED MODEL

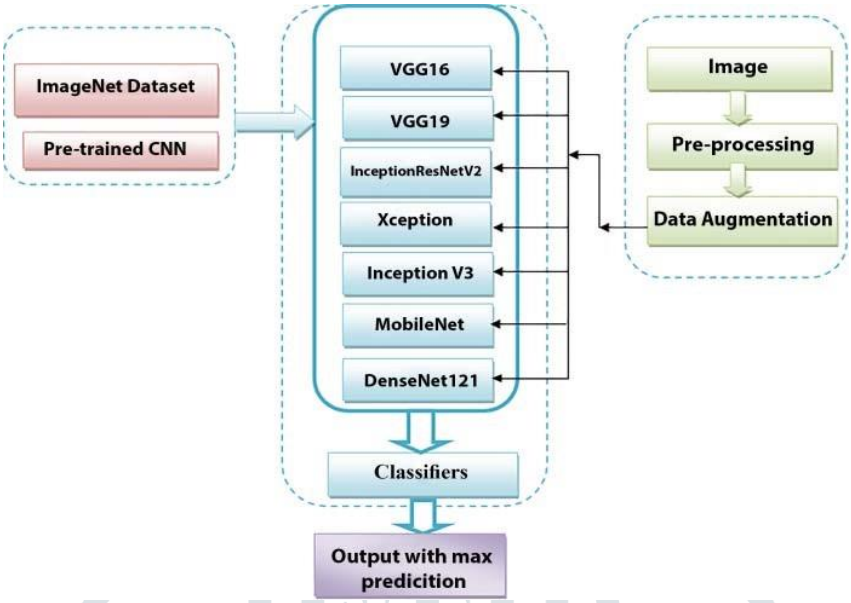

Fig 1: Proposed model procedure

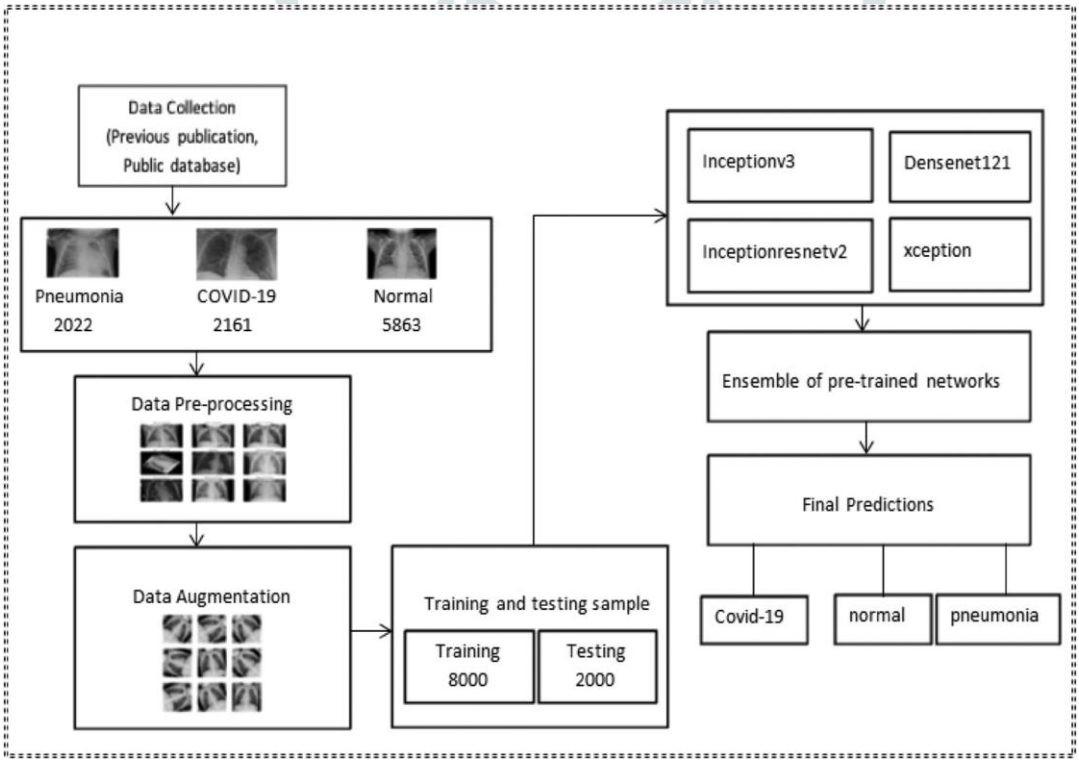

Fig 2: Proposed classification framework

Datasets collections

X-ray pictures are included in two databases that may be accessed by the general public. A chest x-ray database that includes pictures from three different classifications. Pictures of patients who have been diagnosed with COVID-19 are shown in the first class. Images of people who have been certified healthy and free of pneumonia make up the second category. Class 3 photos depict individuals who have previously been diagnosed with a typical inflammatory pneumonia. Images of COVID-19 in the first batch are 146 X-rays (radiological). In the second dataset, 5863 X-ray pictures JPEG were classified into two groups: Normal and Pneumonia. Take 210 photos at random from each class's second dataset. Over 560 X-ray pictures might be collected by using all of the available X-ray data. 70 percent of the

dataset was employed as a training set and 30 percent as testset in the experimental analysis.

Data pre-processing andaugmentation

The use of pre-processing techniques may help reduce the amount of unwanted noise in a picture. It is shown in Figure 3A that a technique of contrast enhancement and picture normalization is used to alter the pixel intensity value in order to get a more improved image. Modifying image pixels reveals information hidden with in reduced spectrum of gray level images.

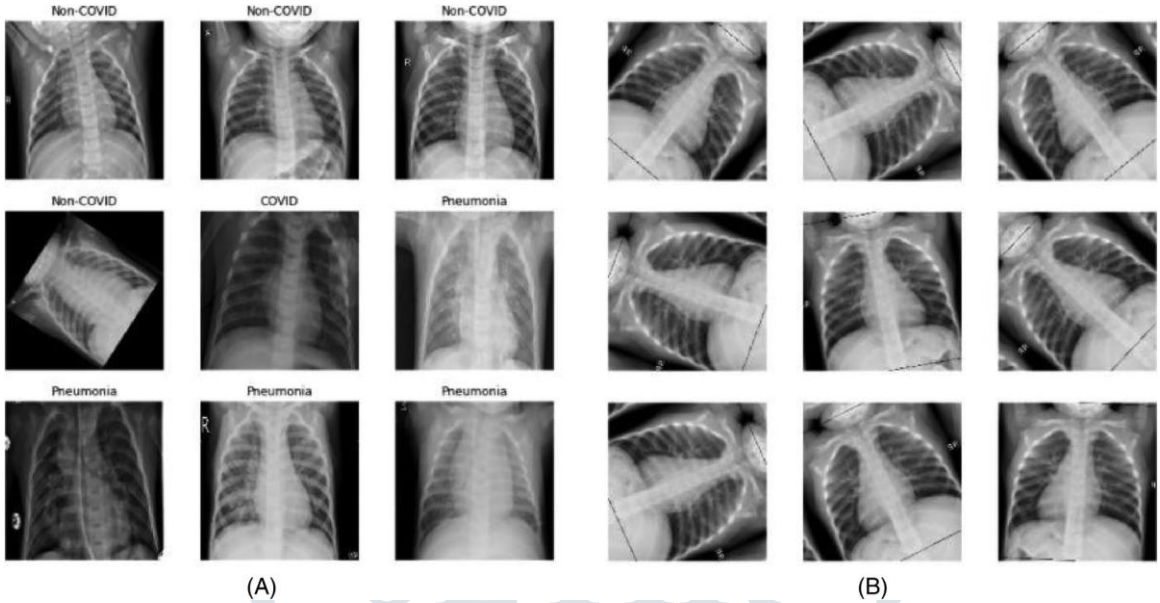

Fig 3: Data pre-processing andaugmentation

In addition, data augmentation approaches were used to provide new training samples that were varied without sacrificing essential information. Using a variety of picture augmentation techniques improves the system's overall performance by supplementing the existing dataset with more diversified data. The original dataset was enhanced using the techniques illustrated in Figure 2B, which include data flipping, picture rotation, image scaling, & translation. Stabilizers like this help to minimize effects of over-fitting.

CNN & using Transfer learning

Transfer learning utilizing DenseNet121 (VGG16), MobileNet (VGG16), InceptionV3, Xception (VSG19), & InceptionResNetV2 neural networks are used in the technique. The suggested global model has two modes. Pre-trained start modes turn input pictures into descriptor vectors, whereas other start modes use many classifiers that are tightly coupled and each of which produces its own prediction. The global system will use the forecast with the highest score as its final result.

Pre-trained neural networks

We used seven distinct pre-trained models using ImageNet dataset, taking use of Transfer Learning and using VGG16, VGG19, MobileNet, DenseNet121, InceptionV3, Xception, and InceptionResNetV2 as inputs.

1. Layers 1 through 10 of the conv2D-10 architecture are being used as pre-trained layers having preset weights in VGG16 architecture. As a final step, radiographic lung pictures were utilized to train the remaining layer..

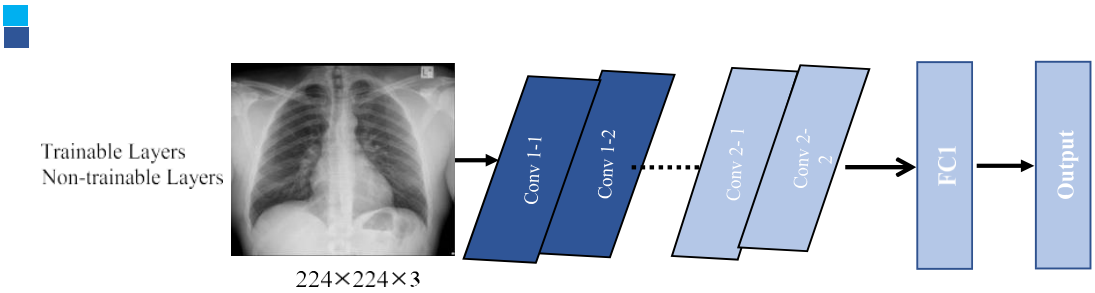

Fig 4: VGG16 Model with trainable & frozen layers

2. **VGG19 architecture:** It employs pre-trained layers with preset weights from the first through block5 conv1. Finally, remaining layer was utilized to train on dataset of X-ray lung pictures.

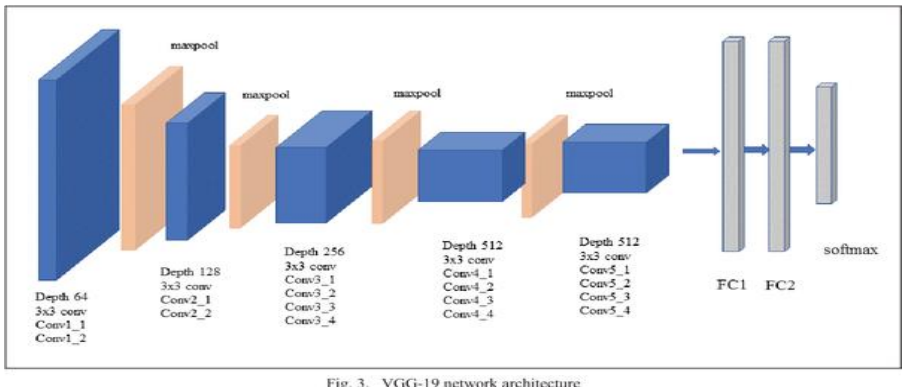

Fig 5: VGG19-Network Architecture

3. MobileNet architecture

Developed for portable & integrated vision applications, this neural network is a CNN. For mobile and embedded devices, they are built on a simplified architecture that leverages depth-wise separable convolutions to generate lightweight deep neural networks. Google came up with the idea for the MobileNet architecture. Pretrained layers with fixed weights are used in the suggested model, which includes layers 1 to 75 in the proposed model. The remaining layers, as indicated in Fig., were trained using our data of radiographic pulmonary pictures that had previously been collected. MobileNet has layers that can be trained and frozen.

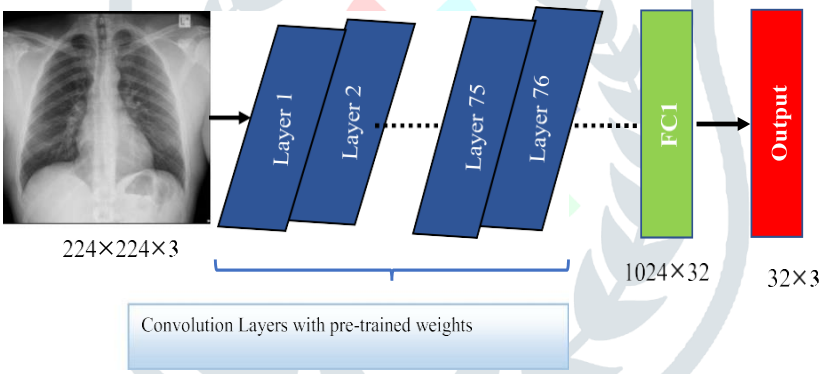

Fig 6: MobileNet with trainable and frozen Layers.

4. InceptionV3 architecture

As a result of its deep learning approach, the Inception V3 uses Convolutional Neural Networks for picture categorization. Pre-trained layers from first to mixed 10b layers were employed in our proposed model, which had fixed weights. As can be seen in the figure, we employed the remaining layers to train on our existing dataset of radiography lung pictures.

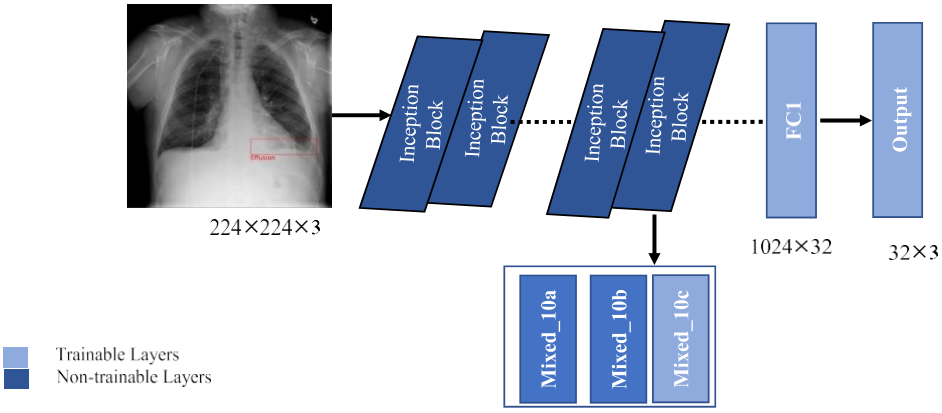

Fig 7: InceptionV3 architecture with trainable and frozen Layers.

5. Xception

When it comes to Xception, you're getting the "ultra-inception" treatment. On the other hand, the Xception architecture is a convolutional neural network with 71 layers of convolutional layers. As illustrated in Fig., the proposed model uses pre-trained weights using ImageNet like a starting point for learning upon that data of radiography lung pictures.

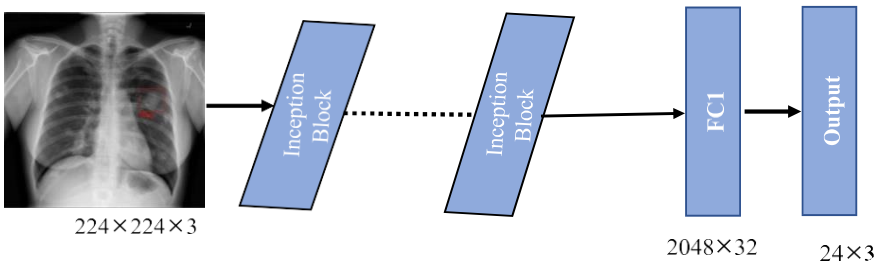

Fig 8: Xception architecture with trainable layers.

6. InceptionResNetV2 architecture

There are over a million photos in the ImageNet collection used to train the Inception-ResNet-v2 neural network. The network consists of 164 levels. We employed pre-trained layers with fixed weights from first to conv2D-58 layers in our model. These layers were then utilized to train on our data set of radiographic lung pictures, as seen in the figure.

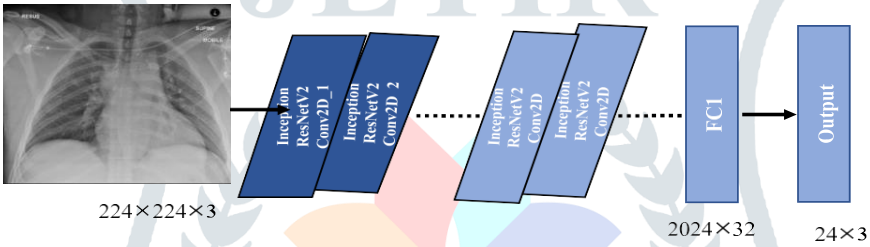

Fig 9: Inception-ResNetV2 architecture with trainable and frozen Layers

7. DenseNet121 architecture

The term "Densely Connected Convolutional Network" comes from the fact that every layer in this system is linked to every other layer. There's many L(L+1)/2 obvious ties between layers L and L+1. All previous layers' feature maps are utilized as inputs for the first layer, and the first layer's own local features were utilized as inputs for second and third. DenseNets link each layer to any layer, which is as straightforward as it sounds. This is the most important point to grasp. Feature mappings from preceding layers are concatenated to provide a layer's input in DenseNet.

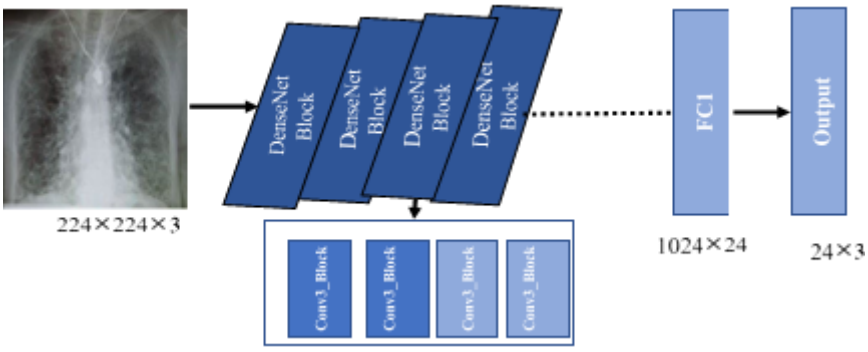

Fig 10: DenseNet121 architecture with trainable and frozen Layers

Ensemble Classification

By integrating seven pre-trained models, ensemble classification improves the outcomes of deep learning When compared to a single model, this strategy yields a more accurate prediction and outcome. Its key premise is to teach a classifier set

and then give it the power to vote. The outputs of the pre-trained CNN are integrated in prediction vector, so it utilizes the majority vote to arrive at a final prediction via ensemble classification.

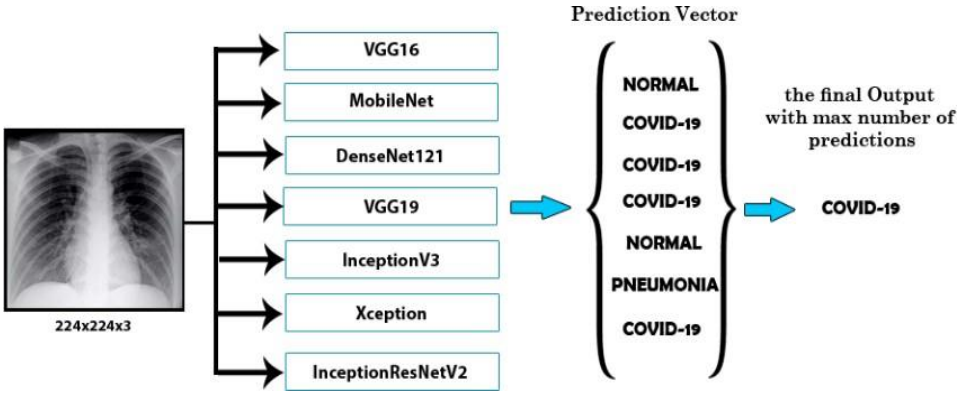

Fig 11: Seven distinct pre-trained architectures and outputs are used in the ensemble model.

V. EXPERIMENTAL RESULT

The CNN models are created in Python using Tensorflow and the Keras wrapper package. NVIDIA Quadro M2200 8GB GPU & 8GB of RAM were used in the research on a Lenovo ThinkPad P51. Cross-entropy was employed as a loss function for training CNN models using Adam's hyper parameter optimization approach. If the loss value does not improve with the callbacks function, the learning rate is reduced after four epochs, starting at a value of 0.001. The models are built for 60 iterations of training.

Datasets are stratified using the stratify parameter to maintain their original target proportions for improved prediction and repeatability. The greatest test accuracy was attained by VGG16 and VGG19, with scores of 96.88 and 95.31, respectively (see figure).

The table below shows the results for each type of neural network. VGG16, VGG19, IceptionV3, Xception and DenseNet121 were the seven models that predicted the most accurate outcomes when combined. The projected class of every modeling in a vector is merged with the class that was most commonly predicted by all models. With the help of ensemble models, the final classifier was able to obtain the highest performance with 99 percent test accuracy, f1-score 98 percent, precision 98.60 percent, and sensitivity 98.30 percent, respectively.

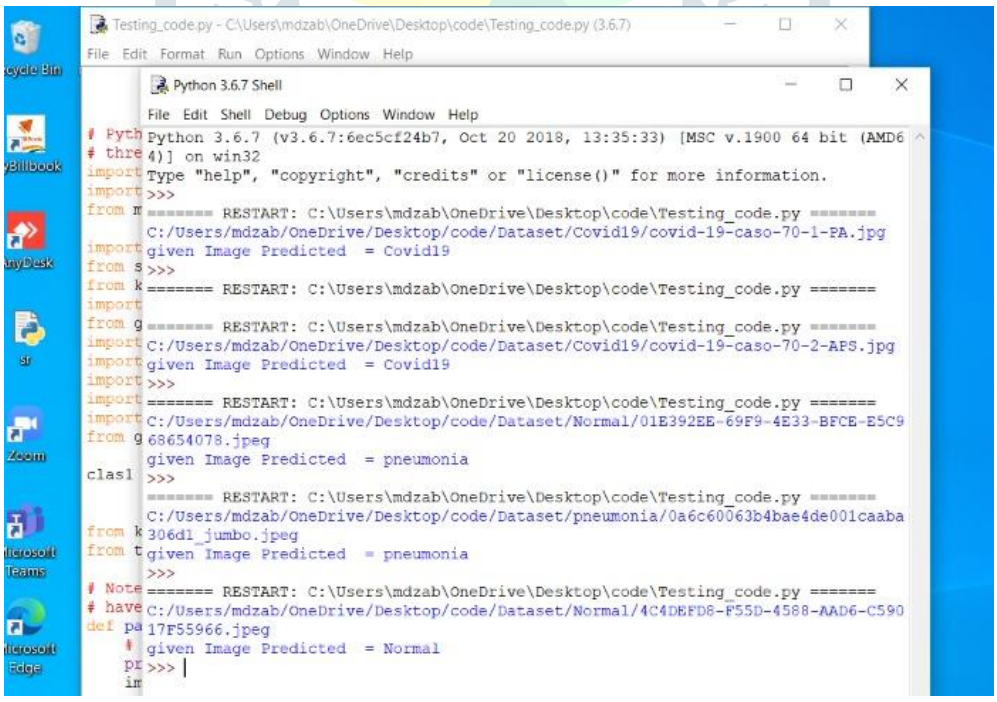

Fig 12 : Experimental Results.

Table 1 : Ensemble Method And Each Model On The Test Set Result.

MODEL	PRECISION (%)	RECALL (%)	F1-SCORE (%)	TEST ACCURACY (%)
VGG19	96.60	97	96	95.31
VGG16	91.66	90	90	96.88
MOBILENET	92	89.66	90.33	89.06
INCEPTIONV3	92.33	93	92.66	92.66
INCEPTIONRESNETV2	96	95.66	95.66	89.06
XCEPTION	95.66	95	95.33	95.31
DENSENET121	97	97.21	97.66	92
ENSEMBLE METHOD	**98.66**	**98.33**	**98.30**	**98**

VI. CONCLUSION AND FUTURE WORK

To categorize 3 types COVID-19, Pneumonia as well as normal utilizing Transfer Learning using pre-trained architectures like DenseNet121, VGG16, VGG19, InceptionResNetV2 and Xception, MobileNet and InceptionV3, we took advantage of 7 models for building an prediction method which outperformed all other models. This is done by using the seven models to build an ensemble model. Overall, the finale classifier had the greatest performance in terms of test accuracy (99%), F1-score (98.8%), precision (99.60%), and accuracy (98.30%).

However, there is room for improvement. A huge dataset and deep learning will be used in the future to provide precise and efficient outcomes. However, the suggested concept is by no means a ready-to-go commercial product.. In order to speed up the production of extremely precise deep learning systems for identifying COVID-19 in chest X-ray pictures and help individuals in need, scientists & data analysts alike want to take advantage of and improve on the promising findings produced from this study.

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