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Classification of COVID-19 and Pneumonia from Chest X-ray Images using Deep Learning Techniques

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Abstract: **A Covid-19 diagnosis utilizing nasopharyngeal swabs and RT-PCR has a low positive rate. Chest X-rays are crucial for early diagnosis of COVID-19, normal and pneumonia. Its symptoms differed from the common cold, influenza, and healthy people. COVID-19 is a major hazard to global health. The diseases are detected through the chest x-ray image dataset by using image classification for deep learning techniques. The image classification for deep learning techniques recognizes the image data and generates the categorized output. As deep neural networks perform the most essential aspect of medical image recognition, pre-processing of the raw image, which are converted into an understandable format by models are required. The models trained for this research include pre-trained CNN models such as VGG, Xception and Dense Net versions. The proposed model's performance validation is summarised in terms of accuracy, precision, recall, F1 score and AUC values that can aid in early diagnosis and differentiate COVID-19 from other kinds of pneumonia when all the deep learning classifiers and performance parameters were considered, the DenseNet121 achieved the highest model classification of accuracy for COVID-19 at 100%, the Xception of the normal class achieved 95.49% and the DenseNet201 achieved the highest for the viral pneumonia class at 97.14%. Additionally, the suggested method is useful and aids medical professionals in recognizing disorders from chest X-ray images. Even though our architectures are easier to use, the performance of the classifiers is used to prove that the therapies are effective and efficient.**

Index Terms: **COVID-19, Pneumonia, CNN, Deep Learning Techniques, chest X-Ray Images, classification.**

I. Introduction

Image classification involves examining a picture and figuring out which "category" it fits into. This resembles a human version of a virtual machine. Despite of being a straightforward process, classifying photos has proven challenging for computers. A classification system is built, utilizing a database of established trends to identify which group the detected image belongs to. The classification phase involves processing digital data, extracting features, gathering training sets, making decisions, and analysing the outcomes. The virtual camera or another X-ray imaging technology produces digital data to record images. The photos are improved by pre-processing. The matched grayscale picture in binary compression format is resized by a normalized augmentation of the comparison image in binary format. Feature extraction is the process of measuring, computing, or recognizing features in sample images to extract them. The two better typical methods of extracting features are feature extraction in space and feature extraction in colour. The feature that the best describes the sequence is chosen to serve as the basis for choosing the training data. The input image turns into the output image a week after pre-processing. By contrasting image patterns with attack patterns to determine the most effective tactic, photos are selected and categorized to be assigned to predetermined sets of classes. An outcome will be categorised by using the sample image.

In 2019 Hubei, China detected SARS-CoV-2. Each mammal has a coronavirus. Mammalian viruses are safe. These viruses affected how they spread from animals to people. COVID-19, SARS-CoV-2, entered the body through the nostrils. Coronavirus spreads through touch, handshakes, and face-touching. This makes healthy individuals become sick then 80% of people are acquired mild COVID-19, but this may change. Symptoms vary. In rare situations, the 5-day illness is fatal. At 3 months, SARS-CoV-2 reinfection is possible. Omicron grew rapidly after being discovered in 2021. High-dose vaccines prevent severe disease. COVID-19 causes fever, chills, and breathlessness. Migraines cause headaches, nausea, and odour/taste loss. Rare Symptoms Examine COVID-19. Saliva, nose, or throat swabs can be used to alter test results. If you have COVID-19 and know someone with the virus, evaluate them. COVID-19's side effects demand self-isolation. Follow your doctor's test-and-separation recommendations. If you have a weak immune system or a serious disease, stay home. I recommend day 5 labs. Test availability determines containment length. Expiring MMRs must wait 5 days. False-negative COVID-19 test results may signal that you have the virus, but the test missed SARS-CoV-2. fewer mistakes depending on prognosis, monoclonal injections may help some COVID-19 patients. Antifungal or immunotherapeutic drugs aren't indicated outside the clinic. Medicines reduce infection risk, but not entirely. Even though no vaccination is 100% accurate, outbreaks were estimated as SARS-CoV-2 caused less damage. COVID-19 should clear up in a week.

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Pneumonia is caused by bacteria in one or both lungs. About 30 types of pneumonia have various causes. Common ones are bacterial, viral and mycoplasma. TB impacts everyone. Following training is willing: People 65 and older, with major health conditions, and smokers are "seniors." Most of the lung disease patients cough crimson, green, and yellow sputum. Chills, dyspnea, weakness, and weariness are symptoms. A medical record and physical exam identify pneumonia. Blood, sputum, and lungs are tested. Like viruses and bacteria, antibiotics must help many people in the UK and throughout the world get healthy quickly. Most of the viral pneumonia recover without medical intervention. A balanced diet, lots of fluids, enjoyment, inhalers, suffering, sneezing, and flu medications are all remedies. Most kids and teens at risk for pneumococcal bacteria should get vaccinated. Most of the lung disease patients respond to treatment, but those who don't may have complications. You're more critical if you're unwell or have a weakened immune system. Risks include acute respiratory syndrome, chest irritation, and septicemia. Pneumonia strikes anybody, anytime. Children over 2 and seniors over 65 are at-risk. Heart surgery, emergency surgery, ECMO, viruses, breathing Healthcare examines lungs.

A chest X-ray is an imaging procedure that employs X-rays to examine the organs and structures in your chest. It may assist your doctor in determining how well your lungs are working in certain medical disorders that can create abnormalities in the lungs. Certain illnesses can produce anatomical changes in the lungs.

This paper is further comprised as follows: section II is related work, section III elaborates upon the methodology used for the following workflow, Section IV elaborates on the model process, Section V shows the proposed work observations, section VI explores the future goals and section VII deals with the conclusion for better analysis, and classification of viral pneumonia, normal and COVID-19 diseases via CXR images.

II. Related Work

At the end of 2019, China witnessed a COVID-19 pandemic [1]. Medical experts investigated the illness's symptoms, including fever, cough, myalgia, and weariness. Uncommon are permanent diseases. Influenza causes chest discomfort. COVID-19 transmits through particles or aerosols when a patient coughs, talks, or sneezes. COVID-19 differs. It spreads fast and is dangerous when variants breed freaks. Results show abnormalities grow in severity. Fast computing advancements have resulted in the widespread use of digital image processing in medicine, including image segmentation and augmentation. Medical image processing uses Deep Learning technologies like Convolutional Neural Networks [2]. Deep learning models improve forecasting, testing, and categorising.

Sohaib Asif et al. [3] aimed to detect COVID-19 pneumonia patients digitally using X-ray images. This deep learning model identifies COVID-19's special effects, increasing categorization. 864 COVID-19, pneumonia, and normal X-rays. The data was pre-processed and enhanced, even though the system was built on massive data. M.Qjidaa et al. [4] created a clinical decision-support system to detect COVID-19 from chest X-rays. Open sources provided COVID-19, pneumonia, and normal X-rays. 30% of the three-class collection was analysed. Data from two streams were inappropriately obtained and highly processed.

Khasawneh et al. identified CNN's chest X-rays. The first photos were taken at Jordan's King Abdullah University Hospital. 63.15 years old. 31-month-old to 96-year-old. Clinics destroy. After system training and testing, data stores were employed for evaluation. Eventually, CNN, Mobile Nets, and VGG-16 models are used. Model's overfitting photographs and generalised additional details. Pooled data revealed 98.7% detection performance, while maximal techniques were somewhat less effective. COVID-19 was identified by Haiti et al. [6]. -Ray dataset images are reduced to 6400 by 80 x 80. Photo resizing and vectorizing. Reduce inequality by using 135 normal and 135 COVID-19-positive patient images. COVID-19 includes 135 drug-induced blood clots, 135 normal people, and 135 intensive-treatment patients. T2-weighted MRIs are diagnostic. 80x80 MRIs. 1:6400 image vectors X-ray-focused. Categorization strategies failed on all three datasets. The prototype compared DL and ML algorithms.

Alhwaiti, Y. et.al. [7] recommended deep learning to identify coronavirus x-rays. Since COVID-19 was released in December 2019, there was no public science dataset. The hospitals must share multiple data sources. CNN classifier, Google Net, ResNet18, and ResNet50 are pre-trained models. Also, grid search. This approach is global. CNN's training was changed. ILR, L2 regularisation, momentum, and minibatch size are coming. Precision, accuracy, sensitivity, and F1-score are estimated. Using various performance indicators, the prototype's ability to predict COVID-19 occurrences from records was objectively evaluated. GS and ResNet50 prototypes made breakthroughs. COVID-19 and CNN were created by Abiyev et al. Input image processing procedures include normal pneumonia and X-ray image database analysis, image splitting into training, validation, and testing sets, size, feature extraction, and information resampling. Comparing the newest responses to the target classes yields the error rate. The error function and learning algorithm later affect CNN signals. Images are categorised as upcoming, scaling down, feature extraction, and picture restoration. The intended modelling is a fraction of the network model that identifies if X-rays reveal COVID-19, pneumonia, or a normal case. The learning algorithm refreshes CNN's models.

Umar Ibrahim et al. [9] developed assays for viral chest infections and COVID-19. The collection contains 5856 positive and negative X-rays. 1-5-year-olds with various health issues are involved. Training, validation, and testing files. The image database is 30% of proposal testing. Training the prototype involved 50:50, 60:40, 70:30, 80:20, and 90:10. Using an 80/20 training/testing dataset, they analysed split ratios. An algorithm trained with 5740 intercepts, 20 epochs, and a 0.0001 learning rate. Later, a CNN-based model identified viral pneumonia in x-rays. Convolutional layers comprise Alex Net. Convolution, max pooling, and normalising are CONV layer processes. Two layers are joined, and one is SoftMax. In categorization training, 70:30 worked effectively. 99.84% specificity, 98.59% sensitivity.

Elshennawy et al. [10] used chest X-rays for deep-learning pneumonia models. Pneumonia Detection offered a chest X-ray dataset for training and testing. 712*439 to 2338*2025 pixels are in the image dataset. 6.5% were under 20, 26.4% were aged 20-40, and 24.3% were over 60. Next, training and validation photos are split 70/30. Photos were randomly divided into training and validation. CNN RNN, LDTM, ResNet 152v2, Mobile Net v2, and Deep Pneumonia are recommended. The recommended concepts were evaluated by using accuracy, precision, F1-score, recall, and AUC. ResNet152V2 accuracy was 99.22%, 99.43%, and 99.75%.

Shah S. et al. [11] used Convolutional Neural Networks and Kaggle's photographic resources to identify pneumonia early. Researchers used Kaggle to design this approach. Shah S. designed and built the system. Each diagnosis is generated from a publicly available chest X-ray dataset and public dataset. The American College of Radiology made this dataset public. These are all grayscale X-rays. No photo is coloured. Then, a CNN-based recommendation is made. Cengil E. et al. [12] provided a method for detecting COVID-19 as a system for deep feature concatenation in classification. This procedure detects the illness. Hypothetical occurrence order before COVID-19 diagnosis, Pipeline processes normal, COVID-19, and pneumonia data sets. Normal data is first then created a new set of attributes by applying distinct algorithms to each dataset. Various classification techniques were used to classify the components.

Deep-COVID-19 identifies COVID-19 in X-rays [13]. The COVID-19 X-ray pictures were analysed using six commercial convolutional neural networks. Picture analysis was possible. These steps were needed to analyse the study findings. VGG16, VGG19, and Mobile Nets are dependable, according to the trial. B, M., S., and others [14] classified pneumonia using chest X-rays and a CNN model. Researchers did this with CNNs (CNN). Each file contains 5840 chest x-ray images. Name for the data set. "Normal" and "pneumonia" subfolders are in each folder. The Image Data Generator class will change the dataset for training. This increases model accuracy. Our method leverages a CNN-like Xception model.

[15] CNN and deep learning were used to identify COVID-19 in thoracic X-rays. This step came first. CNN's models can now discern between classes and categorise data. After searching Kaggle, 112 pneumonia images and 112 chest X-ray photos were picked for analysis. When determining a person's performance, accuracy, precision, memory, and F1 score are considered. The final dataset is a composite of two available datasets. Deep categorization of COVID-19 radiological pictures was researched and suggested by Baseer, A., and colleagues [16], who are also advised employing neural networks. Researchers developed an innovative method for classifying chest X-ray images and made it accessible to the public on the internet. Transfer learning is utilised to provide an extract from deep neural networks that have been trained and kept up to date. This demonstrates the capability of the technique. In addition to having a classification accuracy of 97.36% overall, it has a COVID-19 classification accuracy of 99.29%.

Guefrechi et al. [17] recommended deep learning to detect COVID-19 in chest x-rays. The author employed two datasets: one with thousands of normal chest X-ray scans and another with 224*224-pixel pictures. Randomize rotation, noise, and 10-degree horizontal flips. Deep-learning techniques pre-process X-rays. Resnet50, InceptionV3, and VGG16 score 97.20, 98.10, and 98.30%. Akter et al. [18] used chest x-rays to discover COVID-19. Below may have updated images. 80:20 test/training split. The dataset uses VGG16, VGG19, MobileNetV2, InceptionV3, NFNet, ResNet50, ResNet101, Dense Net, EfficientNetB7, Alex Net, and Google Net. ResNet101 is 95% correct. MobileNetV2's accuracy is 98%. First, they computerised COVID-19 detection in chest X-rays. 959 X-rays, 250 cases of bacterial and viral pneumonia. Dataset-2 covers bacterial and viral pneumonia. Pre-processing lowered photo sizes so all pretrained models had the same resolution. Photos are 1102 to 2280 pixels wide. The image has been pre-processed to enhance certain aspects while hiding other details. ResNet50, InceptionV3, NASNetMobile, and VGG16 are some of the CNN transfer learning models. MobileNetv2, one of the usable models, was shown to be 81% as accurate as DenseNet121 [19].

III. METHODOLOGY

The goal of this project is to identify several methods for quickly identifying a disease from X-ray chest images and then to reliably classify the diagnostic images into COVID-19 or normal, viral pneumonia using multiclass classification.

A deep learning model often entails various workflow processes.

a). Data collection
b). Data Pre-processing and Augmentation
c). Select the model.
d). Prepare your model
e). Assess the model.

Finding relevant data and gathering data to be sent as input to the network are the first steps in this study. Several image processing techniques are used to pre-process the data. Pre-processing is a technique for performing operations on low-quality photos to enhance the image quality or to extract relevant data from the images, including feature extractions. The next stage is to choose a deep learning model that operates well and produces cutting-edge outcomes. The most crucial stage in the process flow is then training the model, where the best model is chosen to train the data and the entire evaluation is based on how the model is trained. The training model is a dataset used to train the model, which compares the input and output data against a sample output and modifies the model as needed. This is referred to as "Model fitting." The model that has been trained must be evaluated as the last stage. In this step, the model will be evaluated using the training and validation datasets. The general process flowchart for our deep-learning survey is shown in Fig.1.

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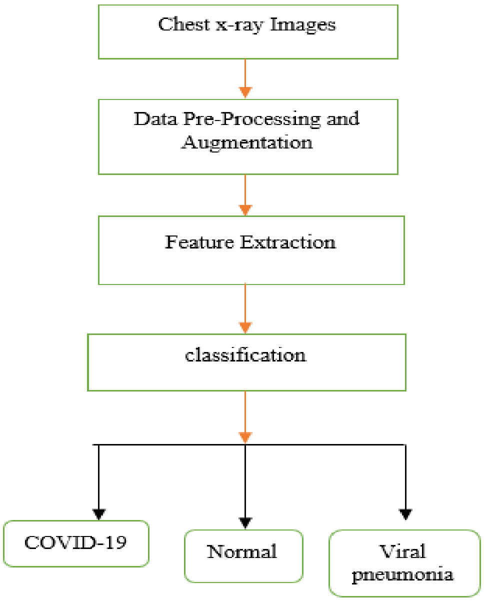

Figure 1. Generic Process Flowchart

A. Data Set

In general, the dataset will be collected from kaggle.com [20] which is under open access, where the dataset consists of CXR images along with the 4 classes covid-19, normal, viral pneumonia and bacterial pneumonia with different input shapes like 224*224 pixels and the colour format of the CXR scan images is grayscale. It has 317 total images, 317 of which are normal chest X-rays and 317 of which are cleaned COVID-19 images organized into the test and training directories.

TABLE I.
CHEST X-RAY DATASET

	Total
COVID-19	137
Normal	90
Viral pneumonia	90

B. Training, Testing

The dataset was divided into 70% training and 30% testing for each class as shown in table 2.

TABLE II.
CHEST X-RAY DATASET DISTRIBUTION DURING TRAINING AND TESTING

	Training	Testing
COVID-19	111	26
Normal	70	20
Viral pneumonia	70	20

C. Data Pre-Processing

The initial steps in the deep learning workflow are to prepare the raw image data into formatted data. The steps present in the image data pre-processing are reading the image, resizing the image, removing the noise and making the images into a Denoising format. In the case of this proposed dataset images had high a resolution but the possible solution is to resize images to smaller dimensions to simplify the model training process. We have chosen 224 * 224 * 3 as our image tensor input to our network input.

D. Data Augmentation

A big dataset is often necessary for DL algorithms to overcome issues like overfitting. As a result, algorithms used in practical applications face a general obstacle. The task of collecting and analysing data can be time-consuming, which is why the task of labelling could also require domain experts. An augmentation technique is commonly used to expand existing datasets. In this study, the considered traditional augmentation methods to study how COVID-19, normal and pneumonia(viral pneumonia) diseases are detected, which have proven effective in numerous studies worldwide. As part of these processes, simple image processing changes like rotations, noise reduction, or blurring are implemented at the pixel level to introduce distortions to images. Our data has been subjected to various rotations by various angles, and perspectives, as well as affine, shearing, shifting, and mirroring procedures that preserve the dimensions of our training data.

E. Deep Models Selection, Training and Validation

The various deep learning models had been selected as shown in fig 3. The hyper matters that are used during the training of the model are shown in table 4.

TABLE III.
THE DEEP LEARNING HYPERPARAMETER

Parameters	Values
Batch size	32
Number of Epochs	150
Optimizer	Adam
The activation function of the last classifier layer	SoftMax
Learning Rate	0.0001
Dropout	0.6

TABLE IV.
4 X 4 CONFUSION MATRIX

	PREDICTED LABELS		
ACTUAL LABELS	TN	FN	TN
	FP	TP	FP
	TN	FN	TN

F. Deep Learning Image Classifiers

Using chest X-ray scans, deep-learning image classifiers can identify COVID-19, normal, and pneumonia diseases. The process of our methodology is depicted in Figure 2 and includes 13 different pre-trained CNN models, including the VGG16, VGG19, Xception, Densenet121, Densenet169, and densenet201.

IV. MODEL PROCESS

In this process, the models developed for one task are used as the foundation for another model. The enormous amount of computing power and time required to develop neural network models for these problems makes using pre-trained models a common approach in deep learning for obtaining skill jumps on related problems. The model process as shown below in fig 2.

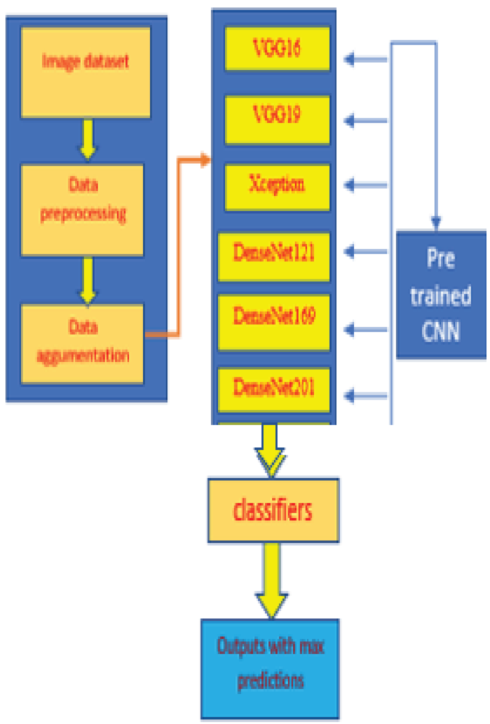

Figure 2. Model Process

VGG16: The 16 in VGG16 denotes the fact that there are 16 layers with weights. This network has roughly 138 million parameters, making it a sizable network. It has a faster training speed, fewer training samples per time, and higher accuracy. If there is not enough data or if the model is too big, then it can't get the good accuracy rate needed.

The VGG16 pre-trained CNN model has some experience with the data from ImageNet. The VGG16 model receives input from images that have a resolution of 224x224x3 pixels. Following that is a pooling layer, which brings the height and breadth of the image down to 112 x 112 x 64, and then there are two convolutional layers, each of which has a size of 224 224 x 64. After that, the image is cut up into two conv128 layers, each of which is 112 by 112 by 128 pixels. This is followed by a pooling layer, which brings the height and width of the image back down to 56 by 56 by 128. The size of the image is then decreased to 28x28x256 by using a pooling layer, and this is followed by three conv256 layers, each of which measures 56x56x256. After that, there are three conv512 layers, and each one has a size of 28x28x512 pixels. Finally, there is a pooling layer that brings the image down to 14x14x512 pixels. The next layer is a pooling layer, which contains 7x7x521 layers, followed by three conv512 layers, each of which contains 14x14x521 levels, and ultimately, two dense or fully connected layers, each of which contains 4096, 4096, and 4096 nodes. The last layer is a dense layer, which is also called an output layer as shown in fig 3. It has a thousand nodes and can put an image network into one of three groups.

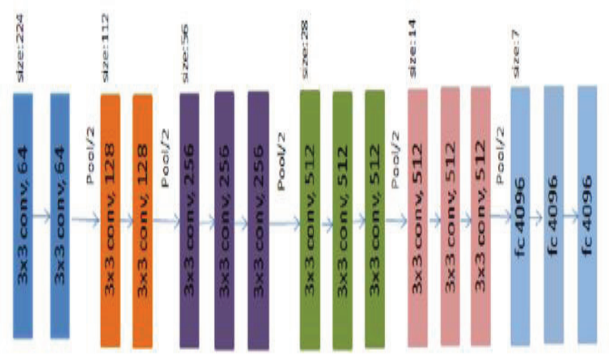

Figure 3. VGG16 Architecture

VGG19: A convolutional neural network with 19 layers is called VGG-19. It is an image recognition model. This survey made use of the pre-trained CNN network. In ResNet50V2, a modification was made in the propagation formulation of the connections between blocks. The deep networks are hard to train because of the vanishing gradient problem. The complexity of the architecture is more.

The VGG19 network contains two completely connected layers with a total of 4096 channels in each, followed by a third fully connected layer that predicts three different labels using 512, 256, and 128 channels, respectively. When it comes to classification, the SoftMax layer is the very last fully connected layer that is employed. Convolutional layers with 3*3 filters make up the first two layers of this image. Because the first two layers each utilise the same 64 filters, the total volume of the effect is 224*224*64. This is because the convolutions used are the same. Each of the filters always consists of a 3 x 3 step. The height and width of the volume were then reduced from 224 by 224 by 64 units to 112 by 112 by 64 units with the use of a pooling layer that had a maximum pool size of 2 by 2 and a stride of 2. The subsequent two convolutional layers, each of which has 128 filters, are identical. The result is a new dimension of 112 x 112 x 128. As soon as the pooling layer is utilized, the volume is reduced to 56 by 56 by 128. Down sampling brings the size down to 28*28*256 after the addition of two further convolutional layers, each of which has 256 filters. Following that will be two further stacks, each one consists of three convolutional layers and being separated by a max-pool layer. The last layer of pooling, which is a 7*7*512 volume, is flattened to an FC

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layer, which has a set number of channels and a soft maximum output of three classes.

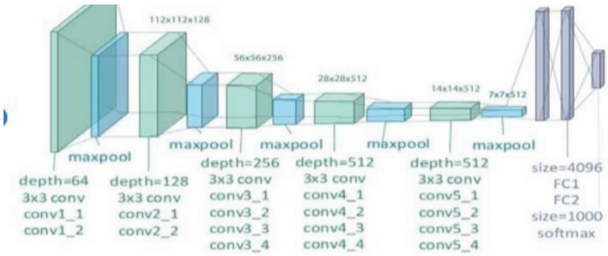

Figure 4. VGG19 Model

Xception: It is an extreme improvisation of Inception that serves as a different pre-trained model in many ways. This model consists of 3 blocks entry flow, middle flow, and exit flow as shown in fig 5. The implication of greater computational efficiency is the advantage It is still computationally inefficient because of convolutions.

In the xception model, the entry flow consists of the input image with a size of 299x299x3, then conv32 followed by 3x3 and with a stride of 2x2. Then conv64, followed by a 3x3 size of the convoluted image size. Then it adds three conv of 1x1 followed by the stride of 2x2. Internally, it consists of separable conv128,256,728 and max pooling of 3x3 with a stride of 2x2. Then it adds 19x19x728 feature maps. The middle flow consists of separable conv728 with a 3x3 convoluted image size, and the same step repeats 8 times. Then later moves to the exit flow by adding the 19x19x728 feature maps to one conv1x1 followed by the stride of 2x2 internally consisting of separable conv728,1024 and max pooling of 3x3 with a stride of 2x2. Finally, the exit flow is separable from 1536 and 2048 with a 3x3 convoluted image size. All layers are made up of Relu and global average pooling, then 2048 dimensional layers and fully connected layers that can be turned on or off.

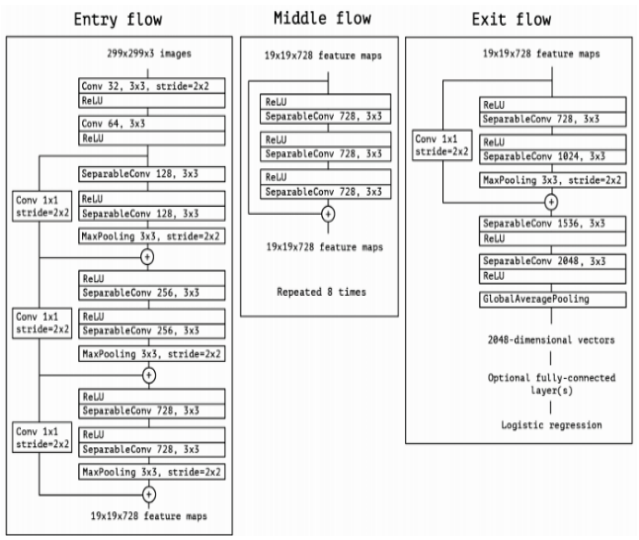

Figure 5. Xception Blocks

DenseNet121: It is a CNN that connects to the deeper layers of the network, with the first layer connecting to the second, third, and fourth layers, and the second layer connecting to the third, fourth, and fifth layers, etc. Therefore, in this survey, this was chosen as the pre-trained model. they alleviate the vanishing gradient problem, strengthen feature propagation, and encourage feature reuse. substantially reduce the number of parameters. The class imbalance is the major challenge while training the model as shown below in fig 6.

The DenseNet121 consists of input with the size of 224x224x3. The DenseNet-121 has [6,12,24,16] layers in the four dense blocks consisting of Conv(7x7,1x1,3x3), with an average pooling of stride 2 and maximum pooling of 3x3 and global average pooling of 7x7 then finally the fully connected layer with SoftMax activation function then finally classifies the output.

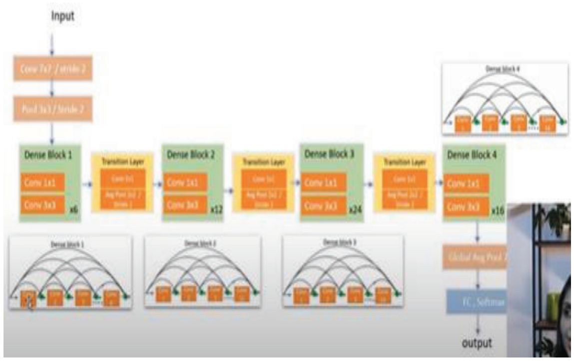

Figure 6. DenseNet121 Blocks

DenseNet169: The Dense Net -169 model is one of the models in the Dense Net family designed for image classification. The main variations are in the Dense Net -121 model's size and accuracy. The Dense Net -169 is larger at just over 55MB compared to the Dense Net -121 model's roughly 31MB size. The strong gradient flow, High parameters and high computational efficiency. Maintains low complexity features.

The DenseNet169 pretrained model consists of an input image with a size of 224x224x3. Then it consists of the convolution layer. In DenseNet-169, it has 3 dense blocks. Each dense block has [6, 12, 32, 32] layers. In between each block, there is a conv, pooling layers where the pooling layers are used to reduce the feature map size. The feature map sizes match each block. Finally, it consists of a pooling layer and FC as linear. Then it displays the output as depicted in fig 7.

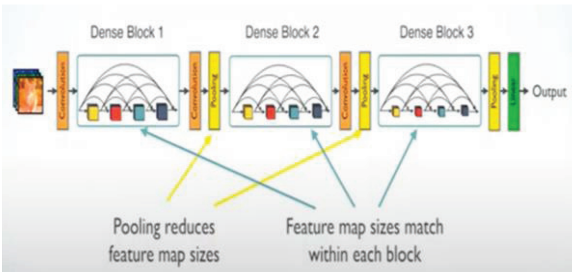

Figure 7. DenseNet169 Architecture

DenseNet201: A convolutional neural network with 201 layers is called DenseNet-201. A version of the network that

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has already been trained on more than a million images is stored in the ImageNet database. They alleviate the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse and substantially reduce the number of parameters. The disadvantage of the classifier is more prone to overfitting.

The pretrained DenseNet201 consists of an input with a size of 224x224x3, DenseNet-201 model optimization, where the number of hidden layers is 512, 128, 64, 32. In this model, each dense block consists of 16 convolutional layers. In batch normalization, the transition layer is used as a connecter between every block. Relu activation function and a SoftMax activation function are used as shown in fig 8.

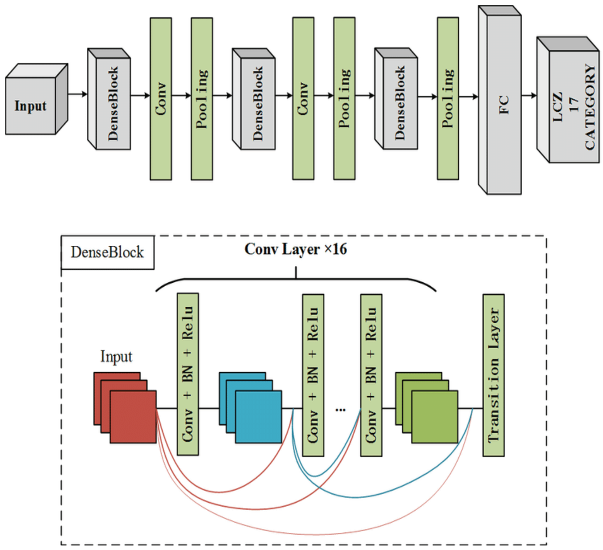

Figure 8. DenseNet201 Blocks

Experimental Setup

To implement the proposed work deep learning techniques the following hardware and software support shown below: Processor: 11th Gen Intel(R) Core (TM) i5-1135G7 @ 2.40GHz 2.42 GHz, RAM: 8.00 GB, Storage: 476 GB, Nvidia GPU. OS: Windows, Python: 3.10.5 version, TensorFlow: 2.8.2 version, Open CV2 python: 4.6.0 version, other necessary modules.

V. OBSERVATIONS

The proposed models are trained for 150 epochs using the Adam optimizer, learning rate and the momentum to 0.0001, Loss is employed here as the loss criterion and is used as the output of the procedure to correct any existing labels.

The models were trained by using an augmented dataset that included images from augmentation and actual images. A validation test was then performed to assess its generalizability. The training and validation phases of the proposed network show good convergence showed in Figure 16 illustrates the training loss and validation loss distributions based on the number of epochs in both phases. The curve shows the number of images that were correctly identified during validation as shown in fig 9.

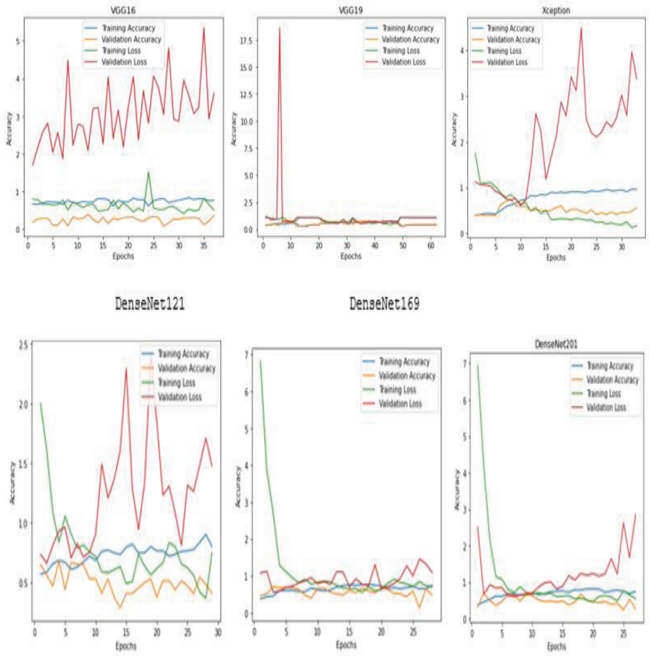

Figure 9. Corresponding Accuracy and Loss Curves

In a confusion matrix, the numerical values of test data for which the true values are known are used to rate the performance of a classification model. Fig.18 shows the confusion matrix on the detection dataset. The matrix shows the misclassified and correctly classified images. As shown in the matrix y-axis represents the true labels and the x-axis shows the predicted/detected labels., Class predictions are of two types: yes or no. In our example, positive results would indicate the presence of a disease, and negative results would indicate the absence of the disease.

Further, The evaluated classifiers using the following metrics: Accuracy, Precision, Recall, and F1-score metrics as shown in fig 10.

Accuracy: The accuracy of data classification refers to the percentage of correct classifications over total instances.

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

Precision: For a good classification system, the precision should be as high as 1. TP = TP + FP and FP is equal to zero when TP = TP + FP which means that precision is 1 when the numerator and denominator are equal. Due to the increase in FP, the denominator's value becomes larger than the numerator's value, and when this happens, precision will decrease.

$$\text{Precision} = \frac{\text{TP}}{\text{FP} + \text{TP}}$$

Recall: For a classifier to be effective, the recall should be high. A classifier is effective only when both the denominator and the numerator match; TP = TP + FN, which also implies FN is zero. As FN increases, the numerator increases, and the denominator decreases. The recall rate is also referred to as the sensitivity rate or true positive rate, and it is calculated in the following way:

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

F1-Score: This would like ideally for both precision and recall to be a weighted sum of ones within a good classifier, which also means that FP and FN count for nothing. As a consequence, they developed a metric that takes precision as well as recall into account. In the F1-score measurement system, accuracy and recall are both taken into account, and what is defined as follows:

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

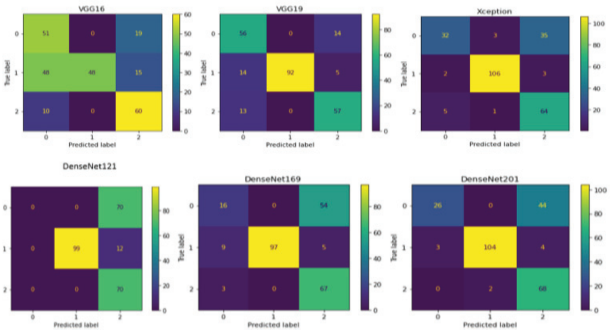

Figure 10. Corresponding Results of The Confusion Matrix

The statistics of accuracy, precision, recognition, F1 score and AUC are shown in Table 5 to illustrate the performance validation of the different models. Of all the classification methods, A classification accuracy of 100% was achieved by densenet121net, densenet201 had the highest percentage of correct classifications (89.66%). The VGG19 highest recall score is 80.00%. For general classification purposes, VGG19 performed best compared to all other methods with an F1 score of 73.20%. Overall, densenet201's AUC for classification is the highest at 97%.

TABLE V.
OVERALL COVID-19 CLASS ACCURACY, PRECISION, RECALL, F1-SCORE, AND AUC VALUES FOR COVID-19

COVID-19					
Models	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Accuracy**
VGG16	72.85	46.79	72.86	56.98	87
VGG19	80.00	67.47	**80.00**	**73.20**	94
Xception	50.00	82.05	45.71	58.72	94
DenseNet121	**1.00**	00.00	00.00	00.00	92
DenseNet169	77.14	57.14	22.86	32.65	91
DenseNet201	62.85	**89.66**	37.14	52.53	**97**

Table 6 shows performance validation statistics for various models, including accuracy, precision, recall rates, F1 values, and area under the curves. Mobilenetv3large achieved the highest accuracy of 95.49% among the categorization approaches. Densenet121, VGG16, and densenet169 achieved a perfect precision classification rate of 100%. The highest rate of correct recall classification (95.50%) was achieved by Xception and an unprecedented F1 of 97.72%, making it the most effective approach for general categorization. Overall, the best AUC for classification is achieved by densenet201, and mobile Net, all of which achieve a value of 100%.

TABLE VI.
OVERALL NORMAL CLASS ACCURACY, PRECISION, RECALL,

Normal					
Models	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Auc**
VGG16	43.24	**1.00**	43.24	60.38	99
VGG19	82.88	1.00	82.88	90.64	98
Xception	**95.49**	96.36	**95.50**	**95.93**	99
DenseNet121	89.19	**1.00**	89.19	94.29	99
DenseNet169	87.38	**1.00**	87.39	93.27	99
DenseNet201	93.69	98.11	93.69	95.85	**100**

In Table 7, the accuracy, precision, area under the curves, F1 values, and recall rates along with the performance validation information for a variety of models. The different classification strategies of densenet201 achieved the highest accuracy of 97.14%. VGG19 classified the precision as 75%. Densenet121 was classified with a recall value of 100%. VGG19 was found to be the most effective method for broad-based classification with an F1 score of 78.08%.

TABLE VII.
OVERALL ACCURACY, PRECISION, RECALL, F1-SCORE, AND AUC VALUES FOR PNEUMONIA (VIRAL PNEUMONIA)

Pneumonia (Viral pneumonia)					
Models	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Auc**
VGG16	85.71	63.38	85.71	73.17	93
VGG19	81.42	**75.00**	81.43	**78.08**	95
Xception	91.42	62.75	91.43	74.42	88
DenseNet121	1.00	46.05	**1.00**	63.06	97
DenseNet169	95.71	53.17	95.71	68.37	94
DenseNet201	**97.14**	58.62	97.14	73.12	**99**

VI. FUTURE SCOPE

The possible future directions for developing this research is consisting of multiple models are used and their predictions combined, an ensemble approach is employed, which can improve results. Image classification and the identification of

COVID-19, normal and pneumonia illnesses can be improved using various deep learning algorithms, such as Deep CNN and hybrid models. The Adam optimizer and other optimization methods can be used because they are efficient and have low memory traces. Efficient Net is the latest version of the Efficient Net family network that was developed in 2021. Efficient Net improves accuracy by introducing several architectural reforms.

VII. Conclusions

This study shows that CXR images with a variety of deep learning algorithms can be used to sort images into three groups: pneumonia (viral pneumonia), normal, and COVID-19. In the above study, an automated prediction model based on CXR scan image processing and classification approaches was built to detect and classify COVID -19, normal, and pneumonia disease from real-time chest radiographs. Model performance and graphs of many other transfer learning models were compared. For a deeper CNN model, more image data are needed to generalize it effectively. Therefore, the dataset was enlarged after pre-processing. The last step was to apply transfer learning to known pre-trained models. The proposed model and dataset were both perfected through several tests. When comparing the VGG, Dense Net, and Xception families with different versions of the COVID -19 image dataset, densenet121 achieved the highest model classification accuracy for COVID-19 at 100%, xception of the normal class achieved 95.49% and densenet201 achieved the highest for the viral pneumonia class is 97.14%. Doctors and researchers use the model for computer-aided diagnosis of COVID -19, normal and pneumonia (viral pneumonia) including cancer and diabetic retinopathy. The model was developed using medical imaging techniques for healthcare applications.

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