A Review of COVID-19 Patients in Chest X-Ray Imagesusing InceptionV3

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Abstract- COVID-19 is a viral infection caused by a novel coronavirus. It causes the lungs' air sacs to enlarge. It can be diagnosed with a chest X-ray (CXR) imaging, which is usually less expensive and safer than a CT scan and is always available in small or remote facilities. X-ray machines, on the other hand, do not always diagnose COVID-19. Because the COVID-19 dataset is small and cannot be diagnosed from a CXR, coronavirus diagnosis can be done using pre-trained neural networks. The major purpose of this research is to use pre-trained deep transfer learning (DTL) architectures and traditional machine learning (ML) models to autonomously diagnose COVID-19 from CXRs. Because there aren't many photos, DTL is employed to extract image features that aid in classification.

Keywords- CXR, deep transfer learning etc.

I. INTRODUCTION

The Wuhan Municipal Health Commission in China presented the first report on COVID-19 in December 2019. One of the deadliest global pandemics in history, itis caused by the SARS-CoV-2 (severe acute respiratory syndrome coronavirus) [1]. Since the World Health Organization (WHO) declared the COVID-19 outbreak a pandemic in March 2020, there have been 203,944,144 cases and 4,312,902 fatalities globally, according to WHO estimates as of 12 August 2021 (available at https://covid19.who.int/table; seen on 12 August 2021). The pandemic condition has had a negative social, medical, and economic impact on people. When this infectious disease is severe, it commonly results in pneumonia and acute respiratory syndrome. The outbreak was thought to have started due to zoonotic spread from seafood markets in Wuhan, China. Later, it was thought that human-to-human transmission was responsible for the virus's spread across populations around the world, affecting 200 or so countries [2,3,4,5]. Although persons of all ages are susceptible to infection, those 60 and older, as well as those with coexisting diseases, are at a higher risk of developing severe COVID-19 symptoms.

II. RELATED WORKS

CHANGJIAN ZHOU et al. [2021] As the COVID-19 virus spreads over the world, countries are taking proactive steps to combat the outbreak. To stop it from spreading, a COVID-19 detection method with great sensitivity and efficiency is required. This work presented
a combination technique for image regrouping with ResNet-SVM based on the COVID-19 breast X-ray pictures. The lung region was segmented and separated into little parts from the source chest X-ray images, and afterwards the small bits of lung region was randomly reunited into a regular image. For feature extraction, the regrouped images were also sent into the deep residue encoder block. Finally, the collected features were fed into a recognition support vector machine. [1]

Tatiana Chakravorti et al. [2021]On the prepared dataset, the suggested model was trained and evaluated, and it was discovered that the accuracy rate for the two class categorization (COVID 19 vs Healthy) was 95 percent, with precision and recall rates of 95 percent. Because of its simplicity, the suggested model's performance is highly promising, and it could be a very useful tool for radiologists & clinical practitioners in the detection and categorization of COVID 19.

Furthermore, this paper presents a comparison of the suggested technique to ELM, which will aid researchers intheir subsequent research. [2]

Shivani Sharma &Shamik Tiwari. [2021]In the classification of Chest X-Ray images, the suggested model achieved an accuracy rate of 94% for three classes. The primary motivation for creating this model was to reduce computing time by employing fewer layers and much more hyper parameter adjustment. The suggested model is contrasted to previous models, which were more sophisticated and took a long time to train. On the test dataset, 94 percent accuracy has been attained so far. The impacts of a global pandemic outbreak have been seen in the year 2020, thanks to the extraordinary spread of the novel coronal virus COVID-19. [3].

Kavya Garlapati et al. [2021] The goal of this study was to present an automatic detection based on lung X-ray pictures, as radiography modalities are a potential way to diagnose diseases quickly. We used X-ray pictures from publically available sets of data of 2000 pictures to create a deep learning model in this study. Prior to applying correct segmentation to the X-ray pictures, the significant bits from of the photos were taken for developing the model. X-ray pictures are susceptible to noise & spatial aliasing, making the boundary indistinct, necessitating accurate image segmentation [4].

Zehra KARHAN &Fuat AKAL. [2021] The Covid-19 virus, which developed in the Chinese government for unknown reasons, soon spread throughout the world. To prevent the outbreak from spreading further, it is critical to find positive cases as soon as possible. The RT-PCR (Reverse Translation Chain Reaction) test, as well as radiographic imaging of the chest, are both diagnostic in the diagnostic phase. The ResNet50 model, which really is a deep neural networks design in Covid-19 detection utilising chest x-ray images, was used to classify it. Artificial intelligence allows for fast analysis of chest X- ray images and identification of diseased individuals. In terms of the utilisation of computer-aided in pathology, thetrial results are promising. [5]

Sohaib Asif et al. [2020] aimed to use deep cnn to detect COVID-19 influenza patients utilizing digital chest x-ray pictures while maximising detection accuracy (DCNN). There are 864 COVID-19, 1345 viral pneumonia, and 1341 normal chest x-ray images in the collection. In this study, a DCNN-based model called Inception V3 plus transfer learning was developed for detecting coronavirus pneumonia infected people using chest X-ray radiographs, with a classification accuracy of above 98 percent(training accuracy of 97 percent and validation accuracy of93 percent). The findings reveal that transfer learning for COVID-19 detection is effective, has a stable performance, and is a simple to implement method[6]

Irma Permata Sari et al. [2020] On March 12, 2020, the World Health Organization (WHO) declared a global pandemic due to an increase in Covid-19 infections. Around 188 countries have been affected by the pandemic. Healthcare experts have regularly done laboratory tests to ensure that patients receive accurate results, such as checking the patient's lungs' chest CT pictures. This is an important role in clinical therapy and instruction. We attempted to classify a chest CT image of a Covid-19 patient in this paper. Because CNN extracts spatial characteristics from images, it provides a quick technique to solve image classification problems. Experiments are used to evaluate three strategies. [7]

Ronaldus Morgan James et al. [2020] analyses how to process two-dimensional information from patients' X-ray images using in-depth features and algorithms. The Convolutional Neural Network (CNN) is indeed a variation of the Multi-Layer Perceptron (MLP), which would be designed to analyse two-dimensional or image input. The convolution layer CNN model's deep featuresare recovered and can be categorised without the use of any further approaches. The CNN method is chosen because of its high performance when dealing with big datasets for training and validation. The dataset contains
160 x-ray pictures in the classification process and is divided into two categories: COVID-19 and normal, which reflect a positively or negatively classification for Covid- 19 infection in a patient. [8]

SaiYeshwanthChaganti et al. examined a range of research publications on image classification, each from a different angle, and then opted to use the limited resources. They hand on to implement image categorization on a small scale. They started using SVM and a very minimal dataset and were able to attain a 93 percent accuracy. Even though SVM is a powerful approach, getting such high accuracy is still unusual. Theyconcluded that the results were so accurate because they didn't have a large enough dataset. As a result of data augmentation, they were able to increase the size of our dataset by more than threefold. [9]

III Types of Classification Techniques

Based on the interaction between the researcher and the machine during classification, there are two forms of classification: supervised and unsupervised.

1. Unsupervised Classification (UC)

UC is done without the assistance of an analyst, as the name implies. Similar pixel values are automatically grouped by an algorithm, which serves as the foundation for distinct classes. Clustering is a technique that is solely dependent on the details of the image data distribution. Lacking the use of any knowledge-based controller, the procedure is inevitably optimized based on cluster statistics. As a result, the process is objective and data- driven. It's especially well-suitable to photographs of goals or places wherever no ground knowledge exists. Unsupervised categorization, even for a well-planned area, may uncover spectral patterns that were previously undetectable. Figure 1 depicts the essential phases of unsupervised categorization.

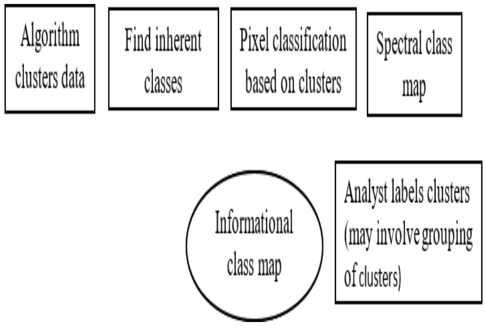

Figure 1 Steps of UC.

An image of arithmetical collections is the outcome of unsupervised classification, Image Classification, where the classified image still requires interpretation based on data of the clusters' subject contents. For unsupervised categorization, there are hundreds of clustering algorithms to choose from, each with its efficiency and purpose.

2. Supervised Classification (SC)

As the term suggests, supervised classification necessitates human intervention. An expert chooses a set of contiguous pixels from a training area in an image to establish DN values in each channel for a class. A classification method determines the attributes of a group of training pixels, such as the mean DN for each channel. The properties of the training set are then compared to the DN values of each pixel in the image. This is dependent on the statistics of training regions that represent various ground objects that users subjectively choose based on their knowledge or experience. Users' knowledge controls classification, but itis confined and may even be prejudiced by their subjective viewpoint. Unsuitable or erroneous training, range information, and/or limited user expertise can all lead to classification errors. Figure 2 depicts the steps involved in supervised categorization.

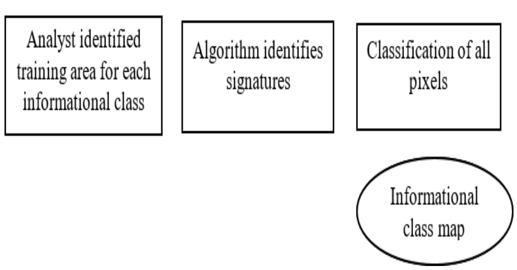

Figure 2 Steps involved in supervised classification

3. Architectures of Pre-trained Models

For feature extraction (FE), all of the CL was used in all pre-trained networks. To categorize the images, we substitute the fully connected and dense layer with our layers. We unfreeze the last handful of blocks before fully connecting the layers after fine-tuning. Using the back propagation technique, these blocks modify their weights about the loss function. Take a look at some of the architectures. **4. LeNet-5**

Originally, the LeNet-5 was used to classify digits and identify handwritten numbers in checks that were digitized in a 32*32-pixel input image. The use of the LeNet-5 for high-resolution images was aided by the addition of more convolutional layers. The LeNet-5 CNN architecture is displayed in figure 3. The LeNet-5 is a with five distinct planes and five convolutional layers. The planes are essentially featured maps that display a group of units with weights that have been determined to be related. The first of five convolutional layers has six learning filters. To update values, filters must be stepped across. Kernel standards are computed and then fed forward to calculate the loss, after which back propagation is used to update the model. Several convolution filters are utilized for the layers, resulting in various sizes.

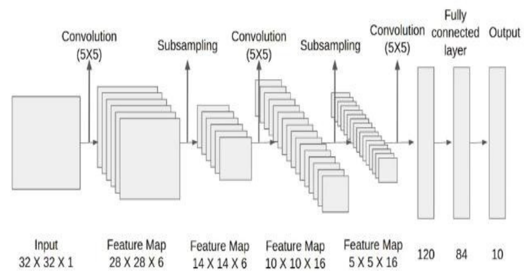

Figure 3 Architecture of Lenet-5

5. Alexnet

AlexNet was a significantly larger CNN than others at the time, such as VGG, and it was initially utilized in computer vision tasks. AlexNet had 60 million parameters. It has 650,000 neurons and, in comparison to the GTX 580 3GB GPUs of the past, is now supported by much faster GPUs. It has three fully linked layers and five convolutional layers. Kernels are multi-convoluted structures that can extract features from single images. The first convoluted layer contains up to 96 kernels, each of which is 11*11*3 in size. The kernels are the same diameter and height and are sized at 11. The number of channels employed will determine the depth[30]. AlexNet has max-pooling layers, starting with the fifth CL and ending with the max-pooling layer, the output of which is displayed in a connected series of layers. In this case, a soft-max classifier is applied.

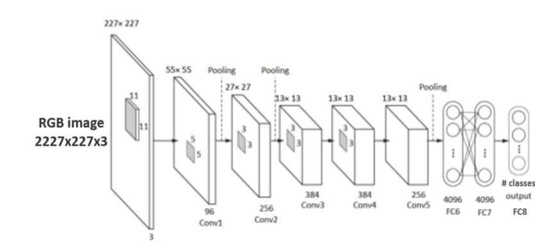

Figure 4 shows the basic architecture of Alexnet.

6. VGG 16

VGG Net also known as VGG-16 includes roughly 16 CL.It has a fairly consistent framework, which is one of its advantages. The VGG Net and AlexNet have a lot in common. The VGG has only 3x3 convolutions, just like AlexNet. However, because of the number of filters applied, it differs from AlexNet. VGG employs a large number of filters in comparison to AlexnNet.The architecture of VGG 16 is shown in figure 5. The CNN training takes place over 2-3 weeks. The training is done on four GPUs. This looks to be the preferable choice in current performance and CNN circumstances due to its uniform architecture and the filters it employs, making it excellent for sophisticated mage extraction or categorization. The VGG-16's weight configuration is open to the public. The weights are often used as a starting point for developing feature extraction in many applications. While these are some of the beneficial characteristics of the VGG Net that make it easier to use, others, such as its settings, add to the complexity. VGG Net has over 138 million parameters, which can be confusing and difficult for some users.

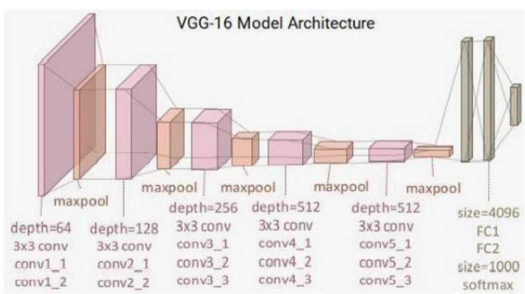

Figure 5 Architecture of VGG- 16

7. ResNet

In comparison to other CNN architectures, the residual neural network was introduced with a revolutionary architecture as shown in figure 6. It has skip connections, often known as gated units. Batch normalization is one of its key features. The ResNet-20 can train NN with up to 152 layers thanks to this capability. In other CNNs, these layers result in a large level of complexity, but not for the ResNet. This CNN has low complexity and a 3.57 percent error rate on datasets, making it a top performer.

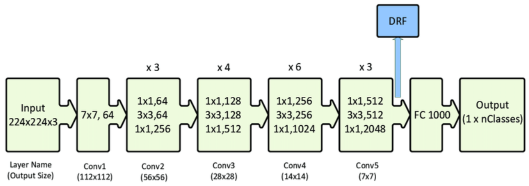

Figure 6 Architecture of ResNet

IV. CONCLUSION

A new coronavirus disease (COVID-19) emerged at the end of 2019 and had a huge impact on the world. More than 150 million people have been infected and more than 3 million have died as a result of the rapidly spreading virus as of April 8th, 2021. It is still a hindrance to us today. Deep learning researchers have devoted a lot of time and effort to the study of COVID-19 by analyzing chest CT and X-ray images. In order to diagnose COVID- 19, laboratories around the world use real-time reverse transcription polymerase chain reaction (RT-PCR) This method, however, has some drawbacks due to the insufficient quantity and quality of nucleic acids isolated. False-negative results can result from this. Another drawback is the requirement for both human effort and expertise. Because of this, an alternative method to the RT-PCR test that can be automated, assisted, or even replaced, could have a significant effect.

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