Covid 19 Recognition Using Deep Learning Algorithm

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Abstract- *Because of the COVID-19 epidemic, the whole globe is now experiencing a health catastrophe that is unprecedented in its sort. Researchers are worried about finding ways to halt the pandemic and preserve lives as the coronavirus spreads. The issues brought on by pandemics have been addressed partly through adopting artificial intelligence. In this paper, we construct a deep learning system to recognize COVID-19 from chest X-ray pictures and extract characteristics from the photos. An expanded dataset, created by combining COVID-19 and standard chest X-ray pictures from public sources, has been fine-tuned on two potent networks, namely CNN and VGG19. The findings provide excellent performance and simple COVID-19 identification techniques, demonstrating the effectiveness of transfer learning. This makes it possible to accurately automate the process of interpreting X-ray pictures, and it may also be used when the materials and RT-PCR tests are few.*

Keywords- COVID-19, X-ray, RTPCR, AI, CNN, VGG19.

I. INTRODUCTION

Wuhan, China, had the first COVID-19 case in December 2019. Two months have seen over 5000 suspected cases, and 1000 confirmed cases. New coronavirus pneumonia became a global epidemic by September 2020 as cases increased daily. Early in the pandemic, the new coronavirus was unknown. Dr. Nanshan Zhong's COVID-19 explanation states that the new coronavirus and the SARS bat-like coronavirus (Bat-SL-CoVZC45) share approximately 85% homology. China's novel coronavirus pneumonia clinical characteristics were studied by the Zhong Nanshan academic team.

Clinical samples and studies, encompassing 1099 positive subjects, were analyzed to determine the clinical features of the novel coronavirus pneumonia infection.Particular attention was paid to the radiological characteristics of the patients as well as their essential symptoms.Isolation should persist for 1–14 days, according to the "Novel Coronavirus Infection Pneumonia Diagnosis and Treatment Plan" by the National Health Commission. Epidemiological studies also advise monitoring based on clinical pneumonia symptoms, illness features, laboratory nasopharyngeal swabs, and the findings of negative or positive tests.

SARS-CoV-2 is an uncommon coronavirus, even though coronaviruses are not new. It is quite likely that this virus got its start in an animal reservoir. Treatments used for other coronavirus transmissions differ from those used to evaluate and treat patients with COVID-19. Yet as the epidemic spreads, so does our understanding of the illness, which is still restricted. Fever, coughing, exhaustion, sore throats, and body pains are typical COVID-19 symptoms, and several cases of loss of taste or smell have been documented globally. Patients may have breathing difficulties, a high temperature, chills, exhaustion, muscular or body pains, or even pass away in infrequent but often more severe instances.

The polymerase chain reaction (PCR) test, utilized in the standard COVID-19 test, looks for the presence of infection antibodies. These tests, however, are time-consuming, require great accuracy, and carry a non-negligible risk of false negatives. It should go without saying that drawing the incorrect conclusion that the virus does not exist may have negative consequences and is inconsistent with efforts made by governments to control the virus' spread.In addition, many countries lack the financial resources to use COVID-19 exams and testing facilities broadly. An alternate approach to the PCR test is radiography chest image analysis, which avoids these problems.

The rapid spread of COVID-19 puts healthcare systems under a lot of strain, but if a reliable technique is created for detecting infections, this spread may be significantly slowed down.Finding rapid means to identify the illness was a tremendous task for medical professionals and researchers. Serious issues include acute renal failure, septic shock, heart attacks, and pulmonary edema may be brought on by a COVID-19 infection. It is essential to locate and isolate infected individuals as soon as possible to stop and manage the COVID-19 epidemic.The frequency of COVID-19 incidence reported in the most affected nations globally is shown in Fig.1. Out of a total of 185,039,249 documented illnesses, and the United States leads the world with 63,390,876 cases.

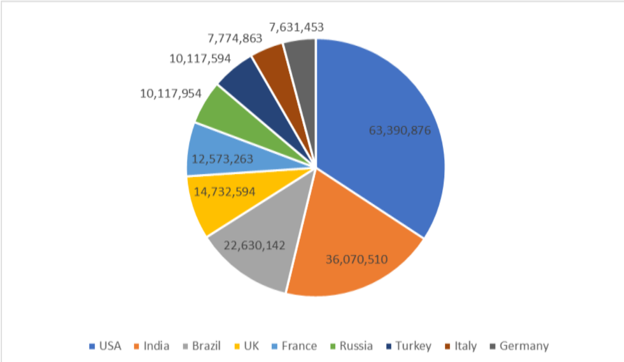


Fig.1. Confirmed COVID-19 cases globally (January 15, 2022)

Real-time polymerase chain reaction is the most used method of COVID-19 detection (RT-PCR). It may take up to two days to get results, generate a significant number of false-negative results, and have a sensitivity range of 70 to 90 [9]. Additionally, it has a significant percentage of false-negative results. Due to the enormous volume of tests that need to be evaluated, it might take up to five days or more in certain nations.

Moreover, radiological screening procedures, including computed tomography and CXR, are used to identify and diagnose COVID-19 (CT). Since it is a quick, low-cost, widely used clinical technique that exposes the patient to less radiation than CTs, CXR is one of the most successful ways to detect pneumonia worldwide. On a CXR, COVID-19 symptoms may be seen, but radiologists must seek the radiological markers that indicate this. The labor-intensive and error-prone CXR analysis technique should be automated to reduce time and effort. The labor-intensive and error-prone CXR analysis technique should be automated to reduce time and effort

II. LITERATURE SURVEY

Deep learning-based image classification techniques were used for the photos in [1] after they had been adjusted to extract more valuable attributes. Five cutting-edge CNN systems, VGG19, MobileNetV2, Inception, Xception, and InceptionResNetV2,were evaluated to separate COVID-19 from control and pneumonia photos in a transfer-learning scenario. One study utilized 504 control photographs, 700 COVID-19 photos, and 224 COVID-19 photos. With 96.78% and 94.72 % accuracy in two- and three-class classifications, respectively, MobileNetV2 net fared best.

Transfer learning was implemented in [2] using the VGG16 CNN and the Resnet50, both trained on color camera photos from ImageNet. Both of these networks were used to train the transfer learning model. To determine whether or not using chest X-rays to diagnose COVID-19 is effective, a 10-fold cross-validation study was conducted, and the findings indicated that the test had an overall accuracy of 89.2%.

In [3], researchers evaluated the effectiveness of three different CNN architectures (ResNet50, InceptionV3, and InceptionRes-netV2) for detecting COVID-19 using a database containing just 50 controls 50 COVID-19 cases. The accuracy rate of ResNet50 was measured at 98 %.

Deep Convolutional Neural Networks were able to effectively and efficiently identify between 21,152 normal and abnormal chest radiographs, as the findings of this study on the accuracy of diagnosis demonstrated (as shown in [4]), as can be seen in [4]. The CNN model showed a distinction between normal and pneumonia with an accuracy of 94.64%, a sensitivity of 96.5%, and a specificity of 92.86% after it was pre-trained on datasets of adult patients and refined on datasets of pediatric patients. Additionally, the CNN model had a sensitivity of 96.5%.

Transfer learning was performed in [5] with the assistance of four CNN networks. These networks were ResNet18, ResNet50, SqueezeNet, and DenseNet-121. During the study, a database was used that had a total of 184 COVID-19 photographs, 5000 images that did not provide any findings, and images of pneumonia. The presented numbers indicated that the sensitivity was close to 98%; however, the specificity was just 92.9%.

Using an X-ray image dataset indicates that COVID-CAPS performs better than prior CNN-based algorithms. This is according to the model that is presented in [6]. Despite having a much-reduced number of trainable parameters compared to preceding models, COVID-CAPS attained accuracy rates of 95.7%, sensitivity rates of 90%, and specificity rates of 95.7%.

Eight deep-learning algorithms, including ResNet15V2, MobilenetV2, NasNetMobile, DenseNet201, InceptionResNetV2, VGG16, ResNet50, and VGG19, were used to identify people with COVID-19 symptoms from a set of 400 chest X-ray pictures. This was accomplished by analyzing the chest radiographs. NasNetMobile's accuracy of 93.94% in chest X-ray datasets surpassed that of all other models by a significant margin.

The authors of [8] used a corpus with 50 controls and 25 COVID-19 patients to assess seven deep CNN models. The most significant results were obtained from the VGG19 and

DenseNet models, each with F1 values of 0.89 and 0.91 for the control and sick groups, respectively.

The authors of [9] used a database that included 127 COVID-19, 500 controls, and 500 pneumonia patients for both the binary classification of COVID-19 and controls and the multiclass classification of COVID-19, controls, and pneumonia. This database was comprised of patients who had been diagnosed with pneumonia. This database was compiled using information obtained from a wide range of various resources. Following the implementation of modifications to accommodate transfer learning and five-fold cross-validation, the Darknet model achieved an accuracy of classification of 98% for binary classification and 87% for multiclass classification.

Only two multiclass classification tasks were used to assess the Xception transfer learning technique (initially described in [10]): I control vs. COVID-19 against viral and bacterial pneumonia; and (ii) controls versus COVID-19 versus pneumonia. Both of these comparisons were made using only control subjects and COVID-19. After the chest X-ray images for the 290 COVID-19, the 310 controls, the 330 cases of bacterial pneumonia, and the 327 instances of viral pneumonia were acquired, an under-sampling strategy was utilized to remove registers from larger classes to balance the corpus arbitrarily. This was done after the acquisition of the images. The accuracy was determined to be 90% by a three-class cross-database experiment conducted by Prasad et al. (2020) [11]; the authors of this paper devised a method for categorizing COVID-19 and CXR pictures using a technique based on deep learning. The accuracy of three classes was reported to be 94%, while the accuracy of four classes was reported to be 89%. The recommended approach has an accuracy of 98.56%, a sensitivity of 99.51%, and a specificity of 96.62%, respectively.

J. Narin et al. [12] in this study proposed the use of convolutional neural networks as a deep learning-based approach for discriminating between COVID-19 and regular CXR photos (CNN). The strategy that was proposed has rates of accuracy that are 98.5%, sensitivity that is 99.2%, and specificity that is 96.2%.

A. A. M. Fathima et al.[13] present the categorization of COVID-19 and standard CXR pictures in this work; the authors developed a hybrid strategy employing transfer learning and ensemble learning. The suggested approach has a 98.13% accuracy, 98.66% sensitivity, and 97.60% specificity.

III. PROPOSED SYSTEM

The block diagram of the proposed system is shown in Fig. 3.1.

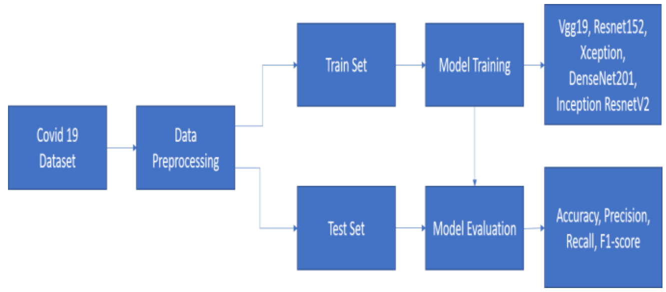


Fig.2. Block Diagram of the proposed system

A.Dataset

Chest imaging is routinely used in medicine and is essential for identifying COVID-19. When establishing a diagnosis based on chest imaging, medical practitioners can more fully comprehend the imaging modal features of COVID-19 patients, such as the early-stage interstitial changes and many small patchy shadows. Then it grows into many ground glass and penetrates the shadows in both lungs. Pleural effusion and lung consolidation are uncommon in severe instances. It provides helpful advice for accurately determining the condition and how it is progressing, developing treatment plans, and determining prognoses. While there are several COVID-19 databases, there aren't many samples. Then it multiplies into many ground glass and invades the shadows in both lungs. Pleural effusion and lung consolidation in severe instances are uncommon.

(a) (b)

Fig.3. Dataset image sample (a) Covid 19 (b) Normal image

B. Preprocessing

The crucial step in removing noise from the input frame is preprocessing. The segmentation procedure is smoother and more precise thanks to the preprocessing stage. Much of the input from the camera is salt and pepper noise, which the median filter will eliminate.

C. Training and testing

Several deep-learning techniques are available to train the network. Still,our method uses a network already trained to train the covid19 image classification algorithm. The CNN and Vgg19 networks are trained in this method.

a) CNN

The architecture of the CNN algorithm is shown in Fig. 4.

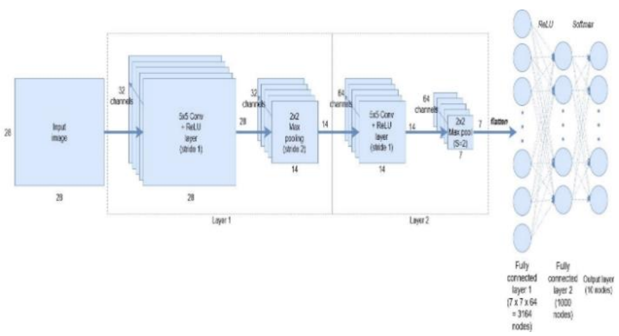


Fig.4. Block Diagram of CNN algorithm

CNNs are a specific kind of neural network that excels at classifying and recognizing pictures because oftheir unique architecture. Multi-layered feed-forward neural networks include CNNs as a subclass. With biases, parameters, and learnable weights, CNNs comprise filters, kernels, or neurons. Each filter accepts inputs, carries out convolution, and offers a non-linearity option as an additional feature. Fig. 3.3 depicts a design that is representative of a standard CNN. The Convolutional Neural Network (CNN) is comprised of many layers: convolutional, pooling, Rectified Linear Unit (ReLU), and FCL (Fully Connected).

- Convolutional Layer

The convolutional layer is the core component of a convolutional network, which controls most of the computational effort. Feature extraction from the input data, an image, is the primary goal of the convolution layer. Convolution uses tiny squares from the input picture to retain the spatial connection between pixels to learn the image's attributes. A group of teachable neurons is used to change the input images.

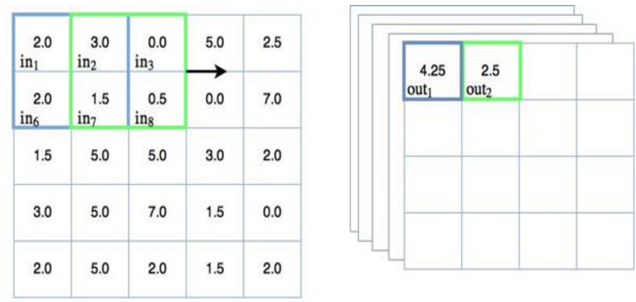


Fig.5. Moving 2X2 filter (all weights = 0.5)

The output image is left with a feature map or activation map as a consequence of this process; this map is then used as input data by the subsequent convolutional layer. In terms of mathematics, it is represented as

$$G[m,n] = (f * h)[m,n] = \sum j \sum j\, h[j,k][m - j, n - k] \quad (1)$$

The result is a feature map or activation map in the output picture, which is then used as input data by the next convolutional layer. The following formula denotes it in mathematics:

- ReLU Layer

The outcome is a feature map or activation map in the output image, which is subsequently utilized as input information by the next convolutional layer. It is represented in mathematics as

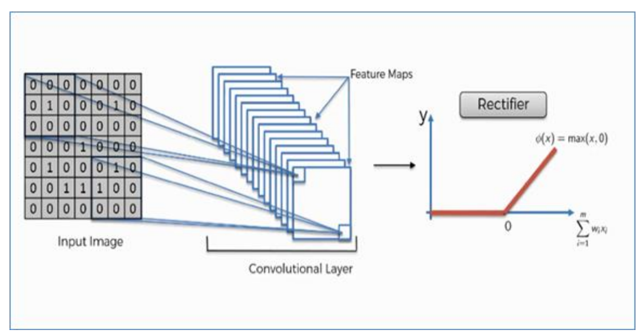


Fig.6. ReLU

- Pooling Layer

Each activation map is made less dimensional, but the pooling layer retains most of the essential data. Using the provided photos, several non-overlapping rectangles are produced. Similar to previous sliding window approaches, it applies a statistical function to the contents of its window rather than weights that can be taught. The most well-liked pooling method, called max pooling, uses the contents of the window and the max() function. Other types are sometimes used, such as mean pooling. In this lesson, we'll be concentrating on max pooling. The graphic below provides a visual representation of the max pooling procedure.

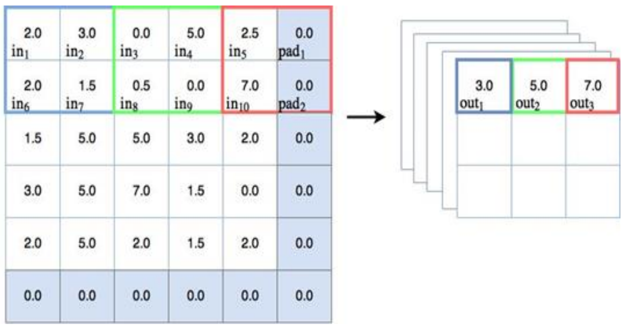


Fig.7. Max pooling example (with padding)

- Flattening Layer

Using a convolutional neural network, high-resolution data is effectively resolved into representations of things. To "understand" the results and eventually offer a classification result, it is reasonable to think of the fully connected layer as adding a traditional classifier to the network's information-rich output. The output of the convolutional neural network's dimensions must be flattened to link this fully connected layer to the network.We should have a pooled feature map when the first two steps are finished.

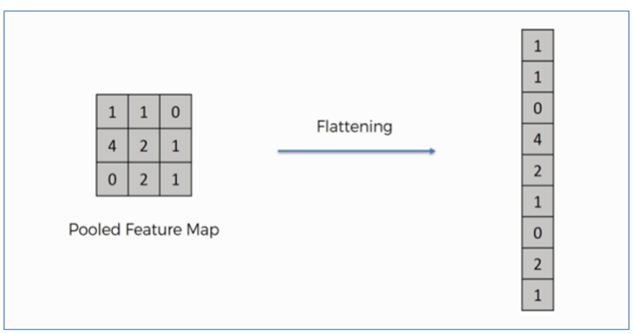


Fig.8. Flattening Layer

The name of this stage suggests that we will turn our pooled feature map into a column, as seen in the image that follows this paragraph.

- Fully Connected Layer

The FCL divides the input picture into categories based on the training dataset using these properties. The Softmax activation function classifier receives features from the final pooling layer or FCL. The FCL's output probabilities add up to one. Softmax is used as the activation strategy to guarantee this. The Softmax function may transform each real-valued score into a vector of summable values between 0 and 1.

b) Vgg19

The VGG19 model is a variant of the VGG model with nineteen layers (16 convolution layers, 3 Fully connected layers, 5 MaxPool layers, and 1 SoftMax layer). In addition to VGG1, VGG2, and VGG3, there are several more variants of the VGG gene. The value of VGG19 is 19.6 billion FLOPS. Over a million images were used to train the VGG-19 convolutional neural network from the ImageNet collection. In other words, VGG is a deep CNN used to classify images.

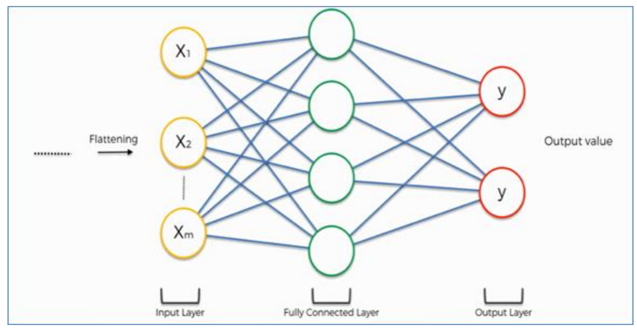


Fig.9. Fully Connected Layer

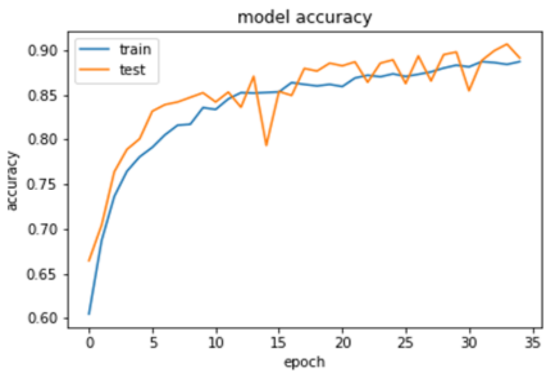
The following is a list of the layers that make up the VGG19 model: The 19-layer network is capable of recognizing photographs of over a thousand various item categories, including a keyboard, mouse, pencil, and a large number of different animals. As a direct consequence, the network can now produce exhaustive feature representations for a diverse set of pictures.

- The RGB picture with a predetermined size (224 224) served as the input for this network, which exemplified the matrix's structure (224,224,3).
- The only preprocessing was to compute the mean RGB value for each pixel throughout the training set, and then each pixel had that value removed.
- They employed kernels of three by three and a stride size of one pixel to cover the whole picture.
- The spatial resolution of the picture was preserved by using spatial padding.
- Stride 2 was used to do max pooling across a 2 by 2-pixel frame.
- The Rectified Linear Unit (ReLu), which added non-linearity to lengthen the model's classification and computing time, was introduced after that. This model performed far better than previous ones using tanh or sigmoid functions.

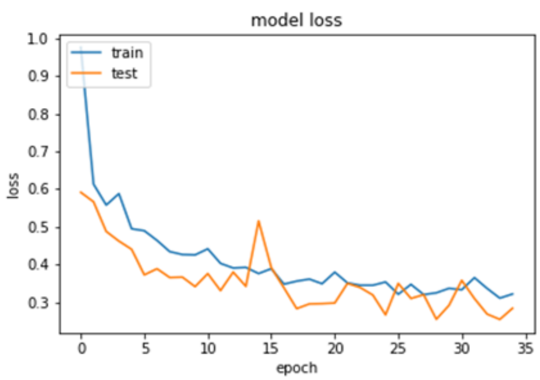
It resulted in the production of three completely connected layers: the first two had a total size of 4096; the third layer, which featured a SoftMax function, had 1000 channels for classification, making use of a 1000-way ILSVRC; and the process of adding a third layer was referred to as "layering."

IV. RESULTS

The proposed system uses CNN, and the Vgg19 algorithm is implemented, and the results are explained below. The training accuracy and loss plot of the CNN and Vgg19 algorithm is shown in Fig. 10.

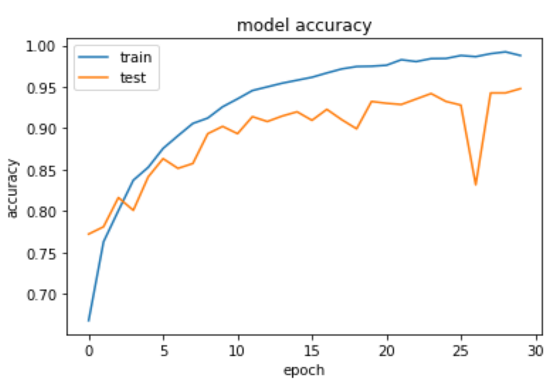


(a)

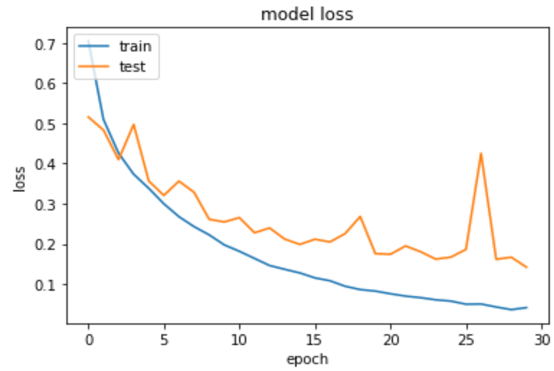


(b)

Fig.10. Training progress graph of CNN algorithm (a) model accuracy (b) model loss



(a)



(b)

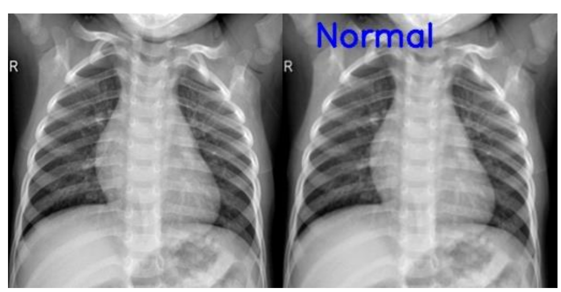
Fig.11. Training progress graph of Vgg19 algorithm (a) model accuracy (b) model loss

The chest X-ray pictures in this system are divided into Normal and Covid-19 algorithms. The CNN algorithm's training accuracy, training loss, and validation accuracy were 0.8870, 0.3217, and 0.2837, respectively. The performance of another method, vgg19, was 0.9879 for training accuracy, 0.0414 for training loss, and 0.9478 for validation accuracy, with a training loss of 0.1421.The comparative analysis of the CNN and Vgg19 algorithms is presented in Table 5.1.

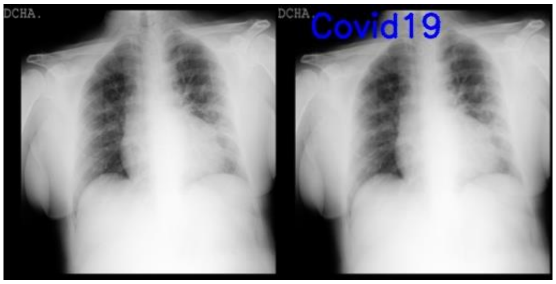
Table I: Comparative analysis of CNN and Vgg19

Algorithm	**Training**		**Validation**		**Execution Time (Sec)**
	Accuracy	**Loss**	**Accuracy**	**Loss**	
CNN	0.8870	0.3217	0.8912	0.2837	5313
Vgg16	0.9879	0.0414	0.9973	0.1421	956

From Table 5.1. it is observed that the vgg16 algorithm outperforms the CNN algorithm in terms of accuracy, loss, and Execution time. The proposed system's qualitative analysis is shown in Fig.5.6.



(a)



(b)

Fig.12. Training progress graph of CNN algorithm (a) model accuracy (b) model loss

V. CONCLUSION

In this approach, a chest X-ray is classified as normal, and covid19 is presented. This system uses CNN and Vgg19 algorithms for classification. The proposed system has dataset collection, training, and testing phase. The training accuracy, training loss, and validation accuracy for the CNN algorithm were 0.8870, 0.3217, and 0.2837, respectively. The performance of another method, vgg19, was 0.9879 for training accuracy, 0.0414 for training loss, 0.9478 for validation accuracy, and 0.1421 for training loss. The qualitative analysis of the proposed system shows promising results for classification.

The chest X-ray pictures in this system are divided into Normal and Covid19 algorithms. The CNN algorithm achieved a validation accuracy of 0.8912, a training accuracy of 0.8870, a training loss of 0.2837, and a validation loss of 0.3217. A different approach, vgg19, produced training accuracy, training loss, and validation accuracy, all of which were 0.9879, 0.0414, and 0.1421, respectively.

REFERENCES

[1] Apostolopoulos, I.D.; Mpesiana, T.A. Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Phys. Eng. Sci. Med. 2020, 43, 635–640.

[2] Hall, L.O.; Paul, R.; Goldgof, D.B.; Goldgof, G.M. Finding Covid-19 From Chest X-Rays Using Deep Learning on a Small Dataset. arXiv 2020, arXiv:2004.02060.

[3] Narin, A.; Kaya, C.; Pamuk, Z. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. Pattern Anal. Appl. 2021, 24, 1207–1220.

[4] Tang, Y.-X.; Tang, Y.-B.; Peng, Y.; Yan, K.; Bagheri, M.; Redd, B.A.; Brandon, C.J.; Lu, Z.; Han, M.; Xiao, J.; et al. Automated abnormality classification of chest radiographs using deep convolutional neural networks. NPJ Digit. Med. 2020, 3, 1–8.

[5] Minaee, S.; Kafieh, R.; Sonka, M.; Yazdani, S.; Soufi, G.J. Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning. Med. Image Anal. 2020, 65, 101794.

[6] Afshar, P.; Heidarian, S.; Naderkhani, F.; Oikonomou, A.; Plataniotis, K.N.; Mohammadi, A. COVID-CAPS: A capsule network-based framework for identification of COVID-19 cases from X-ray images. Pattern Recognit. Lett. 2020, 138, 638–643.

[7] Ahsan, M.; Gupta, K.; Islam, M.; Sen, S.; Rahman, L.; Hossain, M.S. COVID-19 Symptoms Detection Based on NasNetMobile with Explainable AI Using Various Imaging Modalities. Mach. Learn. Knowl. Extr. 2020, 2, 490–504.

[8] Hemdan, E.E.; Shouman, M.A.; Karar, M.E. COVIDXnet: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images. arXiv 2020, arXiv:2003.11055.

[9] Ozturk, T.; Talo, M.; Yildirim, EA; Baloglu, U.B.; Yildirim, O.; Acharya, U.R. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput. Biol. Med. 2020, 121, 103792.

[10] Khan, A.I.; Shah, J.L.; Bhat, M.M. CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Comput. Methods Programs Biomed. 2020, 196, 105581.

[11] Venkataramana, L., Prasad, D.V.V., Saraswathi, S. et al. Classification of COVID-19 from tuberculosis and pneumonia using deep learning techniques. Med Biol Eng Comput 60, 2681–2691 (2022). https://doi.org/10.1007/s11517-022-02632-x

[12] Narin, A., Kaya, C. & Pamuk, Z. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. Pattern Anal Applic 24, 1207–1220 (2021). https://doi.org/10.1007/s10044-021-00984-y