COVID PREDICTION USING X-RAY IMAGES

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***Abstract*—COVID-19, or Novel Coronavirus Disease, is a highly contagious disease that first appeared in China in late 2019. SARS-CoV-2 is a coronavirus that causes SARS. The illness first occurred in Wuhan, China in December 2019 and soon spread to over 213 nations, becoming a global epidemic. The most characteristic signs of COVID-19 are a high temperature, a cough that is dry, and extreme fatigue. Patients may also have aches, pains, and difficulties breathing. Most of these signs and symptoms point to lung infections and anomalies that radiologists can diagnose. COVID-19 chest x-rays show patchwork, hazy lungs, not clear, healthy lungs. Pneumonia and chronic lung diseases can resemble COVID-19 on x-rays. Radiologists must distinguish COVID-19 from a less contagious sickness. Our AI technology estimates deteriorating risk for doctors. Triage and treat high-risk patients efficiently. Despite efforts to forecast COVID-19, the virus's characteristics and mutation make diagnosis difficult. To aid in early diagnosis, a model that accurately predicts COVID-19 from CXR pictures is needed. As part of this study, we introduce a severity score prediction model for frontal chest X-rays in the context of COVID-19 pneumonia using ReLu (Rectified Linear Unit) model. This tool can be used to escalate or de-escalate care and track therapy efficacy, especially in the ICU. Pre-trained (non-COVID-19) chest X-ray datasets are utilised to build predictive characteristics for COVID-19 pictures. Training a regression model on a subset of a pre-trained chest X-ray model predicts our geographic extent Our model's capacity to evaluate COVID-19 lung infection severity could be employed for escalation or de-escalation of care as well as monitoring treatment efficacy, especially in the critical care unit (ICU).**

***Index Terms*—chest x-ray,positive,negative,CNN,ReLU.**

I. Introduction

SARS (Severe Acute Respiratory Syndrome) and MERS (Middle East Respiratory Syndrome) are both diseases caused by the coronavirus . The SARS-CoV-2 illness is brought on by a brand-new coronavirus called COVID-19. The country of China's Hubei province received its first reports of COVID-19 infections in December 2019 . On March 11 2020, the World Health Organization (WHO) proclaimed COVID-19 a pandemic By July 13 of that year, there had been 188,404,506 documented cases worldwide, resulting in 4,059,220 fatalities These illnesses result in respiratory issues that are treatable without specific medication or tools. However, underlying medical conditions like diabetes, cancer, cardiovascular, and respiratory diseases might exacerbate this illness (World Health Organization, 2020). The primary procedures for COVID- are now reverse transcription polymerase chain reaction (RT-PCR), gene sequencing for respiratory samples, and blood samples. Other research indicates that COVID-19 possesses abnormalities that are comparable to those seen in pneumonic disease, leaving the chest diseases that can be seen in medical photos. Recent Artificial Intelligence (AI) research, particularly in Deep Learning approaches, demonstrates how these algorithms performed well when applied to medical imagery. The COVID-19 Image Data Collection, which was built with images from COVID-19 reports or articles in collaboration with a radiologist to confirm pathologies in the pictures taken, is used as a foundation in the majority of published studies because it is one of the few large open access datasets of COVID-19 X-ray images.

some common operations include standardisation, resizing, and normalisation to lessen data variability, which could negatively impact the performance of the classification models, and a segmentation model to extract the region of the lung that includes the essential information and ignore environmental information that could result in false information. Here we are going to use a frontal chest X-ray severity score prediction model employing a CNN (convolutional neural network) model with ReLU activation function in the setting of COVID-19 pneumonia.By using relu function we achieved 99 percent accuracy for detecting COVID -19 is positive or negative.This tool can be used, particularly in the ICU, to track therapeutic effectiveness and escalate or de-escalate care.

The visual representation of heatmaps for various images, which supports the significance of X-ray in the preprocessing stage, gives useful information about the regions of the images that contribute to the prediction of the network, which in ideal circumstances should focus on the appearance of the lungs.The remainder of the study is organised as follows: first, the methodology used for these approaches; next, the tests and test results achieved; then, a discussion of the products; and finally, the conclusions.

II. LITERATURE SURVEY

This machine learning-based automated system's primary goal is to study disease features and make some insightful predictions. Thus, picture pre-processing, segmentation of the disease-related regions of interest, computation of useful features, and development of feature-based machine learning models for detection and classification constitute the primary processes. For the purpose of characterizing and identifying COVID-19 instances, numerous DL models have

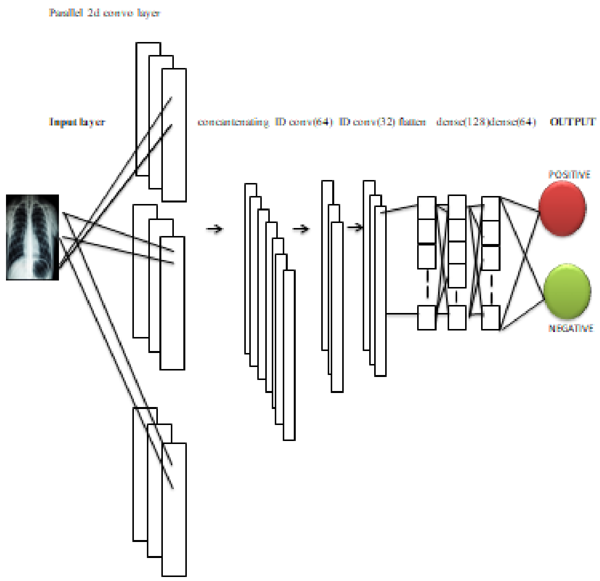

Fig. 1. ARCHITECTURE OF CNN

been used in the literature. The suggested method predicts covid from chest X-ray pictures using deep learning. This system separates photos into COVID-19-infected and non-COVID-19-infected categories. CT scans of the chest are a more reliable imaging method for diagnosing lung-related issues However, a thorough chest x-ray is a less expensive procedure in contrast to a chest CT. X-ray pictures from COVID-19 have revealed opacity-related findings . Patients in one study had both bilateral and unilateral ground-glass opacity. In between 50 percent and 60 percent of pediatric patients with COVID-19 instances, consolidation and ground-glass opacities were discovered. The development of a deep learning model that makes it easier to screen through huge amounts of radiograph images for COVID-19 suspicious cases may benefit from this crucial trait. The most effective machine learning method, deep learning, provides valuable analysis to examine a huge number of chest x-ray pictures, which can significantly affect Covid-19 screening. In this study, both patients with covid-19 disease and healthy individuals' chest x-ray scans were viewed from the PA perspective. We will experiment with deep learning-based CNN models and evaluate their performance after cleaning up the photos and adding data augmentation. Deep learning has the potential to completely change how lung radiography interpretation is automated. The use of deep learning in this area has been covered in more than 40,000 research articles, including those on organ segmentation, artefact removal, multilabel classification, data augmentation, and disease severity grading. The availability of training and testing datasets, as well as their accessibility for enabling comparison and replication of the research, is a crucial factor in deep learning research. A method used frequently in deep learning called transfer learning enables reuse of previously trained models in a specific application. As can be seen in the ImageNet database,

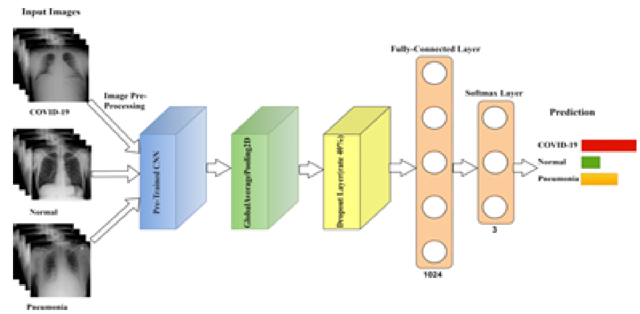

Fig. 2. ARCHITECTURE OF TRANSFER LEARNING

hundreds of items have been recognized by pre-trained deep neural networks that have been demonstrated to work. The photographic collection includes both common and unusual objects, including pencils, animals, structures, textiles, and geological formations. Freezing all layers aside from the final three—fully linked, SoftMax, and classification layers—is one technique of transfer learning. The following step is to train the final three layers to recognize new categories. Pre-trained models have occasionally produced results that are comparable to those of seasoned radiologists, which is encouraging. Radiologist-judged labels for the lung X-ray 14 data set were developed in recent research. These labels are unique in that they required adjudication by a team of certified radiologists with at least three years of experience in general radiography. The terms "pneumothorax," "nodule/mass," "airspace opacity," and "fracture" were all introduced. This study aims to develop a deep learning model for COVID-19 case prediction based on an established pre-trained model that was then retrained using adjudicated data to recognize images with airspace opacity, a COVID-19 abnormality. This is due to the recent discovery that opacity is a significant feature in COVID-19 patients.

III. METHODOLOGY

To evaluate the models performance and determine how the various process stages affect it, our technique comprises of three key studies. Every experiment adheres to the process depicted in Figure. The dataset used differs between studies. For all COVID-19 positive cases, the same photos were utilized. For negative situations, three separate datasets were employed. We evaluate positive vs. negative case by using x-ray images.

A. DATA COLLECTION

Data for this study came from the Kaggle repository, which contains Chest X-Ray pictures of pneumonia patients, healthy people, and people with Covid-19. The dataset (covid-chestxray-dataset-master) was created and used to compile COVID-19 X-ray images. It takes into account images from several open sources like kaggle and github and is continually updated.To validate the proposed method, the chest X-ray images have been collected from

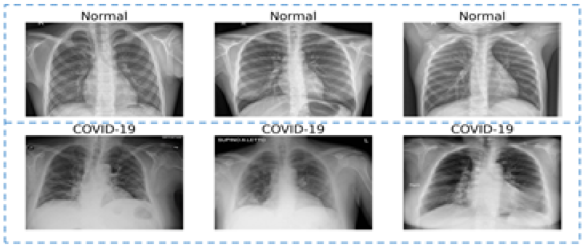

Fig. 3. COVID POSITIVE AND NORMAL PERSON'S CHEST X-RAY IMAGE

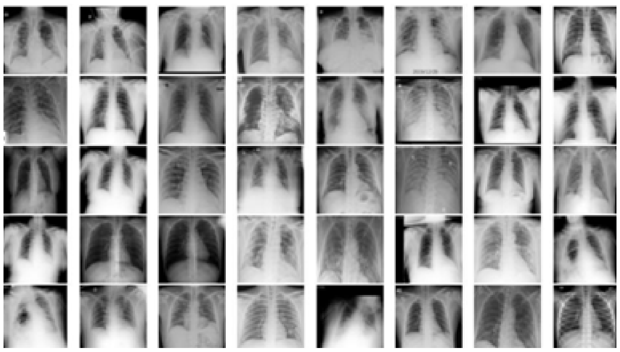

Fig. 4. COVID POSITIVE IMAGES

two different sources. (https://github.com/ieee8023/covid-che...)(https://www.kaggle.com/praveengovi/co...) we have taken our dataset from those links .A dataset of 930 chest X-ray images was utilized to build the model and tune the hyper-parameters. Patient crossover between the training and test sets didn't occur.While chest X-ray images of normal category have been collected from a GitHub repository1 which contains 930 images selected from Chest X-ray dataset Here,403 COVID-19 frontal-view chest X-ray images have been selected from covid-chestxray-dataset-master. To deal with the data imbalance problem, the same 403 frontal-view chest X-ray images of healthy lungs have been randomly selected from . The example of chest X-ray images from both normal and COVID-19 classes are depicted in Figure.

B. DATA PRE-PROCESSING

The input images should be resized to match the input layer's scale for the pre-trained network. Figure displays a few examples of COVID x-ray pictures.

1) NORMALIZATION: In order to ensure numerical stability in CNN systems, normalization of data is a crucial step. A CNN model is likely to learn more quickly and the gradient descent is more likely to be stable with normalization. As a result, in this study, the input photo pixel values have been normalized to fall between 0 and 1. The grayscale images used in the datasets under consideration were rescaled by multiplying the pixel values by 1/255.

2) DATA AUGMENTATION: The CNN models have demonstrated to perform better on larger datasets and require a significant quantity of data for optimal training. However,

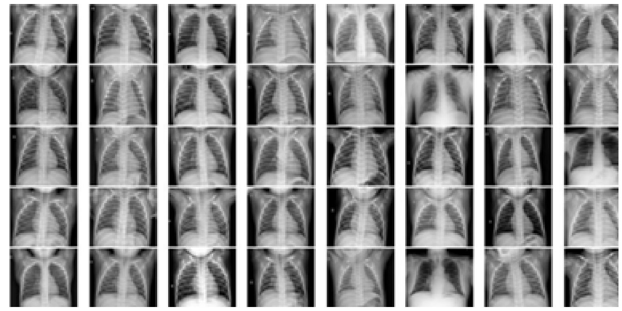

Fig. 5. COVID NEGATIVE IMAGES

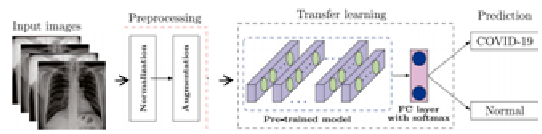

Fig. 6. COVID-19 DIAGNOSIS METHOD USING FRONTAL VIEW CHEST X-RAY IMAGES

there are very few training X-ray pictures present in the dataset under consideration (i.e., 430 X-ray images). Given how challenging it is to gather medical data, this has been a big worry when utilising Deep Learning systems to analyse medical images. The data augmentation technique, which helps to increase the amount of images via a set of modifications while keeping class labels, has been frequently used to address this issue. Additionally, augmentation makes the photos more variable and acts as a dataset regularizer. Figure 6 illustrates the methods used in this work to enhance the training photos. The photos were enhanced by applying the following techniques: horizontal flipping, scaling by 15 percent, rotating by 5 degrees clockwise, and adding Gaussian noise with a zero mean and 0.25 variance to the images. It is important to note that all of these strategies have been tested on training data, with examples of each technique's results shown in Figure 7. Finally, a larger training set with 2150 images—five times as many as the initial training set—was acquired.

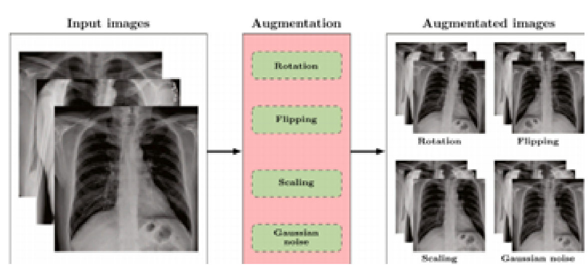

Fig. 7. ILLUSTRATION OF DIFFERENT DATA AUGMENTATION TECHNIQUE USED IN THIS STUDY

C. FEATURE EXTRACTION

A substantial amount of data is required to obtain trustworthy findings from a deep learning algorithm. But it's possible that there are data gaps in every issue. Data collection can be time consuming and expensive, especially when it involves medical issues. These issues can be resolved through augmentation. Overfitting can be avoided via augmentation, which also improves the proposed model's accuracy.

D. MODEL SELECTION

Organize the information into training and test sets; 80 perccent of the images will be the network will be tested with the remaining 20 percent being used for training.

E. IMAGE PROJECTION FILTER

The frontal (posteroanterior and anteroposterior) and lateral image projections are labelled on the COVID-19 datasets' images. Given the differences in the information available from the two perspectives and the fact that not every patient had access to both views, a number of mismatched labels were discovered upon human examination, which had an impact on the model's performance. A classification model was trained on a subset of Covid19 Chest x-ray Master with 930 images in order to efficiently filter the COVID-19 datasets and maintain the projection images that offer greater information. This allowed us to automate the process of filtering the images according to the projection.

F. IMAGE CLASSIFICATION

Modify the network to determine the likelihood of COVID-19 and the usual class .The pre-trained network's last layers, "average pooling," "fully-connected layer," and "softmax," are replaced with a "classification output" in the architecture. Develop the Network.

G. HYPERPARAMETER

Convolutional layers have a 3 cross 3 kernel size with the same padding and normal kernel initialization. The pool size for Maxpooling layers is 2 cross 2. The dropout rate is 0.1 for the first two expansion and contraction blocks, 0.2 for the next two, and 0.3 for the fifth contraction block. Transposed convolutional layers employ a 2 cross 2 kernel, 2 cross 2 strides, and equal padding. With a kernel size of 1 cross 1, the final convolutional layer employs a single filter.

H. TESTING AND PREDICTING

Utilize the testing dataset to evaluate the classifiers. We applied the CNN (convolutional neural network) model to a collected dataset of chest X-ray images. Analyze the model's performance by plotting the accuracy and loss throughout training.

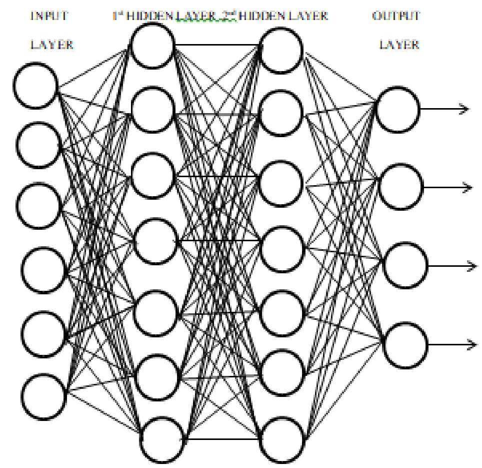

Fig. 8. CONVOLUTIONAL NUERAL NETWORK

IV. MODEL EVALUATION

A. CNN(CONVOLUTIONAL NEURAL NETWORK) MODEL

Convolutional neural networks, often known as convnets or CNNs, are a type of machine learning. It is a subset of the several artificial neural network models that are employed for diverse purposes and data sets. A CNN is a particular type of network design for deep learning algorithms that is utilized for tasks like image recognition and pixel data processing. (Fig 1 shows the architecture of CNN(convolutional neural network)).

A ConvNet's architecture was influenced by how the Visual Cortex is organised and is similar to the connectivity network of neurons in the human brain. Only in this constrained area of the visual field, known as the Receptive Field, do individual neurons react to stimuli. The entire visual field is covered by a series of such fields that overlap. (Fig 8 shows the Convolutional Nueral Network). Here in the Fig 8 consists of a INPUT layer,HIDDEN layers and OUTPUT layer. A Convolutional Neural Network or CNN is a type of artificial neural network, which is widely used for image/object recognition and classification. Deep Learning thus recognizes objects in an image by using a CNN.

B. ACTIVATION FUNCTION

In artificial neural networks, an activation function is a function that outputs a smaller value for tiny inputs and a higher value if its inputs are greater than a threshold.The activation function fires if the inputs are big enough; otherwise, nothing happens.To put it another way, an activation function functions like a gate that verifies that an incoming value is greater than a threshold value. Activation functions are advantageous because they introduce non-linearities into neural networks, which enables the neural networks to learn robust operations. A feed forward neural network's ability to do complicated tasks like picture recognition would be

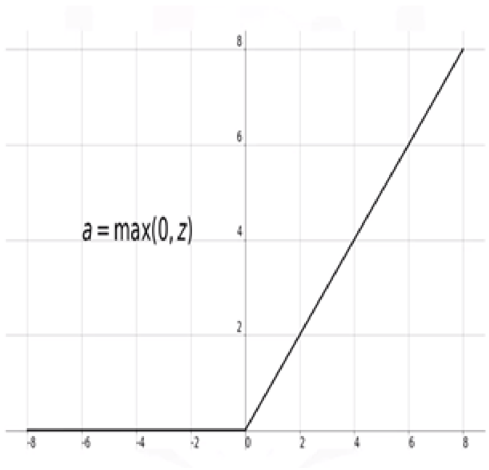

Fig. 9. ReLU ACTIVATON FUNCTION

lost if the activation functions were taken out. Instead, the network would be reduced to a simple linear operation or matrix transformation on its input. The rectified linear unit (ReLU) and the logistic sigmoid function are two frequently utilised activation functions. The sigmoid shows a progressive change in behaviour, whereas the ReLU has an abrupt cutoff at 0 where its behaviour changes. The sigmoid tends to 1 for large x, but both trend to 0 for small x.

1) ReLU(RECTIFIED LINEAR UNIT) ACTIVATION FUCNTION: If the input is positive, the rectified linear activation function, or ReLU for short, will output the input directly; if it is negative, it will output zero. Because a model that utilizes it is simpler to train and frequently performs better, it has evolved into the standard activation function for many different kinds of neural networks.

2) How ReLU handles input-output interactions and takes into consideration non-linear outcomes?: ReLU typically provides a model for a functional activation function in a neural network using concepts like gradient descent. In order to help the technologies converge or address certain issues, engineers also create layers of neurons in Artificial Nueral Network and improve the algorithmic work of machine learning programmes. Tanh and sigmoid functions can be used as ReLU substitutes. ReLu is a non-linear activation function that is used in multi-layer neural networks or deep neural networks. This function can be represented as: f(x) = max(0,x) where x is the input to a neuron. This is also known as a ramp function. ReLU function graph (fig.9) displaying flat gradient for negative x.

V. RESULT

Using X-ray images, here we used 20 epoch for predicting the accuracy and loss of the training data, from that we found that it results in minimum loss and maximum accuracy has shown in the graph for different epoch values it shows increase in the accuracy values and increase in validation accuracy for different epoch it shows 99 percent validation accuracy and 99

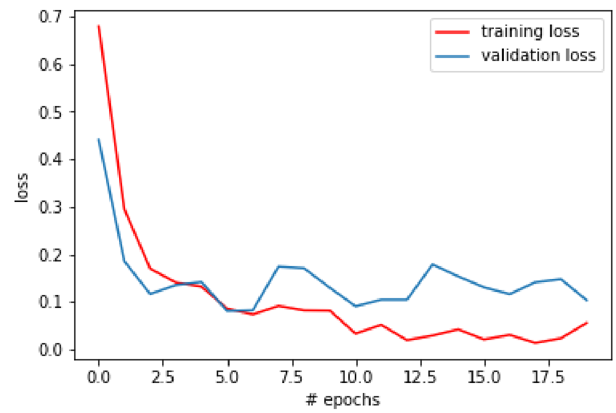

Fig. 10. GRAPHICAL REPRESENTATION FOR LOSS

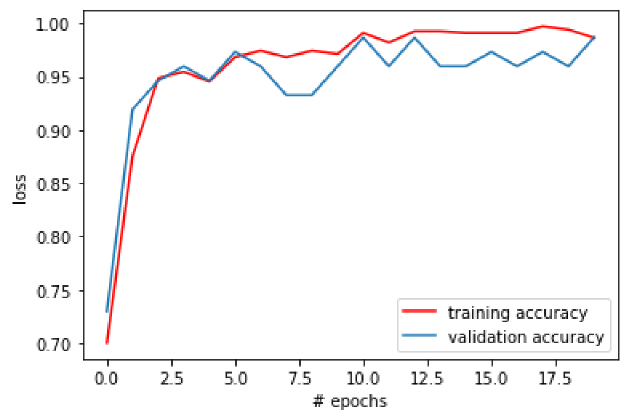

Fig. 11. GRAPHICAL REPRESENTATION FOR ACCURACY

percent accuracy and it shows decrease in the loss and decrease in validation loss and gives 0.05 percent loss and 0.03 percent of validation loss and by evaluating test data and test target we achieved 100 percent accuracy and 0.01 percent loss.(Fig 10 and 11 shows the result in graphical representation for loss and accuracy).

VI. CONCLUSION

Here we are having lots of ACTIVATION FUNCTIONS like linear activation function and as well as non linear function in non linear function we are having different types like ReLu, sigmoid or logistic,TanH(Hyperbolic Tangent),leaky Relu,GELU,SELU .So comparing to all other activation function ReLU given the best accuracy for predicting the COVID using x-ray images .The ACCURACY percentage is 99 percent for predicting COVID using x-ray images.According to our result ReLU is the Best Activation function to Predict COVID using x-ray images. For the disease to stay under control and to not spread, quick and fast diagnosis of COVID positive patients is essential. The goal of this research project was to develop a quick and low-cost method for identifying

COVID-positive individuals from chest X-ray pictures. Ninety-nine percent classification accuracy was attained using the suggested model.

VII. FUTURE WORK

In future it can be extracted using web applications for user-friendly .We have highlighted two key areas for further research: first, semantic segmentation of lung pathologies, particularly the identification of consolidation and ground glass opacity disorders. The second step entails expanding COVID datasets in order to generalize data and get over issues with using various image sources. Our key goal for the future is to train this model on a larger dataset so that we can train the model well and thus increase accuracy, because in machine learning, training with more data allows the model to perform much better on unseen data. It is also possible to improve this further to forecast the likelihood that the affected person will survive.On this, too, we are focusing.Our goal is that this study will continue advance and perhaps provide information that helps advance medical research on COVID-19.

REFERENCES

[1] Zhu N, Zhang D, Wang W et al (2020) A novel coronavirus from patients with pneumonia in China, 2019. N Engl J Med.

[2] World Health Organization (2020) Coronavirus disease 2019 (COVID-19) situation report–39. World Health Organization, Geneva. Available via https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200228-sitrep-39-covid-19.pdf?sfvrsn=5bbf3e7d2

[3] World Health Organization (2020) Coronavirus disease 2019 (COVID-19) situation report–42. World Health Organization, Geneva. Available via https://www.who.int/docs/default-source/coronaviruse/20200302-sitrep-42-covid-19.pdf?sfvrsn=d863e0452

[4] Xie X, Zhong Z, Zhao W, Zheng C, Wang F, Liu J (2020) Chest CT for typical 2019-nCoV pneumonia: relationship to negative RT-PCR testing. Radiology. https://doi.org/10.1148/radiol.2020200343

[5] Huang P, Liu T, Huang L et al (2020) Use of chest CT in combination with negative RT-PCR assay for the 2019 novel coronavirus but high clinical suspicion. Radiology. https://doi.org/10.1148/radiol.2020200330

[6] Fang Y, Zhang H, Xie J et al (2020) Sensitivity of chest CT for COVID-19: comparison to RT-PCR. Radiology. https://doi.org/10.1148/radiol.2020200432

[7] National Health Commission of the People's Republic of China (2020) The diagnostic and treatment protocol of COVID-19. China. Available via http://www.gov.cn/zhengce/zhengceku/2020-02/19/conten-5480948.htm Accessed 3 Mar 2020

[8] Wang D, Hu B, Hu C et al (2020) Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China. JAMA. https://doi.org/10.1001/jama.2020.1585

[9] Author, A. Majkowska, S. Mittal, D. F. Steiner et al., "Chest radiograph interpretation with deep learning models: assessment with radiologist-adjudicated reference standards and population-adjusted evaluation," Radiology, vol. 294, no. 2, pp. 421–431, 2020

[10] . N. Darapaneni et al., "Deep convolutional neural network (CNN) design for pathology detection of COVID-19 in chest X-ray images," in Lecture Notes in Computer Science, Cham: Springer International Publishing, 2021, pp. 211–223.Author, S. Wang, B. Kang, J. Ma, et al., A deep learning algorithm using CT images to screen for coronavirus disease (COVID-19), MedRxiv (2020), https://doi.org/10.1101/2020.02.14.20023028.

[11] Ye, Zheng, et al. "Chest CT manifestations of new coronavirus disease 2019 (COVID-19). A pictorial review." European Radiology 30.8 (2020): 4381-4389.

[12] Heidari, Morteza, et al. "Improving the performance of CNN to predict the likelihood of COVID-19 using chest X-ray images with preprocessing algorithms." International journal of medical informatics 144 (2020): 104284.

[13] Haritha, D., N. Swaroop, and M. Mounika. "Prediction of COVID-19 Cases Using CNN with X-rays." 2020 5th International Conference on Computing, Communication and Security (ICCCS). IEEE, 2020.

[14] Das, Amit Kumar, et al. "Automatic COVID-19 detection from X-ray images using ensemble learning with convolutional neural network." Pattern Analysis and Applications 24.3 (2021): 1111-1124.

[15] Meem, A. T., Khan, M. M., Masud, M., and Aljahdali, S. (2022). Prediction of covid-19 based on chest x-ray images using deep learning with CNN. Computer Systems Science and Engineering, 1223-1240.

[16] Islam, M. M., Karray, F., Alhajj, R., and Zeng, J. (2021). A review on deep learning techniques for the diagnosis of novel coronavirus (COVID-19). Ieee Access, 9, 30551-30572.

[17] Tayarani, Mohammad. "Applications of artificial intelligence in battling against covid-19: A literature review." Chaos, Solitons and Fractals (2020).

[18] Yoo, S. H., Geng, H., Chiu, T. L., Yu, S. K., Cho, D. C., Heo, J., ... and Lee, H. (2020). Deep learning-based decision-tree classifier for COVID-19 diagnosis from chest X-ray imaging. Frontiers in medicine, 7, 427.

[19] Sufian, A., Ghosh, A., Sadiq, A. S., and Smarandache, F. (2020). A survey on deep transfer learning to edge computing for mitigating the COVID-19 pandemic. Journal of Systems Architecture, 108, 101830.

[20] Alshazly, H., Linse, C., Barth, E., and Martinetz, T. (2021). Explainable COVID-19 detection using chest CT scans and deep learning. Sensors, 21(2), 455.

[21] Haghanifar, A., Majdabadi, M. M., Choi, Y., Deivalakshmi, S., and Ko, S. (2022). Covid-cxnet: Detecting covid-19 in frontal chest x-ray images using deep learning. Multimedia Tools and Applications, 1-31.

[22] Ahsan, M., Based, M. A., Haider, J., and Kowalski, M. (2021). COVID-19 detection from chest X-ray images using feature fusion and deep learning. Sensors, 21(4), 1480.

[23] De Moura, J., García, L. R., Vidal, P. F. L., Cruz, M., López, L. A., Lopez, E. C., ... and Ortega, M. (2020). Deep convolutional approaches for the analysis of covid-19 using chest x-ray images from portable devices. Ieee Access, 8, 195594-195607.

[24] Babukarthik, R. G., Adiga, V. A. K., Sambasivam, G., Chandramohan, D., and Amudhavel, J. (2020). Prediction of COVID-19 using genetic deep learning convolutional neural network (GDCNN). Ieee Access, 8, 177647-177666.

[25] Saeedizadeh, N., Minaee, S., Kafieh, R., Yazdani, S., and Sonka, M. (2021). COVID TV-Unet: Segmenting COVID-19 chest CT images using connectivity imposed Unet. Computer Methods and Programs in Biomedicine Update, 1, 100007.

[26] Alyasseri, Z. A. A., Al-Betar, M. A., Doush, I. A., Awadallah, M. A., Abasi, A. K., Makhadmeh, S. N., ... and Zitar, R. A. (2022). Review on COVID-19 diagnosis models based on machine learning and deep learning approaches. Expert systems, 39(3), e12759.

[27] Khan, I. U., and Aslam, N. (2020). A deep-learning-based framework for automated diagnosis of COVID-19 using X-ray images. Information, 11(9), 419.

[28] Al-Rakhami, M. S., Islam, M. M., Islam, M. Z., Asraf, A., Sodhro, A. H., and Ding, W. (2021). Diagnosis of COVID-19 from X-rays using combined CNN-RNN architecture with transfer learning. MedRxiv, 2020-08.

[29] Ranjbarzadeh, R., Jafarzadeh Ghoushchi, S., Bendechache, M., Amirabadi, A., Ab Rahman, M. N., Baseri Saadi, S., ... and Kooshki Forooshani, M. (2021). Lung infection segmentation for COVID-19 pneumonia based on a cascade convolutional network from CT images. BioMed Research International, 2021.

[30] Fang, C., Bai, S., Chen, Q., Zhou, Y., Xia, L., Qin, L., ... and Torr, P. H. (2021). Deep learning for predicting COVID-19 malignant progression. Medical image analysis, 72, 102096.