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SarNet-1 -A Novel Architecture for Diagnosing Covid-19 Pneumonia and Pneumonia through Chest X-Ray Images

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Abstract: Coronavirus (COVID-19) is a contagious disease which begins with flu-like symptoms. COVID-19 arose in China and it rapidly spread throughout the globe, leading to a pandemic. For many, it was noticed that the infection started with fever, cough and finally leading to pneumonia. It is very necessary to differentiate between covid pneumonia and general pneumonia for appropriate treatment. Chest X-ray readings are useful for radiologists to identify the severity of infection. While computerising this mechanism, deep learning techniques are found to be very useful in extracting relevant features from medical images. This can help in differentiating pneumonia, COVID19 pneumonia and x-rays of a healthy person. Computer aided methods for identifying the presence of pneumonia can help health providers to a great extent for quick diagnosis. The X-ray's gathered from freely available datasets are used in this work to propose an architecture for categorising X-ray's into pneumonia and covid pneumonia.

Keywords: *Deep learning. Convolutional Neural Network(CNN). Chest X-ray images (CXR) · Pneumonia detection · COVID-19*

I. INTRODUCTION

The coronavirus illness (COVID-19), which posed a major threat to public health as the year 2019 came to a close, started to spread around the world. The virus was found in Wuhan, an Eastern Chinese city, in December of this year. It is termed by as "Public health emergency of international concern" by the World Health Organization (WHO) in 2020, and by March 2020, the sickness had become a pandemic [1]. If COVID- 19 is not recognised, the condition may worsen and may even develop in pneumonia [2]. Its clinical indications are quite similar to those of pneumonia. It's important to distinguish since the infections are spreading quickly and a suitable remedy hasn't yet been provided[3]. One of the frequent techniques used by radiologists to diagnose pneumonia early is the examination of chest X-rays [4] [5]. It can be challenging, even for some professionals, to diagnose pneumonia just from an X-ray. Experts find it puzzling since an incorrect diagnosis might result if the X-ray is misinterpreted for one of several benign conditions. As a result, a more methodical and automated strategy is required [6] to help doctors identify pneumonia from X-ray. In addition to X-rays, different methods such as pulse oximetry, phlegm and blood gas analysis, bronchoscopy, and a complete blood count are used to diagnose pneumonia [7]. The most popular approach for detecting inflammation brought on by pneumonia is X-ray. When compared to other existing measures, it's also rather affordable. In order to identify the inflammation associated with pneumonia, radiologists examine chest X-rays for white patches on the infiltrates of the respiratory system.

Medical image analysis is greatly aided by neural network-based models, which also provide high classification accuracy. CNN has proven to be a well-liked neural network method for image analysis and categorization [8]. In order to categorise pneumonia, covid-19 pneumonia, chest X-ray of a healthy person, this study suggests a deep learning algorithm. This research gives a thorough explanation of the architecture and the findings so that the best decision can be made. For this investigation, the images are separated into three groups.

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The X-ray in each of these datasets are made up into groups of 100, 250, 500, and ultimately 1000. These batches of image sets are used to train as well as examine the proposed architecture to see how it does with different numbers of photos. The paper highlights the review of various works in section two which enlightens works on pneumonia classification, section 3 on the methods and methodology, section 4 on the architecture developed to define the model, section 5 on the results and section 6 has the conclusion of the work done.

II. LITERATURE STUDY

Since COVID-19 infection can cause pneumonia, it is crucial to distinguish it from common pneumonia in order to administer the proper care. CNN-based algorithms may be used to categorise X-ray since it is the popular ways to diagnose infection from X-ray's. Numerous studies have opted CNN to identify the infection in X-rays since pneumonia and covid-19 pneumonia both result in significant lung infections and are identified by analysing chest X-rays[9]. Even for some radiologists, analysing the x-ray to identify the infection that represents pneumonia can occasionally become a tiresome task. X-ray could be mistaken for another benign ailment, which could result in a misdiagnosis that has disastrous consequences. Therefore, it is imperative to develop a more methodical and analytical technique to help doctors identify pneumonia from radiographic images [10]. CNN is capable of categorising images using useful information. CNN has significantly impacted the field of image categorization and also enables localisation in computer systems[10]. A method for more methodically and accurately identifying images is image classification. Deep learning neural networks like CNN (Convolutional Neural Network) are used to detect and classify. CNN is capable of categorising images using useful information. CNN has significantly impacted the field of image categorization and also enables localisation in computer vision[11]. Chest X-rays may be easily administered to patients, and as they are a low-cost method, using them to find COVID-19 is often possible [12]. Chest X-ray radiographs were employed, together with ResNet50, InceptionV3, and Inception-ResNetV2 convolutional neural networks, to identify pneumonia caused by coronavirus, according to the author in [12]. The classification accuracy of the ResNet50 model was 98%, that of InceptionV3 was 97%, and that of InceptionResNetV2 was 87%. To reduce overfitting, they conducted around 30 epochs for each of the models throughout the training phase. ResNet18, AlexNet, Squeeze Net, and DenseNet201 [13]. Using image augmentation techniques, a twenty-fold training of COVID-19 was produced (specifically, rotation, scaling, and translation). This work has a 98% accuracy rate. The ResNet-18 CNN architecture was used as the research foundation by the authors in [14]. Detection of COVID-19 occurrences was 96% accurate, whereas detection of non-COVID-19 instances was 70% accurate. A ResNet-50 architecture was improved by the authors of [15] in order to classify COVID-19 and pneumonia patients. Their average accuracy was 94.4%. Using ResNet-50 features and SVM (Support Vector Machine), the author in [16] was able to distinguish between healthy and The authors in [17] obtained a 90% accuracy rate for binary classification using a variety of well-known CNN architectures. The dataset used in this investigation included 25 COVID-19 instances and 25 photos of ordinary X-rays. A methodology was developed by the authors of [18] to divide X-ray pictures into three categories: normal, COVID-19, and SARS cases. A modified approach allowed them to achieve a 95% accuracy rate. A distinctive CNN model that learns latent factor filters was developed by the authors of [19]. According to their data, their model has an accuracy of 99.80 percent The writers of [20] used DenseNet-201, SVM, and Mobile Net. The accuracy of the Mobile Net model was 95.6%, whereas the accuracy of the DenseNet-201 model was 95.6%. Three edge models were presented by the authors in [21] for the classification of portable chest X-ray images. Their proposed DenseNet-201 CNN model has accurateness of 79.62 percent.

III. METHODOLOGY

Deep learning automates the training and learning process, making it predictable and easy with neural networks as its foundation. The uniqueness between deep learning and machine learning is that the latter learns from enormous amounts of data using a multi-layer neural network, while the former improves performance when exposed to long-term data. [22] [23]. CNN (Convolutional Neural Network) focuses more on classification. The main advantage of CNN is its ability to learn on its own using training data. Subsampling is also used to strengthen robustness and decrease temporal complexity. Sampling and convolution are the two most common techniques. The authors in [17] obtained a 90% accuracy rate for binary classification using a variety of well-known CNN architectures. The dataset used in this investigation included 25 COVID-19 instances and 25 images of ordinary X-rays. A methodology was developed by the authors of [18] to divide X-ray into three categories: normal, COVID-19, and SARS cases. A modified approach allowed them to achieve a 95% accuracy rate. A distinctive CNN model that learns latent factor filters was developed by the authors of [19]. The writers of [20] used DenseNet-201, SVM, and Mobile Net. The accuracy of the Mobile Net model was 95.6%, whereas the accuracy of the DenseNet-201 model was 95.6%. The fundamental goal of the activation map is to

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conserve features and reduce the amount of data that has to be processed. The second layer, called the pooling layer, is utilised to reduce the size of the map. This implies that just the most important characteristics will be selected to reduce invariance across all the qualities created. Here, Max pooling is used, which separates the largest value from each matrix into two distinct matrices, is the best approach. As a result, the main visual traits will be diminished. The last layer is fully linked, and it is delivered to the neural network [24].

A. *Dataset Research*

In this research, COVID-19 patients xrays of chest have been considered. In addition, the data collected is divided into groups of 100, 250, 500, 750 and 1000 image groups each. The data has been downloaded and integrated from various open source websites. The dataset has been divided into three folders namely COVID-19 pneumonia, pneumonia and xrays of healthy person. The dataset for covid19 pneumonia has been downloaded from [27], pneumonia and normal chest x-ray images from [28]. Few of the sample images from the dataset have been shown below.

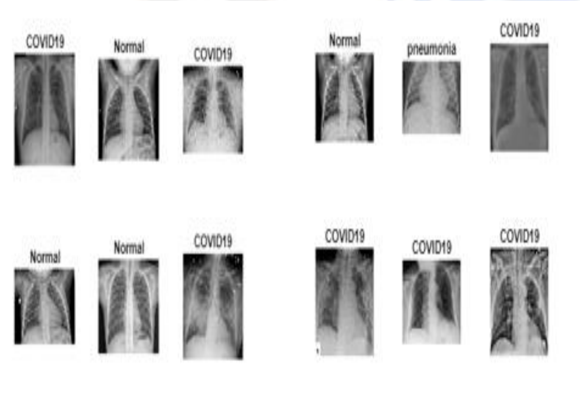

Fig. 1: Sample dataset representation

This dataset has then been pre-processed, the images are resized to 227*227. Also after resizing the images undergo contrast enhancement, sharpening, Noise removal so as to have better quality images.

IV. ARCHITECTURE

According to proposed architecture as seen in figure 2, the output from each convolutional layer has been merged in accordance with the suggested design shown in figure 2. Because the pooling layer performs down sampling after each convolutional layer, or subsampling, the size of each convolutional layer varies. After each layer, activation functions have been introduced. For this architecture, ReLu (Rectified Linear Unit) has been employed as the activation function. Since the activation function imparts nonlinearity to these levels since the convolutional layer is intended to be nonlinear, these layers are employed after each convolutional layer. The result is then generated after using the Softmax layer for classification, which selects the top best probability. Table 1 displays each layer and its properties. According to the technique, 3000 chest X-ray in total were gathered from diverse sources. Images were scaled down to (227*227) in size. a total of 3000 images, divided into 70% training images and the remaining 30% test images. The model was fed with input images. SarNet-1, the suggested model, has 41 layers. The convolutional layer receives a image with an input size of (227*227). The image's channels are increased by this convolutional layer, which results in an output with 32 channels while maintaining the image's original dimensions. Then, batch normalisation and ReLu are used. The image's dimensions are then changed to (113*113) via the use of max-pooling. Following batch normalisation and ReLu, which maintain the image channels as (113*113), are convolutional layers. Until the entire linked layer is reached, this process is continued. The global average pool layer receives input from the final classification layer. The output is then flattened and supplied to a classification layer after the Softmax layer. With Adam acting as the optimizer, the learning rate was fixed at 0.0001. 25 epochs were used to train the model.

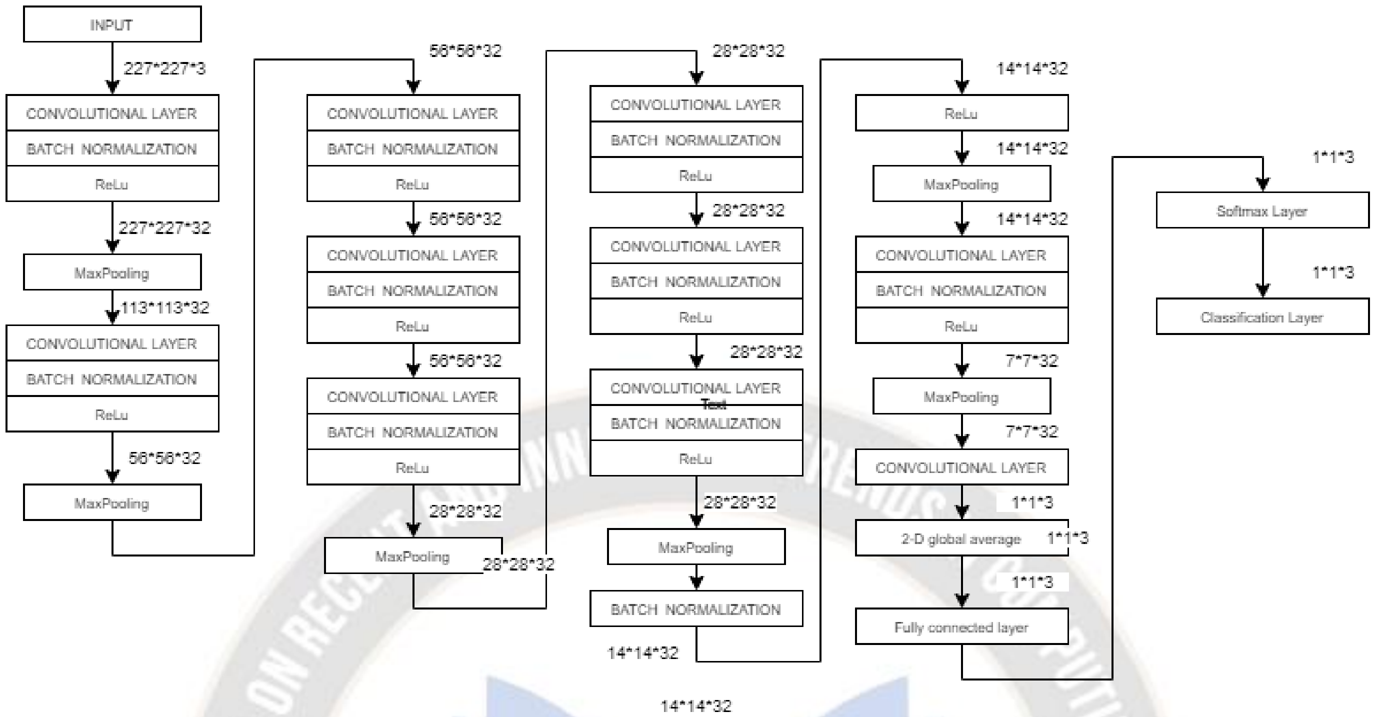

Fig. 2: Architecture of SarNet-1

LAYER NUMBER	TYPE	ACTIVATIONS
1.	Image Input	227*227*3
2.	Convolution	227*227*32
3.	Batch Normalization	227*227*32
4.	ReLu	227*227*32
5.	Max Pooling	113*113*32
6.	Convolution	113*113*32
7.	Batch Normalization	113*113*32
8.	ReLu	113*113*32
9.	Max Pooling	56*56*32
10.	Convolution	56*56*32
11.	Batch Normalization	56*56*32
12.	ReLu	56*56*32
13.	Convolution	56*56*32
14.	Batch Normalization	56*56*32
15.	ReLu	56*56*32
16.	Convolution	56*56*32
17.	Batch Normalization	56*56*32
18.	ReLu	28*28*32
19.	Max Pooling	28*28*32
20.	Convolution	28*28*32
21.	Batch Normalization	28*28*32
22.	ReLu	28*28*32
23.	Convolution	28*28*32
24.	Batch Normalization	28*28*32
25.	ReLu	28*28*32
26.	Convolution	28*28*32
27.	Batch Normalization	28*28*32
28.	ReLu	28*28*32
29.	Max pooling	14*14*32
30.	Batch Normalization	14*14*32
31.	ReLu	14*14*32
32.	Max Pooling	14*14*32
33.	Convolution	14*14*32
34.	Batch Normalization	14*14*32
35.	ReLu	14*14*32
36.	Max Pooling	7*7*32
37.	Convolution	7*7*32
38.	2-D global average	1*1*3
39.	Fully connected layer	1*1*3
40.	Softmax	1*1*3
41.	Classification output	1*1*3

TABLE 1: LAYERS AND ITS PARAMETERS

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V. RESULTS OBTAINED AND ITS ANALYSIS

In this part, the accuracy graph and loss observation are discussed. The confusion matrix and ROC curve are then presented. The model was trained using several data sets, and the outcomes were recorded. The images of pneumonia, normal x-rays, and covid-19 x-rays are separated from the data first. The information is then separated into several sets to examine the operation of the architecture. To start, the data is split into 100-folder for each of the three sets. With 25 epochs and 450 iterations, the results showed a classification accuracy of 92.3%. The training process took 15 minutes to complete. Next, 250 images of the data were distributed across the three sets. The training took 39 minutes to complete, and the results were 94.3% for the same with 25 epochs and 1150 iterations. The data was split into three groups of 500 X-ray pictures each for the next batch. With 25 epochs and 2325 iterations, the classification accuracy was 95.4%, and the training process took 78 minutes to complete. For all three sets, the data was further separated into 750 images each. The training took 113 minutes to complete, and the results were 93.8% for the same with 25 epochs and 3500 iterations. The data was then split into 1000 images for each of the three sets. The training took 160 minutes to complete, and the results were 94.9% for the same with 25 epochs and 4675 iterations. The following figures below show the training, ROC curve, and confusion matrix. The X64-based PC running this course has an Intel(R) Core(TM) i3-6006U CPU clocked at 2 GHz, 2000 MHz, with 2 cores and 4 logical processors (s). All iterations have a learning rate of 0.0001. The training, together with accuracy and loss, are shown in Figure 3. The achieved accuracy is 94.9%. Figure 4 shows the training accuracy and loss for validation, where the accuracy attained was 87.1%. The confusion matrix for the same is shown in figures 5 and 6. Figure 7 is the predicted test images and figure 8 shows the ROC (receiver operating characteristic) curve value as 0.9.

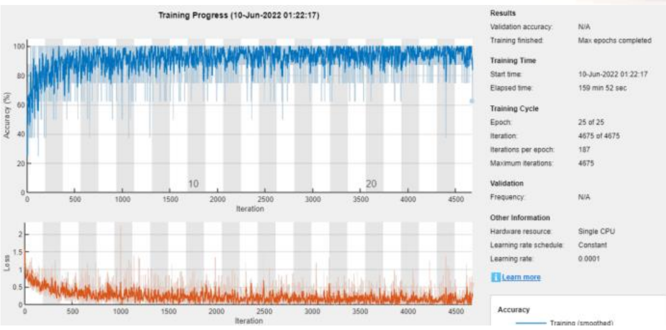

Fig. 3: Training graph containing the loss and accuracy

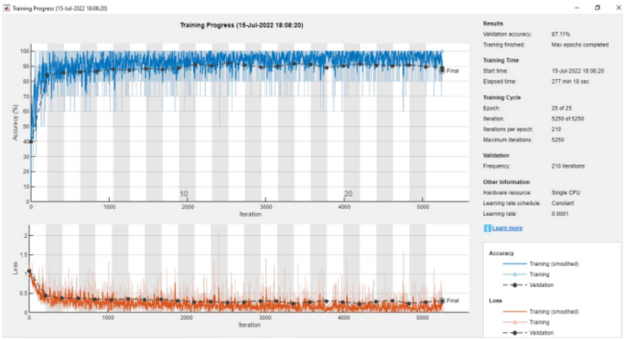

Fig. 4: Training graph with validation containing the loss and accuracy

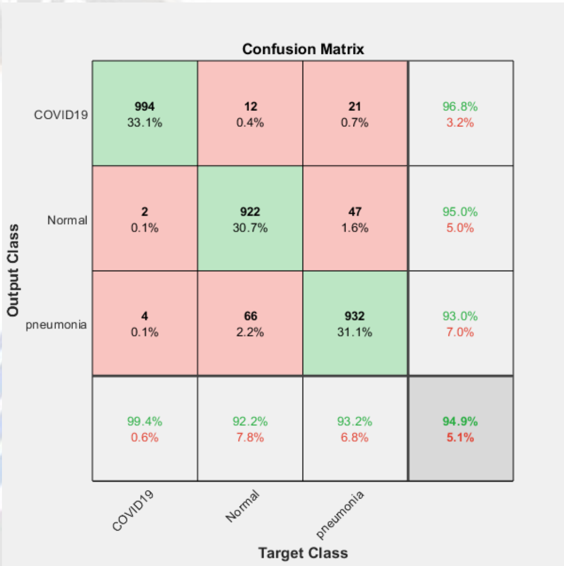

Fig. 5: Confusion matrix

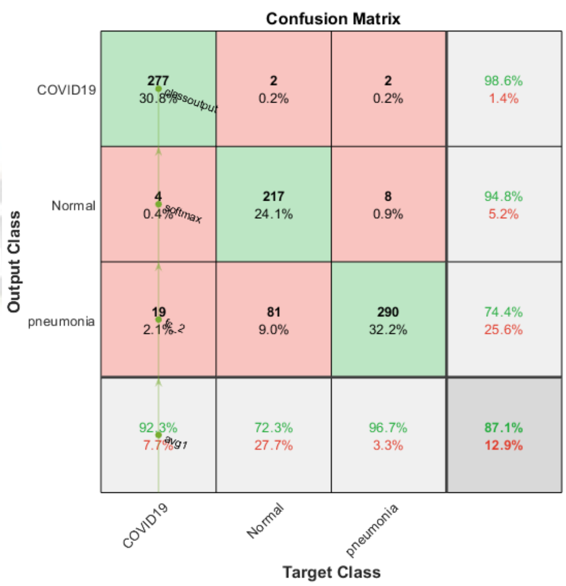

Fig. 6: Confusion matrix after performing validation

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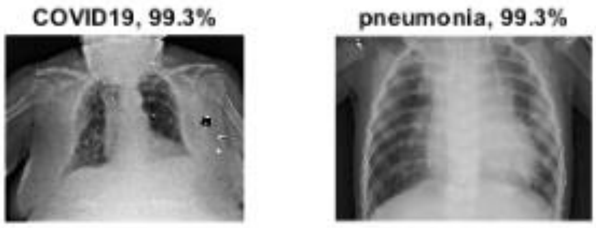

Fig. 7: Predicted Images

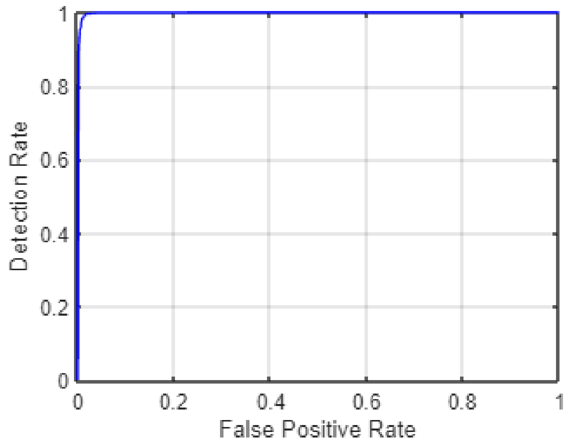

Fig. 8: ROC curve

VI. CONCLUSION

Deep learning techniques for health image examination have shown successful outcomes. In this research, an approach was used to analyse chest x-rays and identify the presence of pneumonia. A dataset of 3000 x-rays of chest was categorized into three sets namely COVID-19 pneumonia, pneumonia, and x-rays' of a healthy person. With the help of these images as training data, the suggested model can classify x-rays' of chest with an accurateness of 94.9%.

REFERENCES

[1]. S. Albahli, "Efficient gan-based chest radiographs (CXR) augmentation to diagnose coronavirus disease pneumonia," Int. J. Med. Sci., vol. 17, no. 10, pp. 1439–1448, 2020, doi: 10.7150/ijms.46684.
[2]. K. H. Shibly, S. K. Dey, M. T. U. Islam, and M. M. Rahman, "COVID faster R–CNN: A novel framework to Diagnose Novel Coronavirus Disease (COVID-19) in X-Ray images," Informatics Med. Unlocked, vol. 20, p. 100405, 2020, doi: 10.1016/j.imu.2020.100405.
[3]. S. V Militante and B. G. Sibbaluca, "Pneumonia Detection Using Convolutional Neural Networks," [Online]. Available: www.ijstr.org.
[4]. P. Rajpurkar et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," Nov. 2017, [Online]. Available: http://arxiv.org/abs/1711.05225.
[5]. K. Hamano-Hasegawa et al., "Comprehensive detection of causative pathogens using real-time PCR to diagnose pediatric community-acquired pneumonia," J. Infect. Chemother., vol. 14, no. 6, pp. 424–432, 2008, doi: 10.1007/s10156-008-0648-6.
[6]. K. El Asnaoui, Y. Chawki, and A. Idri, "Automated Methods for Detection and Classification Pneumonia based on X-Ray Images Using Deep Learning," 2021.
[7]. J. Chastre and J.-Y. Fagon, "State of the Art Ventilator-associated Pneumonia," Am J Respir Crit Care Med, vol. 165, pp. 867–903, 2002, doi: 10.1164/rccm.2105078.
[8]. M. F. Hashmi, S. Katiyar, A. G. Keskar, N. D. Bokde, and Z. W. Geem, "Efficient pneumonia detection in chest xray images using deep transfer learning," Diagnostics, vol. 10, no. 6, Jun. 2020, doi: 10.3390/diagnostics10060417.
[9]. N. K. Chowdhury, M. A. Kabir, M. M. Rahman, and N. Rezoana, "ECOVNet: An Ensemble of Deep Convolutional Neural Networks Based on EfficientNet to Detect COVID-19 From Chest X-rays," Sep. 2020, doi: 10.7717/peerj-cs.551.
[10]. J. C. Gomes et al., "IKONOS: An intelligent tool to support diagnosis of Covid-19 by texture analysis of x-ray images."
[11]. D. Kollias, A. Tagaris, A. Stafylopatis, S. Kollias, and G. Tagaris, "Deep neural architectures for prediction in healthcare," Complex Intell. Syst., vol. 4, no. 2, pp. 119–131, Jun. 2018, doi: 10.1007/s40747-017-0064-6.
[12]. A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks," Pattern Anal. Appl., vol. 24, no. 3, pp. 1207–1220, 2021, doi: 10.1007/s10044-021-00984-y.
[13]. M. E. H. Chowdhury et al., "Can AI Help in Screening Viral and COVID-19 Pneumonia?," IEEE Access, vol. 8, pp. 132665–132676, 2020, doi: 10.1109/ACCESS.2020.3010287.
[14]. L. Alzubaidi et al., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," J. Big Data, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00444-8.
[15]. L. O. Hall, R. Paul, D. B. Goldgof, and G. M. Goldgof, "Finding COVID-19 from Chest X-rays using Deep Learning on a Small Dataset." [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset.
[16]. P. K. Sethy, S. K. Behera, P. K. Ratha, and P. Biswas, "Detection of coronavirus disease (COVID-19) based on deep features and support vector machine," Int. J. Math. Eng. Manag. Sci., vol. 5, no. 4, pp. 643–651, 2020, doi: 10.33889/IJMEMS.2020.5.4.052.
[17]. S. Albahli and G. N. A. Hassan Yar, "Fast and accurate detection of COVID-19 along with 14 other chest pathologies using a multi-level classification: Algorithm development and validation study," J. Med. Internet Res., vol. 23, no. 2, Feb. 2021, doi: 10.2196/23693.
[18]. S. Hassantabar, M. Ahmadi, and A. Sharifi, "Diagnosis and detection of infected tissue of COVID-19 patients based on lung x-ray image using convolutional neural

network approaches," Chaos, Solitons and Fractals, vol. 140, p. 110170, 2020, doi: 10.1016/j.chaos.2020.110170.

[19]. R. Karthik, R. Menaka, and M. Hariharan, "Learning distinctive filters for COVID-19 detection from chest X-ray using shuffled residual CNN," no. January, 2020.

[20]. E. F. Ohata et al., "Automatic detection of COVID-19 infection using chest X-ray images through transfer learning," IEEE/CAA J. Autom. Sin., vol. 8, no. 1, pp. 239–248, 2021, doi: 10.1109/JAS.2020.1003393.

[21]. J. de Moura et al., "Deep convolutional approaches for the analysis of Covid-19 using chest X-ray images from portable devices," IEEE Access, vol. 8, pp. 195594–195607, 2020, doi: 10.1109/ACCESS.2020.3033762.

[22]. Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.

[23]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Dec. 2015, [Online]. Available: http://arxiv.org/abs/1512.03385.

[24]. A. Ajit, K. Acharya, and A. Samanta, "A Review of Convolutional Neural Networks," Feb. 2020, doi: 10.1109/ic-ETITE47903.2020.049.

[25]. T. Liu, S. Fang, Y. Zhao, P. Wang, and J. Zhang, "Implementation of Training Convolutional Neural Networks."

[26]. T. N. Sainath, A. R. Mohamed, B. Kingsbury, and B. Ramabhadran, "Deep convolutional neural networks for LVCSR," ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc., pp. 8614–8618, 2013, doi: 10.1109/ICASSP.2013.6639347.

[27]. "Pneumonia dataset." https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia.

[28]. "covid-19 pneumonia data." https://www.nih.gov/news-events/news-releases/nih-clinical-center-provides- one-largestpublicly-available-chest-x-ray-datasets-scientific-community%0A(National institute of health)%0A.