© June 2021| IJIRT | Volume 8 Issue 1 | ISSN: 2349-6002

Training CNN to categorize Pulmonary Radiological Imaging

Mallisha Patkar[1], Asawari Pensalwar[2], Professor. Rachana Dhannawat[3]
[1,2,3]*Department of Computer Science and Technology, SNDT University*

***Abstract* - Covid-19 is a severe acute respiratory syndrome that can be spread by close contact with an infected person. In this paper, we have proposed two convolutional neural network architectures to classify the image and see if the patient has COVID-19 or not. The first proposed architecture is using dropout layer and the other is without the dropout layer. The models are tested for two datasets: the original dataset and the dataset with augmentation. After testing, we got the highest accuracy of 98% with model 4 i.e. without dropout layer and with no data augmentation. We combined this model with webpage which can be used by normal people to know whether they are suffering from COVID-19 or not with probability of its occurrence.**

***Index Terms* - CNN, Chest x-ray, covid-19 Detection.**

I.INTRODUCTION

On March 11, 2020, the World Health Organization declared the novel Coronavirus as a global pandemic considering its rate of spreading around and being highly contagious [1]. It is said that the rate of getting the infection is high if a person comes in close contact with an infected person or through physical contact with the infected objects or surfaces [2]. By avoiding getting exposed is the best way to protect a person from the virus. About 18 million and rising infected cases around 213 countries in the world have been recorded [1].

The signs and symptoms of covid-19 are almost like to common cold and flu and hence are not detected properly; it can lead to improper diagnosis. Improper detection of pneumonia or non-covid-19 may get categorized incorrectly as Covid-19 ensuing in struggle, and setbacks in high-priced treatments, and chance of being round different covid-19 positive patients.

One of the most significant diagnostic instruments for Covid-19 is Radiographic Imaging that is commonly available at various hospitals. With the use of a radiographic instrument, a chest image of a patient is captured by the radiologist. CXR imaging can help identify cases early to achieve early treatment.

Convolutional Neural Network (CNN) is widely used in medical research because it has been proven to be of great importance for feature extraction and learning through training [3]-[4]. Under low-light conditions, when nodules are found in the airway, when X-ray analysis of respiratory diseases is used for medical purposes, and in many lungs, replacement studies, CNN devices have improved imaging characteristics and excellent results.

The behavioral development process based on learned characteristics or expressions is called learning in the DL method [5]. Dl is one of its sub-fields and has improved its application in the performance of various AI and machine learning applications [3]. DL affects the acceleration of GPU based computing power and the deeper network that is used to improve the operation enabled by nonlinearity [6].

This work proposes deep learning for the classification of chest x-rays for diseases such as Covid-19. A wide ability of CNN is shown in this paper. There is already existing predefined model which gave good result, but it is very time consuming and it does not give a good result on small data. This gave us an idea to build our own CNN model without using a pre-trained model. The main aim of this paper is to make a simpler version by using fewer layers and functions for Covid-19 detection as compared to the pre-trained and existing models and have accuracy as comparable as them and combining this model into a Web Application making the detection much faster and easier. This paper is mostly focused on getting good accuracy with only two convolution layers in CNN and thus integrating it into an HTML page so that the model can be put in use for real-life purposes.

II. LITERATURE REVIEW

In Deep learning algorithms, progressive research is increasing rapidly and the diagnosis of pneumonia in the medical area provides us with its likeness in a widely known area. Image processing techniques are applied for the study of identification. The actual image is cropped, and the lung region of the image is extracted with the use of the algorithms developed. To isolate the disease-infected part of the lungs from the healthy part of the lungs Otsu Thresholding is used. An investigation done by Sharma et al. leads them to help assist in their study in diagnosing patients [7]A study conducted by S.V.Militante associated B.G.Sibbaluca[4] during which five totally different deep learning models were trained and compared with one another to induce the most effective model that finds respiratory disease and healthy chest X-ray pictures mistreatment 26,684 datasets. As a result of their study, it had been found that VGG-Net was the best model with an accuracy of 97% to detect pneumonia [4].

Classification and feature extraction is done by Convolutional Neural Networks (CNN) which is a feed-forward network inspired by the human brain. There are four key players: the convolutional layer, the rectified linear unit (ReLU) the activation layer, the subsampling layer, and the fully connected layer [8]. Usually, a standard convolutional layer with the help of kernels takes an input and creates a feature map [9]. In the convolutional layer several inputs are stored by the neurons and to improve the delineation of input images several connections of neuron connections overlap each other. Additional acceleration for a more complex function is offered by the ReLU activation layer to the CNN and the sharing of weights and every convolutional layer result in the reduced number of parameters [10]. As a subsampling process Pooling is applied to overcome overfitting as well as lower the number of parameters, to eliminate the possibility of overfitting in CNN [9]. In the end, to determine the categorized result encapsulation if the trained features are complemented with one or more numbers of a fully connected layer.

A study was done by D.Varshini et al.[11] on pneumonia, detection used CNN models for the feature extraction which classified the images into normal chest X-rays or abnormal chest X-rays. In this study, they utilized the pre-trained models in CNN to extract the features. They used roughly about 3000 images containing both cases of pneumonia as well as normal equally. In the study, the performance of various pre-trained CNN models along with distinct classifiers was observed. Based on statistical results Dense-Net 169 was selected for feature extraction and support vector machine (SVM) as the classifier which gave them an Area under the curve (AUC) of 0.80 which was the highest among all.

A similar study was done by E.F. Ohata et al. [12] on covid19 detection using transfer learning. In this study, various Convolutional Neural Network (CNN) architectures were trained on ImageNet and adapted to behave as feature extractors from chest X-rays. Established machine learning methods such as k-Nearest Neighbor, Bayes, Random Forest, Multilayer Perceptron (MLP) and the Support Vector Machine (SVM) are then combined with CNN. The data set consisted of approximately 388 images containing 194 x-rays from patients diagnosed with coronavirus and 194 x-rays from normal images. Data sets, the most powerful extractor-classifier pair is the MobileNet architecture with SVM classifier with an F1 score of 98.5% and for other data sets the best pair is DenseNet201 with MLP with an F1 score of 95%.

A novel deep neural network-based model was created by Mangal et al. [13] for covid testing of paitents. This classification was done into 4 types-a) Normal b) Viral Pneumonia c) Bacterial Pneumonia and d) Covid-19. In this a pre-trained model of CheXNet[15], with a 121-layer Dense Convolutional Network (DenseNet) backbone and followed by a fully connected layer. In this approach, CheXNet's final classifier of 14 classes was replaced by their classification layer of 4 classes. This model obtained an accuracy of 87.2% for a 4class classifier and an accuracy of 90.5%for a 3-class classifier. This model was also compared with Covid-Net [14], it was seen that this model outperformed the Covid-Net model as well.

In the study done by S.V.Militante[16] classification of chest X-rays of covid-19, viral and bacterial pneumonia, and normal images were done. This study used a versatile associated economical approach of deep learning applying the pre-trained VGG-16 model of CNN to predict and detect the unaffected and diseased patient based on chest x-rays. This trained model provided an accuracy of 95% during performance training. Their research study could predict and detect Covid-19, viral and bacterial pneumonia based on their chest X-ray images.

A study conducted by H.Sharma et .al[17].in which feature extraction and classification of chest X-ray images was done using CNN to detect Pneumonia. In this, a different deep convolutional neural network (CNN) architecture was proposed to extract the features and classify the chest X-rays to detect if a person has pneumonia. Here, CNN architectures have been presented - one with a dropout layer and another one without a dropout layer. Each of the layers consisted of a convolution layer, max-pooling layer, and a classification layer. The series of convolution layer and max-pooling layer acts as feature extractor and the feature extracted were given as input to a dense layer that classified the images. The results of the performance of the proposed CNN showed that the CNN with dropout trained on augmented data outperformed the opposite models.

III. METHODOLOGY

In this section, we first deliver a quick define of the dataset used on this paper and the steps carried out earlier than training the proposed architecture. Secondly, we present the proposed architecture to extract the features and classify the chest X-rays to detect Covid-19 or Normal. It is a binary-class classification problem.

A. Dataset:

The data set used here consists of images from Kaggle. The link to the data set is" https://www.kaggle.com/tawsifurrahman/covid19radiography-database". These images were then sorted into Covid-19 and normal and uploaded on our repository on github to make a dataset. The dataset was divided into two parts: the train set and the test set. The training dataset was later split into a validation set. There were approximately around 1300 images of each category for training purposes, about 360 images consisted in the validation set and around 484 test images in all. The data set in total consisted of about 2295 images.

At first, the images in the data set were in different sizes and shapes. Since all the input pictures of CNN need to be of the equal size, we resized all of the pictures in the dataset to 64x64.To enhance the generalization capabilities of the CNN structure and keep away from over-fitting, data augmentation techniques like re-scaling, flipping, and so on had been used. Data augmentation guarantees that the CNN sees new versions at every and each epoch for the duration of training.

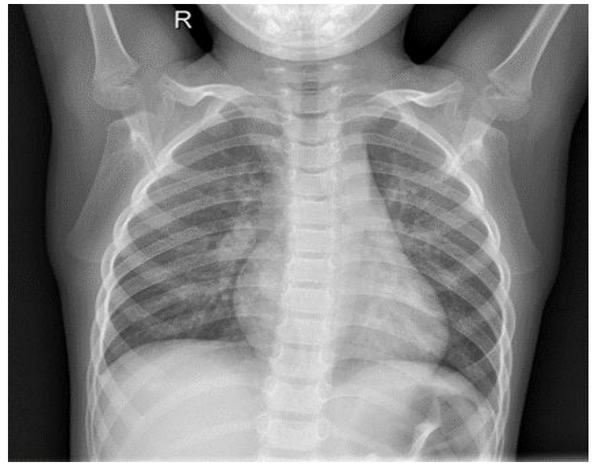

Fig. 1. X-ray of a Normal Person

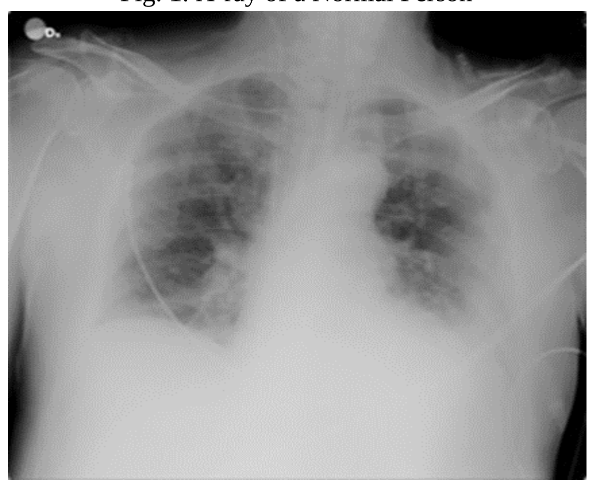

Fig. 2. X-ray of Covid-19 patient

The Fig.1 is an X-ray of healthy lungs from the dataset. The Fig.2 is an X-ray of lungs infected with covid-19 from the dataset.

B. Proposed Architecture:

In this paper, we have presented two CNN architectures one model is with a dropout layer [16] and another model is without a dropout layer. Here, both the CNN model consists of a convolution layer, max-pooling layer, and classification layer. Here, one convolution of 128 runs parallelly with two convolution layers one 32 unit and another one of 64 unit followed by a max-pooling [17] layer of size 2x2 and a Re LU activation layer. In neural networks, especially in CNN Re-LU [17]is a popular activation function that is generally used. This layer introduces non-linearity to the model. Re LU function passes only the positive values and all negative values will become zero. So, the output here we have only the positive values. Implementing this operation in python is quite easy and straightforward.

In the CNN, from the feature extractor part, the features are extracted, and it is provided as input to the dense layer to classify the image. A flattened layer is used before the extracted features are fed into the dense layer. A flatten layer flattens the data feature and gives a 1-Dimensional output. Since the dense layer takes only 1-Dimensional input, the output of the flatten layer is fed as input to the dense layer.

During CNN training dependency of the output of a certain layer might be more on a few selected neural units. Thus, to reduce this dependent behavior and to prevent over-fitting the dropout concept is introduced. Approximation of training a large number of the neural network along with different architectures in parallel is a regularization method called Dropout.[16] While training, a few layer outputs are ignored or 'dropped out' randomly. This makes the layer look like and treated altogether like a layer with a different number of nodes and its connectivity to the prior layer. Usually, the value of the dropout is the probability of 0.5 to retain the output of each hidden layer and chose a value close to 0.1 such as 0.8, to retain the inputs from the visible layer.

In one of the proposed CNN architectures with a dropout layer, as shown in fig 4. first the dropout layer is applied at the part where the features are extracted. i.e. after convolution and max pool layer. Here we assume that the probability of dropout layer is 0.2. Dropout is useful in lower layers because it gives noisy input to the fully connected upper layer and prevents overfitting. Even here. i.e. drop probability of 0.5 has been used in the dense layer. In most cases, a dense probability of 0.5 gives the best regularization.

The second model has the same architecture as the model mentioned above. The only difference is that the dropout layers from the first model are not present here. A model summary of with and without dropout is shown in fig.4 and fig.5

For the deployment of the model, we used website. The website is formed by using flask. The web site tells us whether or not the person has COVID-19 or not with the likelihood. The probability can facilitate the Pearson to require according measures before its written report from doctor is not given. The website page is shown below.

IV. EXPERIMENTAL RESULTS

To draw the results of data augmentation methods on the performance of our proposed CNN architecture, we trained the CNN's with unique dataset in addition to augmented dataset. The information of the CNN alongside the kind of dataset used are given.

We tested our model with different optimizers, and we got the best result from the Adam optimizer [15]. The result we got from different optimizers is listed below in Table 1.

The four models were trained for thirty epochs. Adam optimizer is used with the learning rate set to 0.0001.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_2 (MaxPooling2	(None, 32, 32, 32)	0
dropout_3 (Dropout)	(None, 32, 32, 32)	0
conv2d_3 (Conv2D)	(None, 32, 32, 64)	8256
max_pooling2d_3 (MaxPooling2	(None, 16, 16, 64)	0
dropout_4 (Dropout)	(None, 16, 16, 64)	0
flatten_1 (Flatten)	(None, 16384)	0
dense_2 (Dense)	(None, 256)	4194560
dropout_5 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 3)	771

Total params: 4,204,483
Trainable params: 4,204,483
Non-trainable params: 0

Fig. 3. model with dropout layer

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_4 (MaxPooling2	(None, 32, 32, 32)	0
conv2d_5 (Conv2D)	(None, 32, 32, 64)	8256
max_pooling2d_5 (MaxPooling2	(None, 16, 16, 64)	0
flatten_2 (Flatten)	(None, 16384)	0
dense_4 (Dense)	(None, 256)	4194560
dense_5 (Dense)	(None, 3)	771

Total params: 4,204,483
Trainable params: 4,204,483
Non-trainable params: 0

Fig. 4. model without dropout layer

Fig. 5. Webpage

The batch size is 32. Throughout training and validation, the loss is calculated with the help of binary cross-entropy.

As shown in Table 2. the 4 models were trained and

Optimizers	Accuracy
Adam	90
Nadam	87
Adgrad	72
Stochastic gradient descent (SGD)	77
Addelta	61
RMSprop	83

TABLE I ACCURACY OBTAINED FROM DIFFERENT OPTIMIZERS

Model	Dataset and CNN architecture
Model 1	With Augmentation, With Dropout
Model 2	With Augmentation, Without Dropout
Model 3	Without Augmentation, With Dropout
Model 4	Without Augmentation, Without Dropout

TABLE II TYPES OF MODELS

tested. Model 1 with dropout layer and trained with data augmentation has has a good training accuracy and lower loss as compared to other models with a test accuracy of 96%. Model 2 with augmentation and without dropout layer has the lowest accuracy among all with the test accuracy of 95%. Model 3 without data augmentation and with dropout layer gives us a test accuracy similar to model1 of about 97%. Model 4 without augmentation and dropout give us a test accuracy of 98%.

Even though model 4 gives us the highest test accuracy of them all when we compare all the graphs of the models as shown in fig 6 and 7, it is seen that model 4 has undergone maximum overfitting. Due to this we rule out model 4 for detection since the results given by this model will not be accurate.From here, we can say that the absence of both: dropout layer and data augmentation will surely affect the results and only accuracy is not the outcome to be looked for while building a model. After model 4, model 3 is the model with next highest accuracy, in this model we have used a dropout layer but did not use data augmentation. Again, here when we compare the graphs, we can clearly see that model 3 not only undergoes overfitting but also keeps on deflecting from its values and is not constant. This shows that even with the presence of dropout layer the issue of overfitting is not completely solved, and we can also see that the growth in graph is not constant. Hence, model 3 will also not be a good choice for detection. Now coming to the next model with highest accuracy we have model 1. Here, we have the dropout layer as well as data augmentation and comparing the graphs here we can see that model 1 has the perfect fit without any underfitting or overfitting and also with a constant growth. Therefore, model 1 is a good choice for detection. Now model 2 has the lowest accuracy among all, in this model we have used data augmentaion but without dropout layer. Even though it gives us a lowest accuracy the model cannot be rejected just on the basis of accuracy. After comparing with the graphs, we can see the after model 1 only model 2 has a good graph but we can see deflections as it approaches in the end this shows that there is possibility that the model is going through some overfitting. Here, as it is seen even if only data augmentation is used, and we achieved a better graph compared to other two we cannot rule out the fact that only data augemnation cannot completely remove overfitting.

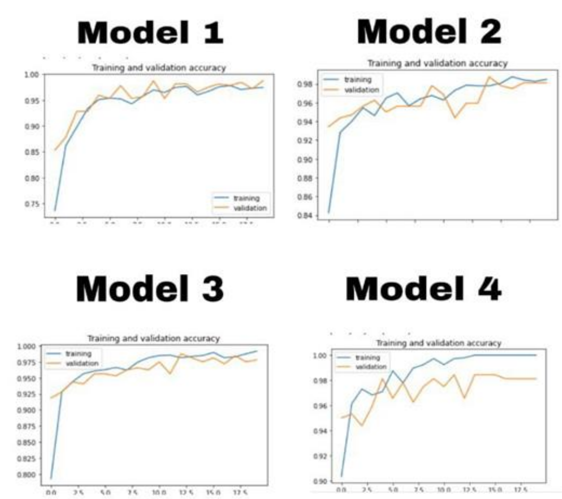

Fig. 6. comparison of accuracy

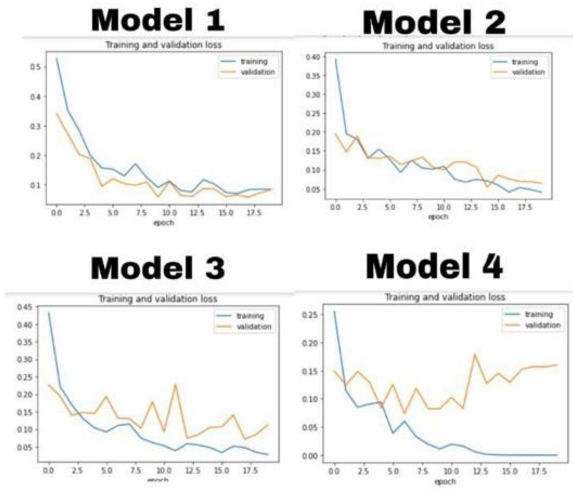

Fig. 7. comparison of loss

After the above analysis, model 1 is the best model among the four proposed model and can be used for detection. The probabilities are also displayed along with the result and the probabilities displayed will also show the reliability of the model.

V. CONCLUSION

In this paper, we created two of our own CNN models to detect COVID-19 from Xray. To increase the size of the dataset we used the data augmentation method. We tested our model with different optimizers and the best result we got it from Adam. After testing with our 4 models, we got very high accuracy which is 98% for model 4. But even though model 4 has highest accuracy among other models this model undergoes overfitting. Among the four models only model 1 has the perfect fit in the graphs. This model is very simple and uses one convolution layer in parallel with 2 convolution layers. This model then being included in a web flask application, in which an X-Ray is uploaded, and the application will detect and display its analysis along with the probability of its prediction. In the future, with some changes we can use this model for classifying and detecting other lung diseases, hence making radiographic image detection easier and faster.

REFERENCES

[1] ” World Health Organization. Coronavirus disease 2019 (COVID-19) Situation Report–”, August 2020, pp. 196.

[2] S. Militante and N. Dionisio, Real-” Time Facemask Recognition with Alarm System using Deep Learning.” 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE),2020

[3] S. Militante, N. Dionisio and B. Sibbaluca,” Pneumonia Detection through Adaptive Deep Learning Models of Convolutional Neural Networks”.

[4] S. V. Militante and B. G. Sibbaluca,” Pneumonia Detection Using Convolutional Neural Networks”, International Journal of Scientific and Technology Research, April 2020, vol. 9, no. 04, pp. 1332-1337.

[5] R. H. Abiyev and M. K. S. Ma’aitah,” Deep Convolutional Neural Networks for Chest Diseases Detection”, Journal of Healthcare Engineering, 2018

[6] M. Cicero, A. Bilbily, E. Colak, T. Dowdell, B. Gra, K. Perapaladas, et al.,” Training and Validating a Deep Convolutional Neutral Network for Computer-Aided Detection and Classification of Abnormalities on Frontal Chest Radiographs”, Investigative Radiology,2017, vol. 52, no. 5, pp. 281-287,

[7] A. Sharma, D. Raju and S. Ranjan,” Detection of pneumonia clouds in chest X-ray using image processing approach”,Nirma University International Conference on Engineering (NUiCONE),2017. pp. 1-4.

[8] Y. LeCun, Y. Bengio and G. Hinton,” Deep learning”, May 2015, Naturevol. 521, pp. 436-444.

[9] S. V. Militante, B. D. Gerardo and N. V. Dionisio,” Plant Leaf Detection and Disease Recognition using Deep Learning”, IEEE Eurasia Conference on IoT Communication and Engineering (ECICE), 2019, pp. 579-582.

[10] A. Krizhevsky, I. Sutskever and G.E. Hinton,” ImageNet Classification with Deep Convolutional Neural Networks”,2012, Neural Information Processing Systems, vol. 25.

[11] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal,” Pneumonia Detection Using CNN based Feature Extraction,” 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364.

[12] E. F. Ohata et al.," Automatic detection of COVID-19 infection using chest X-ray images through transfer learning," in IEEE/CAA Journal of Automatica Sinica, January 2021, vol. 8, no. 1, pp. 239-248 doi: 10.1109/JAS.2020.1003393.

[13] Arpan Mangal 1, Surya Kalia 1, Harish Rajgopal 2, Krithika Rangarajan 3, 1, Vinay Namboodiri 2, 4, Subhashis Banerjee 1, and Chetan Arora" CovidAID: COVID-19 Detection Using Chest XRay", arxiv2004.09803v1 ,21 April 2020.

[14] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., et al.: Chexnet: Radiologistlevel pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225 (2017)

[15] Wang, L., Wong, A.:" Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest radiography images" arXiv (2020)

[16] S. V. MilitanteAU - N. V. DionisioAU - B. G SibbalucaPY" TY CONFTI - Pneumonia and COVID-19 Detection using Convolutional Neural NetworksT2"-2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE)SP - 1EP - 6AU.

[17] H. Sharma, J. S. Jain, P. Bansal and S. Gupta," Feature Extraction and Classification of Chest X-Ray Images Using CNN to Detect Pneumonia," 2020 10th International Conference on Cloud Computing, Data Science Engineering (Confluence), Noida, India, 2020, pp. 227231, doi: 10.1109/Confluence47617.2020.9057809.