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Pneuvid: A CNN Model for Detection of Pneumonia using Chest X-Rays to Help COVID-19 Patients

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Abstract— Pneumonia has the potential to have serious repercussions in a brief period because the fluid that flows into the lungs causes suffocation. Pneumonia can be fatal if not treated with medication at the appropriate time. To diagnose the illness at its earliest stages, this paper reviews the multiple studies on improving the level of detection and offers the methods and outcomes of automation of x-ray pictures based on several parameters. The selected dataset was trained using some well-known convolutional neural networks. In this paper, we present our deep learning framework for the categorization job, which is trained on altered images using several preprocessing procedures. As a result, we can conclude that our proposed model had the best performance with the training and testing set's accuracy being 93.36% and 88.46%.

Index Terms— Convolutional Neural Network, VGG-16, VGG-19, Pooling, ResNet, Deep Learning, Pneumonia.

I. INTRODUCTION

Pneumonia is an infection primarily caused by one or both respiratory organs. It is a dangerous disease that is, by far, known to be the leading cause of death in children worldwide, considering the comparison of pneumonia to other diseases that spread through infected organs.

The disease usually occurs when a person comes in contact with another infected human, which makes the air they breathe susceptible to infecting them in a significant way. A person then breathes the said infected air, which infects the air packets in their lungs and then infects their lungs, filling them up with pus and other liquids, making it harder for them to breathe, eventually leading to death with a heavy decrease in breathing capabilities or by weakening the immunity system of a person's body.

It is essential to detect pneumonia before it becomes fatal and recognize the symptoms that eventually lead to pneumonia. Infectious disease can be prevented by having an excellent and nutritious lifestyle and getting vaccinated against various viruses to ensure that the person does not become a carrier of the viruses that lead to pneumonia.

II. LITERATURE REVIEW

Through extensive research from [1], we also noticed that there were several factors that related the Coronavirus to people who had pneumonia as well. Some factors that stood out were that male sex, people of older age, and people with co-morbidities like hypertension to name one, had an increased risk for people to have Covid-19 Pneumonia if they were infected and admitted to a medical center for treatment. Here, the authors also noted that while 80% of the infected population suffered from mild pneumonia levels, the rest left could've suffered a more serious level of pneumonia in regard to co-morbidity and susceptibility of the said disease.

The average age of the study participants in [2] was 56 years, and 75 (54.3%) of the 138 hospitalized patients with novel coronavirus-infected pneumonia were male. Data on epidemiology, population statistics, clinical aspects, lab, radiology, and treatments were collected and examined. After looking at the Chest computed tomographic scans of the patients, it was evident that something wasn't right. The images revealed anomalous patterns like patchy shadows on both sides of the lungs and ground glass opacities (hazy regions that do not allow precise visualization). As a consequence of various complications, 36 patients (26.1%) were transferred to the intensive care unit (ICU), including 22 patients suffering from acute respiratory distress syndrome, 16 cases had an irregular heartbeat, and 11 patients were impacted by shock.

According to an imaging examination of the 99 patients with 2019 novel coronavirus pneumonia in [3], 74 had bilateral pneumonia, 14 had numerous blotches where some regions emerged darker, some looked lighter and a kind of misty film on their lungs, and one of them had pneumothorax, which is when air leaks into the gap between the lung and chest wall, making the lung collapse. It shows how important it is to detect COVID-19 pneumonia as soon as possible and prevent people from spreading the virus. It offers us beneficial awareness of how this illness advances, which can assist us to deduce the most acceptable ways to cure people.

To classify X-rays as having pneumonia or not, thresholds are determined based on the fluctuation in EMD values. Transfer learning was applied by [4] to create an ensemble classifier for the categorization of pneumonia using five deep

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convolutional neural networks. Yet it's crucial to remember that in the years to come, larger datasets, a data augmentation strategy, and the use of custom features could all lead to even better results.

The significance of deep learning and transfer learning in the area of medical radiology is demonstrated by [5]. These methods for detecting COVID-19 from chest radiographs can help with timely identification and treatment, which is crucial during a pandemic. This study also emphasizes how crucial it is for doctors and computer scientists to work together to create appropriate answers to healthcare issues.

Another study [6] used convolutional neural networks to classify data weekly to undertake early identification of thoracic disease rather than pneumonia. This study successfully identifies patterns in patients with thoracic disease or patients who may have the condition. Nevertheless, it has not been able to classify pneumonia. The early diagnosis of pneumonia symptoms is made successful by our model. It frees medical experts from having to arrive at a conclusion, enabling faster treatment and better results for patients.

The study [7] was capable of diagnosing pneumonia in an individual. Chest X-ray images gathered from Kaggle have successfully undergone training, testing, and validation. Successful image scaling, resizing, and capturing were followed by batch processing using Keras models. The model gave an accuracy of 87.64% on the training set.

[8] preprocessed their images and made some color adjustments. Three separate image editing approaches were used in their research method: increasing contrast, enlarging the image's color space, and adding artificial illumination. Three convolutional layers and max pooling were employed. To avoid overfitting, a dropout layer was inserted after the Softmax algorithm. Their framework was optimized using the Adam algorithm, and their loss function was the Binary cross-entropy function. With an accuracy percentage of 78.73%, their most effective experimentation model categorizes the photos.

Despite the possibility of effectiveness for the aforementioned conventional and radiological approaches, our work offers a deep learning solution for this pneumonia categorization. We describe our system for identifying the presence of pneumonia in an x-ray image. This paper will first describe the methodology used in our experimentation before discussing the current findings.

III. PROPOSED METHODOLOGY

This section provides an insight into the dataset which has been used to develop the Pneuvid model, deep learning models associated, preprocessing and augmentation, as well as the proficiency measures utilized to evaluate the reliability of our model. Described below is a flowchart in Figure 1, which explains the framework of our model.

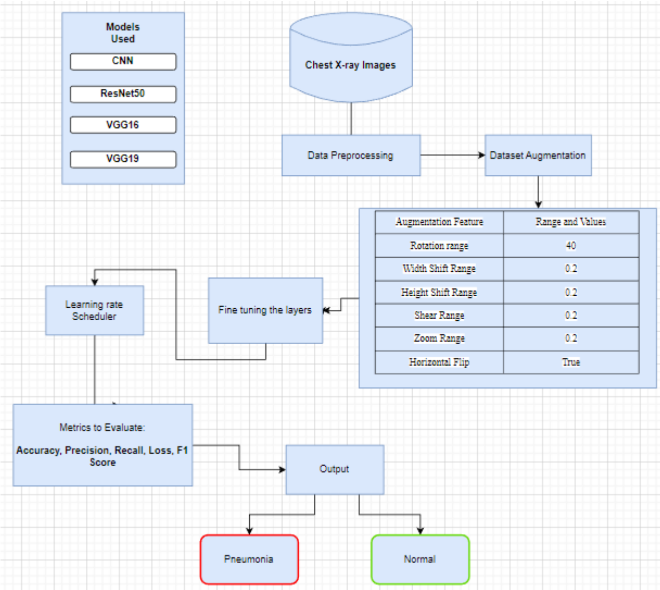

Figure 1: Framework of the model

A. Dataset Used

A set of chest X-ray pictures for binary pneumonia classification can be found in the Chest X-Ray pictures (Pneumonia) data source [9]. Paul Mooney created this dataset, which is openly accessible on Kaggle. There are overall 5,856 JPEG photos in the dataset, 4,273 are pneumonia sufferers, and 1,583 are healthy people as shown in Table 1 and shown in Figures 2 and 3, along with a graphical representation of normal vs pneumonia cases in Figure 4. The data was sourced from several clinics and hospitals and were recorded using multiple X-ray machines.

Table.1 Chest X-Ray Images (Pneumonia) Data Source

Dataset Folders	***Normal***	***Pneumonia***
Training Set	1341	3875
Testing Set	234	390
Validation Set	8	8
TOTAL	1583	4273

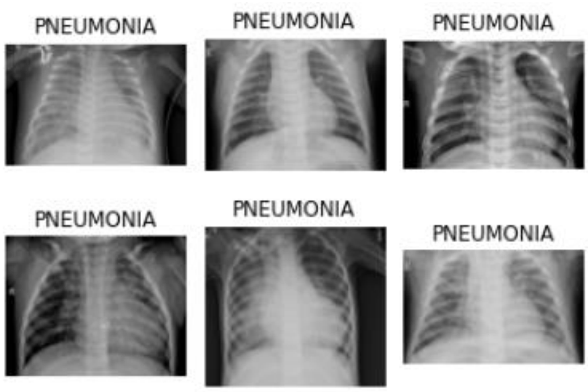

Figure 2: Specimen of Pneumonia pictures in the dataset

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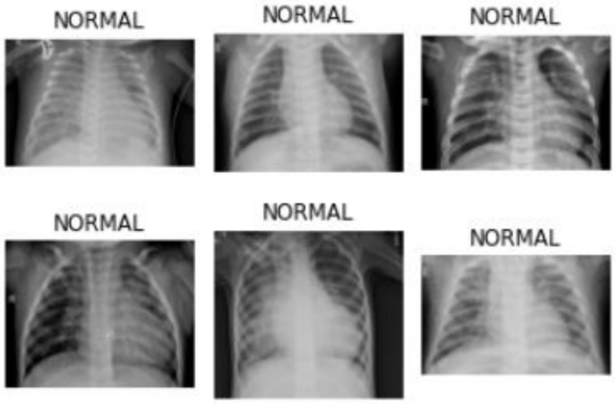

Figure 3: Specimen of Normal pictures in the dataset

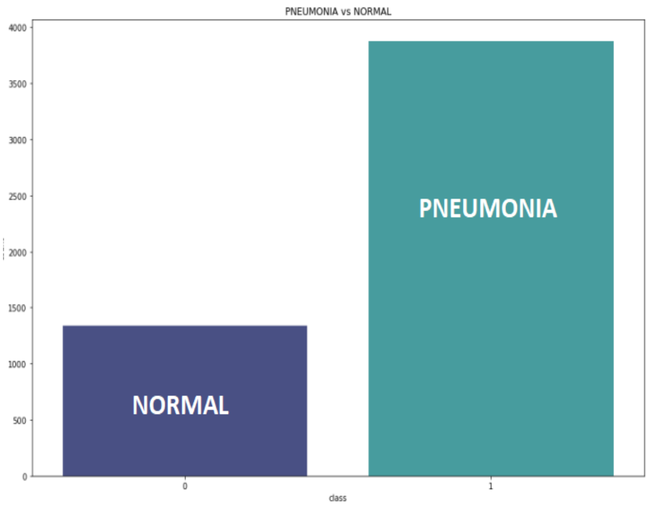

Figure 4: Bar Graph depicting the amount of Normal vs Pneumonia images in the dataset

B. Data Preprocessing and Data Augmentation

Certain pre-processing techniques were used while training the Pneuvid model, like Rescaling and Resizing, which scaled the pixel values of an image by the mentioned factor and resize the image to the necessary parameters as set by the algorithm. Data or Image Augmentation is primarily used to expand the size of the dataset when there is a possibility of a shortage of data to train the model [10]. It is a spectacular way of generating new and transformed images from existing ones which provides us with a greater opportunity to train our model to perfection. The ImageDataGenerator class of the Keras library was used instead of augmenting and storing the images in numpy arrays or folders. The ImageDataGenerator class helps us by providing features like flips, rescaling, rotations etc. It also aids in the prevention of overfitting and underfitting of the model. In our model, we have used the following features that are described in table II, for augmenting images.

Table.2 Values of different data augmentation parameters.

Augmentation Feature	Range and Values
Rotation range	40
Width Shift Range	0.2
Height Shift Range	0.2
Shear Range	0.2
Zoom Range	0.2
Horizontal Flip	True

C. Models Used

Our understanding is based on the Convolutional Neural Network (CNN) which is a deep learning algorithm that can effectively recognize voluminous amounts of information and statistics. The CNN architecture, as described in Figure 5, consists of an input layer, hidden layer, and output layer, with CNN having significantly more hidden layers than a typical neural network. CNN's architecture includes two primary components: classification and feature extraction. Feature extraction involves convolutional layers, max pooling, batch normalization, rectified linear units, and dropouts, while categorizing involves completely interconnected layers and softmax. During the learning phase, backpropagation is utilized to iteratively improve the weights and biases until the desired accuracy level is accomplished, or until the maximum amount of repetitions has been attained [11].

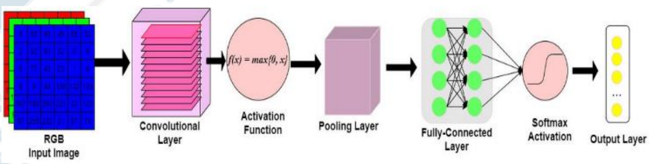

Figure 5: Diagram depicting CNN architecture

While developing Pneuvid, we implemented various CNN architectures on our data to find the one which would suit our purpose the best, and form a reliable base for our model. ResNet was one of the architectures we implemented on the data, which is a CNN architecture established by Microsoft Research in 2015. ResNet is specifically planned to facilitate the learning of profound dense networks with hundreds of layers by utilizing remaining connections to learn residual functions. The ResNet-50 architecture is organized into four stages and is capable of processing input images with measurements which are multiplication of 32 with channel girth. The initial stage of every ResNet structure consists of convolution and max-pooling operations with a kernel measurement of 7x7 and 3x3, each. In the 34-layer net, each 2-layer block is substituted with a 3-layer bottleneck block, which results in a 50-layer ResNet.

Along with ResNet-50, The VGG neural network was also worked upon and it comprises a sequence of convolutional

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layers succeeded by max pooling layers. The convolutional layers utilize small 3x3 filters which facilitate the structure of deep-rooted networks though keeping the amount of gradation within limits. The max pooling layers help in decreasing the spatial dimensions of the feature maps.

VGG16, a configuration of the VGG neural network, is a CNN established by the Visual Geometry Group. It is notable for its use of sequential 3x3 convolutional filters, with 11 and 5 filters in the first and second layers, each. A breakdown of the architecture is given in Figure 6. The network is designed to accept RGB images of size 224x244 as input and is capable of multi-class image classification.

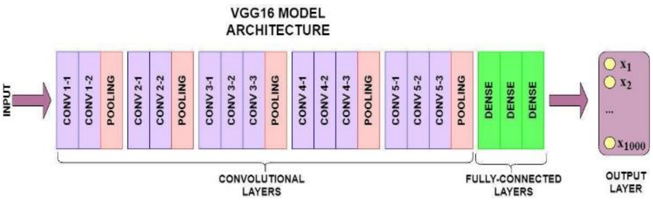

Figure 6: Diagram depicting VGG16 architecture

VGG19, another configuration, is a deeper variant of the same architecture, with 19 layers, trained throughout one million pictures from the ImageNet database. The main concept underlying the VGG architecture is to maintain a small convolutional size while creating a very deep network, resulting in a powerful and efficient image classification model.

The performance of VGG16, VGG19 and ResNet-50 was documented on the selected dataset out of which VGG16 had the best performance, hence it was chosen as the base CNN architecture which would be suitable for our model Pneuvid.

D. Transfer Learning and Fine Tuning

Transfer Learning includes the process of making use of the knowledge of existing, pre-trained models to solve similar problems instead of beginning from square one. In the case of Image Classification, transfer learning can be achieved by using Pre-trained models such as VGG16 along with VGG19. Fine Tuning is an approach to Transfer learning where a pre-trained model is further trained on a new task by adjusting some or all of its layers.

In our model Pneuvid, the top layers have been frozen to put a halt on their ability to get trained so as to ensure that the weights learned during the process of training on Imagenet are not altered. New layers such as dense layers with activation 'relu' and a few fully connected layers with sigmoid activation function for binary classification (pneumonia and normal) and output layers have been added to the model. The use of a flattening layer has also been made in the model.

A total of 14,739,777 parameters were observed upon the implementation of fine tuning on Pneuvid with 25,089 trainable parameters/features and 14,714,688 non-learnable features or parameters, which are shown in Figure 7.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 1)	25089

Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688

Figure 7: Different Layers of built in CNN models

To adjust the training speed of the prototype and to appropriately determine the required learning rate during each epoch cycle, we integrated the concept of scheduling the learning rate into Pneuvid. It is a hyper-parameter that establishes the step size that is to be taken during gradient descent optimization [12]. Figure 8 depicts the motion of the gradient descent operation along large as well as small learning rates.

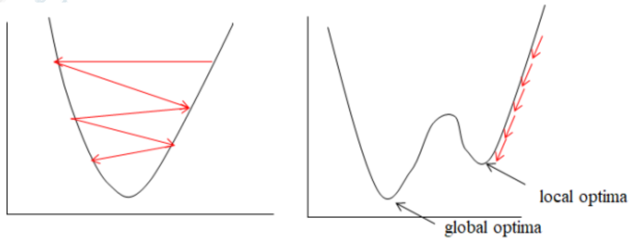

Figure 8: Motion of Gradient Descent operation along different Training ratio

The LearningRateScheduler Callback constitutes an in-built class in the Keras library which updates the callback, which is a group of functions that are to be applied at specified stages of the training process, with the Learning rate value, with the help of which the problem of encountering a static learning rate at every epoch is dealt with. The learning rate value while training the Pneuvid was dynamic in nature due to the implementation of step-based decay Learning rate scheduler. In this way, our learning rate was scheduled to drop systematically by a certain value after every 2 epochs which fit the model according to its requirement at that particular step.

E. Performance Measures

The performance results are represented in the model by a confusion matrix that includes components like True Positive, True Negative, False Positive, and False Negative [13]. We can deduce the following by using the components of the confusion matrix:

Precision or Positive Predictive Value which is the percentage of actual positive tests out of all classes predicted as positive, as explained in equation (1).

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

Recall explains the ratio of the correctly predicted positive classes out of all the positive classes, as explained in equation (2).

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

Support or F-Measure is inferred which amounts to the true samples which reside within each category of target variable [12], as explained in equation (3).

$$F - measure = \frac{2*Recall*Precision}{Recall+Precision} \quad (3)$$

Accuracy is a measure that describes how well a model performs across all classes or how well a model classifies the correct data. It is calculated as the ratio between the number of correct predictions to the total number of predictions, as explained in equation (4).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

F. User Interface of Our Model

For web development, Flask is used to build an interface for Pneuvid that detects pneumonia from chest X-rays. The application allows users to input a chest X-ray image and receive a diagnosis indicating whether or not the image shows signs of pneumonia. To build this, we used Flask's routing capabilities to map URLs to specific Python functions. For example, we defined a route that maps to a function that handles the form submission when a user uploads an image. It provides a templating engine that allows us to render HTML pages dynamically. We used this to render a page displaying the pneumonia detection model results after the user uploads an image.

IV. RESULTS AND DISCUSSION

The study proposed Pneuvid, a VGG-based CNN model, and compared it to traditional VGG-19 and ResNet-50 out of which Pneuvid marked the best performance out of the three for identifying Pneumonia cases in the dataset which consisted of 5,856 images. VGG-19 recorded a learning accuracy of 93.2% and a testing accuracy of 85.5%, ResNet-50 recorded a learning accuracy of 76.90% and a testing accuracy of 67.79%, whereas Pneuvid recorded a learning accuracy of 93.36% and a testing accuracy of 88.46%. All the CNN architectures used (Pneuvid, VGG-19 and ResNet-50) had max epoch 15 and VGG16 had a variable learning rate which ranged from 1e-4 to 7.5e-5. A semblance of the outcome is shown in Table III.

Table. 3 Analyzing Accuracies of Pneuvid, VGG-19, ResNet-50

Model	Training Accuracy	Testing Accuracy
Pneuvid	93.36%	88.46%
VGG-19	93.2%	85.5%
ResNet-50	76.90%	67.79%

The minimum training and validation loss was 1.21% and 30.48% respectively.

The training accuracy recorded was 93.36% while the testing accuracy was 88.46%.

The precision observed during validation was documented as 88.46%, while the precision achieved during training stood at 96.11%.

The validation recall documented was 97.69% while testing recall was 95.85%.

Graph depicting Accuracy, Precision, Recall and F-Measure in the form of a bar graph is shown in Figure 9.

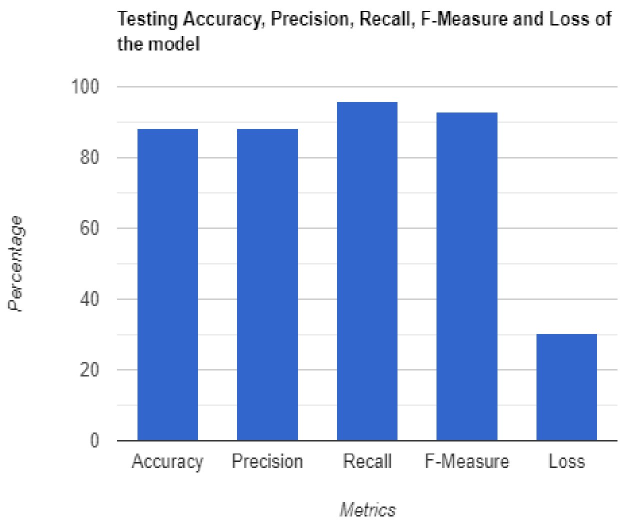

Figure 9: Bar Graph depicting accuracy, precision, recall, f-measure and loss.

Upon investigation of models that were put to work in a similar manner as to how our model was worked upon, we found that our model Pneuvid, which is based on VGG16 performed the best in our classification task, whilst the models used in paper [7] and paper [8] from our citations had a significantly lower accuracy. Our model was 88% accurate in classifying whereas other model mentioned had an accuracy of 87 and 78 percent. Our model is unique and built on fourteen million parameters. To compare the models, the dataset used was common to keep the uniformity intact but was used to differentiate the workings of each model and see how they performed against each other when thousands of images were used. A graphical comparison is shown in Figure 10.

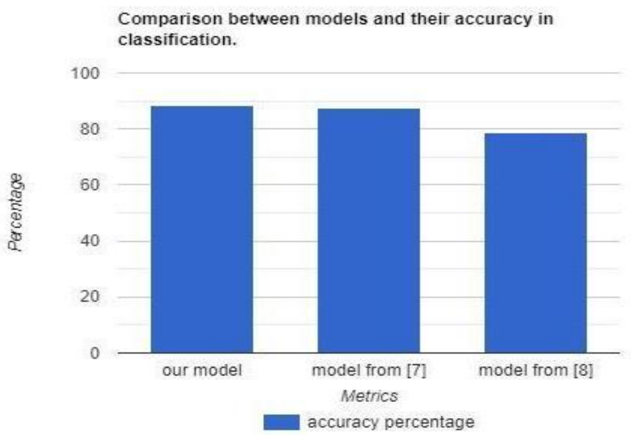

Figure 10: Performance of our model over other similar models

V. CONCLUSION

Predictive Models, which Deep Learning implements are proven to be a reliable source for the detection of anomalies and abnormalities in the reports of patients. These models and techniques could potentially help reveal and detect infection in the beginning stage of the disease so that adequate treatment can start without delay. Deep Learning also holds a very bright and optimistic future with increasing applications.

In [14], the study showed that out of the 250 patients with COVID-19 detected in them, more than 15% were infected with various types of pneumonia-related co-infections from pathogens like C. pneumoniae, respiratory syncytial virus, M. pneumoniae, and adenovirus. Due to having these co-inflection-based pathogens present, they were shown to have prolonged stays in a hospital when compared to other patients.

Finally, we wish to list a few suggestions for improvement: First, it would be incorrect to assert that overfitting for our models has been ruled out because there were not enough Chest X-Ray pictures available compared to the real-life conditions witnessed. To prevent future out-of-distribution problems, more unobserved data from comparable demographics is required for further examination. Second, we haven't yet been equipped to check the radiologists' diagnosis and localization accuracy because of outside factors. As a result, we have a dataset that includes both patients with pneumonia and healthy individuals, however, the validation of each image's pneumonia status is not perfect. There are occasional mistakes. This might have had an impact on the analysis we did and the findings from the other publications we assessed. Therefore, even though the results of our model are intriguing, they may not be used in medical applications until pneumonia datasets have been created using improved external labeling procedures. Thirdly, a binary labeling system for images of pneumonia and normal images has been established. The predictive model has not been investigated in a multi-class scenario when categorizing photos of asthma, COVID-19, and tuberculosis.

We think that our model is an encouraging start in the direction of radiologically automating COVID-19 identification. We think it's conceivable to develop a clinically feasible deep learning model that enables a significantly higher standard of care with a bit more funds and time dedicated to these data-gathering procedures.

In conclusion, it is well-known how pneumonia serves as a complication in the severity of COVID-19. While we are still fighting against COVID, early diagnosis of pneumonia can control the worsening of the existing situation. It will allow doctors to initiate appropriate procedures and treat the patient for a faster recovery. Additionally, it will help in implementing infection management standards, like isolating infected patients, using sanitizers while coming into contact, using proper personal protective equipment (PPE) by healthcare workers, etc. Our model shows great potential in its development to classify patients from the source radiographic images to distinguish between pneumonia and normal cases, which, if put to appropriate use, may help in saving countless lives across the world.

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