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Pneumonia Detection from Chest X-Ray Using Binary Classification

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Abstract: - In this era of science, pneumonia kills thousands of people every year. People get pneumonia from bacteria or sometimes virus-like covid-19. To ensure proper treatment, it is necessary to detect pneumonia at the early stage. For this reason, scientists, researchers, specialists are looking for deep learning and image processing-based systems where they want to use X-Ray images or Computed Tomography (CT) images for detecting pneumonia within a short period and high accuracy as the conventional method of detecting pneumonia is time-consuming and sometimes are subject to disagreement between the specialists. In this paper, the authors have presented an image processing-based system to detect the normal and abnormal (having pneumonia) images from their chest X-rays. This binary classification-based pneumonia detection system takes a total of 5,856 images where 1,583 were normal and 4,273 were the images having pneumonia. For testing purposes, three methods have been used i.e.; ResNet50V2, ResNet152V2, and InceptionResNetV2. Among these three methods, ResNet50V2 shows a maximum accuracy of 95%.

Keywords: Pneumonia, X-Ray image, deep learning, binary classification, ResNet50V2, ResNet152V2, InceptionResNetV2.

I. INTRODUCTION

Pneumonia is one of the serious epidemic diseases of the lungs. This disease is the result of bacterial or viral attacks and affects the pulmonary alveoli [1]. Pneumonia is the number one disease that causes the highest deaths of children all over the world [2]. It is responsible for around 16% of child deaths [2]. In the USA alone more than 1 million people get hospitalized every year for pneumonia and 50,000 people die from this disease [3]. The COVID-19 virus can kill more people because of the support of pneumonia as pneumonia complicates the treatment of it. COVID-19 killed thousands of people because of pneumonia and so recently pneumonia has got more attention from scientists all over the world [2], [4], [5].

The deep learning concept in pneumonia detection and management is appealing to every person. The data on the Electronic Health Records (HER) and the advancement of Artificial Intelligence (AI) or deep learning have made a good connection between AI and disease management [6]. Many scientists are continuously trying to detect pneumonia using artificial intelligence based on image analysis [7]–[10]. Now the AI is not only used to detect and separate viral and bacterial pneumonia but also AI is used for pneumonia management [6].

Binary classification in machine learning algorithms is popular for predicting the outcomes between two variables. This algorithm is used to separate one item from another like one patient may have pneumonia or not. In this case, using binary classification is simple and time-saving as we have only two outcomes.

II. LITERATURE REVIEW

The symptoms and signs for pneumonia may be varied from person to person so an X-ray is needed to ensure it. The problem with conventional pneumonia detection is that specialist's opinions vary for many patients and also it is time-consuming. So, using artificial intelligence is a time-saving efficient method to detect pneumonia at the early stages.

In 2018, Kermany et al. [8] have proposed a neural network (NN) algorithm to detect pneumonia from chest X-rays. For this, they have analyzed 5232 images and found an accuracy of 92.8% with a sensibility of 93.2% and a specificity of 90.1%. They have separated the viral and bacterial pneumonia as a secondary outcome.

Stephen et al. [9] have also used NN to predict the presence of pneumonia by analyzing the X-ray images. They have taken 5856 images for their analysis. These images were collected from a database whose age was under five years, Data augmentation methods were used to enhance the quality of the images found in the database. They have found an accuracy of 0.9531 at the training phase and 0.9373 at the validation stage.

Heckerling et al. [10] have used NN to predict the presence and absence of pneumonia in the patient body. They have collected data from two US centers where patients with missing data were excluded from the analysis. A total of 125 patient's data were used for the prediction and they have found the sensitivity as 0.466 and the specificity as 0.972. They noticed that there was no difference between the training and testing ROCs.

The automated system classifying was reported by Hwang et al. [10]. They have used the NN algorithm that can classify thoracic diseases like pneumonia, pneumothorax, active tuberculosis, etc. The authors have collected 89,852 chest X-Rays from an American institution to train the neural network. Among 89,852 images, 54,221

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were normal and 35,631 were abnormal. It was found that the test sensitivity and specificity were 0.951 and 0.750 respectively. In this study, one additional work has been performed i.e.; the authors have selected 15 physicians randomly and evaluated their report manually by their expertise. At the second stage, the physicians got a chance of changing their decision after using the NN algorithm. It is concluded that the physicians got better results after using the NN algorithm for their decision-making.

III. METHODS

The authors have taken 5,856 images (JPEG) from kaggle.com [11]. Python V: 3.7 has been used for neural network-based transfer learning algorithms. The dataset has three folders i.e.; training, testing, and validation, and also contains sub-holders for every single image category i.e.; pneumonia/normal. The images are categories into two sections (pneumonia and normal). Among the images, 4,273 were infected with pneumonia where 1,583 were the normal case. The chest X-ray images were performed as routine clinical care. The selected chest X-rays were screened first to reject any kind of low-quality images. Two highly qualified specialists graded the images before the AI training system. To re-ensure the results, the evaluation from the two experts has been double-checked by the third physician. The images used for different sections have been shown in Table 1.

Table 1: Images used for AI analysis

Category	Pneumonia	Normal	Total Images
Training	3,418	1,266	4,684
Testing	427	159	586
Validation	428	158	586

Data augmentation has been used to increase the number of training examples because some data seemed to be imbalanced. Data augmentation is the process of doing a small transformation of the data to reproduce the variation, ensuring the same label as previous. Grayscales, color jitters, horizontal flips, rotations, random crops, translations are some examples of popular data augmentations. It is possible to multiple the training data and makes a robust model by applying some of these transformations. The authors have expanded the dataset artificially to avoid overfitting problems. The authors have performed grayscale normalization so that the illuminations' differences are reduced. The framework for this research is presented in the below Fig. 1.

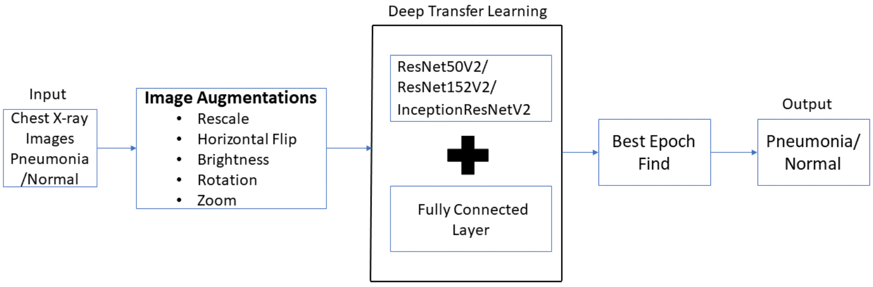
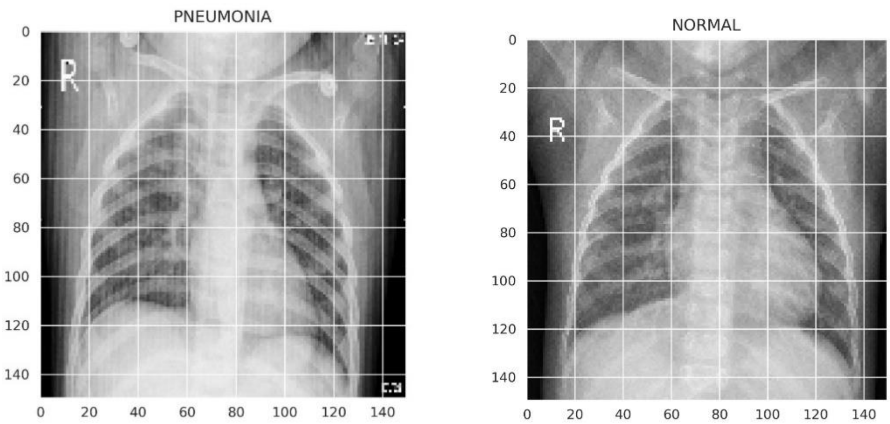


Figure 1: The Framework for pneumonia detection from chest X-rays.

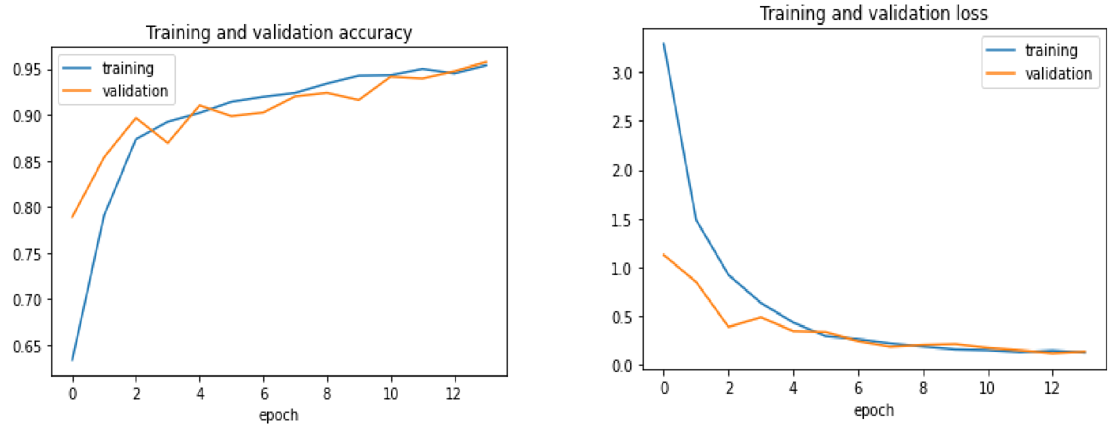
Figure 2 shows two sample images of chest X-rays from the selected dataset with and without pneumonia.



(a) (b)

Figure 2: Sample images of patient's chest X-ray (a) Pneumonia and (b) Normal.

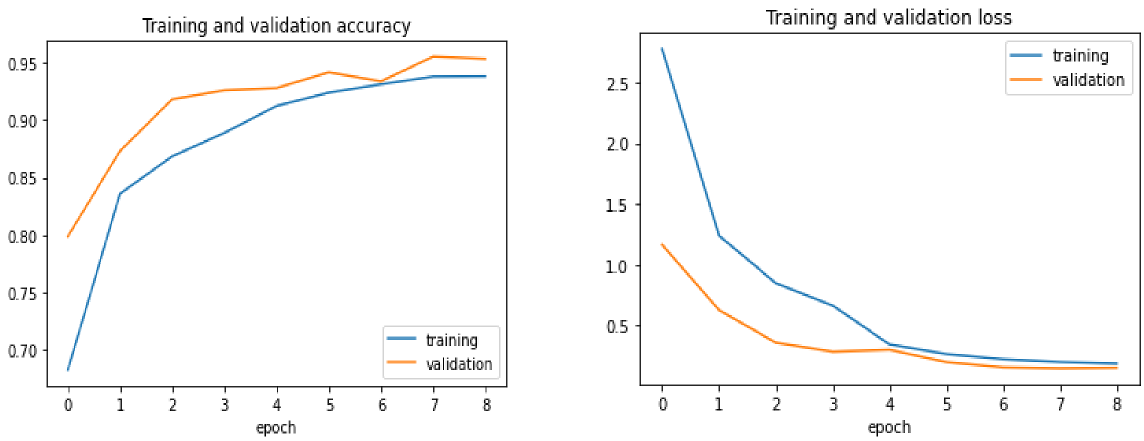
ResNet50V2: ResNet is some sort of artificial neural network based on known contracts of pyramidal cells in the cerebral cortex. The networks of residual neurons do so by using jumps of connections, or shortcuts to jump on certain layers. This ResNet50V2 is an improved version of ResNet50 and also it performs better for the imageNet dataset [12]. The advantage of the ResNet50V2 model is that it uses a transfer learning methodology to achieve greater accuracy than the Simple model. It has a jumper between layers to solve the disappearance gradient problem while containing batch normalization to adjust the input level and increase network performance [13].
The ResNet50V2 model has taken 1876.524 sec for the execution and at the 14th epoch among 20 the maximum accuracy reached. The training and validation accuracy and loss are shown in Fig. 3.



(a) (b)

Fig. 3: Training and Validation accuracy and loss for ResNet50V2 method. (a) The accuracy for both the training and validation increases up to the 14th epoch. Training and testing accuracy were 0.954 and 0.9624 respectively where (b) the loss decreases exponentially for higher epoch up to 14th and testing loss were 0.1348 and 0.115 respectively.

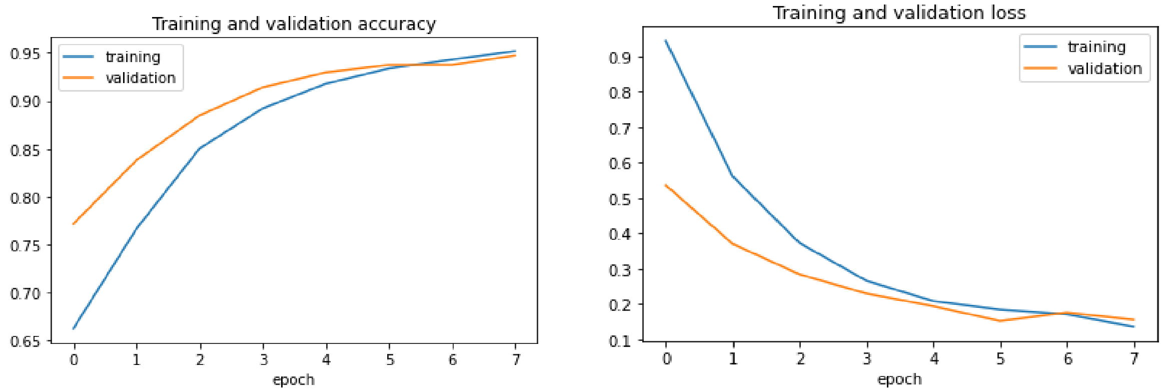
ResNet152V2: As stated earlier, the ResNet uses a vast number of layers for strong performance that was somewhere limited in the original (v1) one [14]. This method has taken 1510.9124 sec for execution. The best results were found at epoch 9. The result of this NN method is illustrated in Fig. 4.



(a) (b)

Figure 4: Training and Validation accuracy and loss for ResNet152V2 method. (a) The accuracy for both the training and validation increases up to the 9th epoch. Training and testing accuracy were 0.9457 and 0.9283 respectively where (b) the loss decreases exponentially for higher epoch up to 9th and testing loss were 0.1545 and 0.1753 respectively.

InceptionResNetV2: This method is a convolution neural network that is trained on millions of images. This method uses a network of 164 layers and classifies images into 1000 object categories. SO, this network can handle a wide range of images. The advantage of InceptionResNetV2 is that it uses convolution kernels of multiple sizes and has a shortcut connection to skip one or multiple layers [15].
The InceptionResNetV2 model has taken 1349.6278 sec for the execution and at the 8th epoch among 20 the maximum accuracy reached. The training and validation accuracy and loss are shown in Fig. 5.

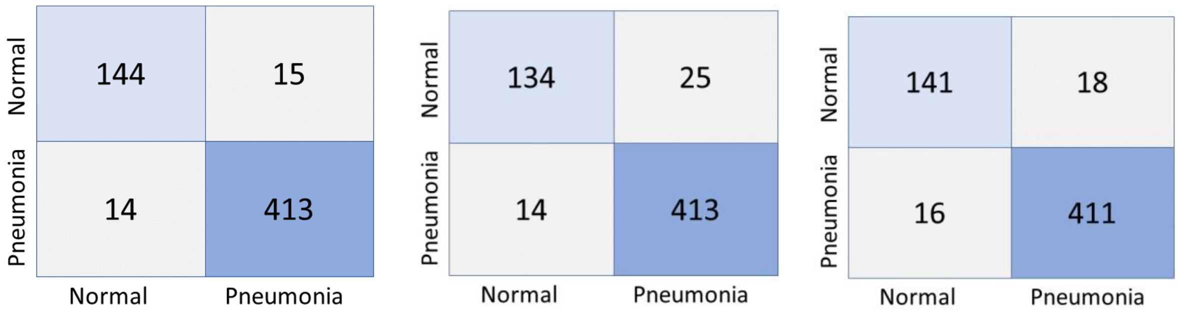


(a) (b)

Figure 5: Training and Validation accuracy and loss for InceptionResNetV2 method. (a) The accuracy for both the training and validation increases up to the 8th epoch. Training and testing accuracy were 0.9487 and 0.9556 respectively where (b) the loss decreases exponentially for higher epochs up to 8th and training and testing loss were 0.1339 and 0.1310 respectively.

IV. Results

The confusion matrix for the ResNet50V2, ResNet152V2, and InceptionResNetV2 methods is presented in Fig. 6.



(a) **(b)** **(c)**

Figure 6: The confusion matrix for (a) ResNet50V2, (b) ResNet152V2 and (c) InceptionResNetV2 methods. The correct and wrong predictions for ResNet50V2 are 557 and 29 respectively. For the ResNet152V2 method, the correct and wrong predictions are 547 and 39 respectively where they are 552 and 34 for the InceptionResNetV2 method.

The classification report is presented in Fig. 7 and the accuracy and loss for the three methods have been analyzed and summarized in Table 2.

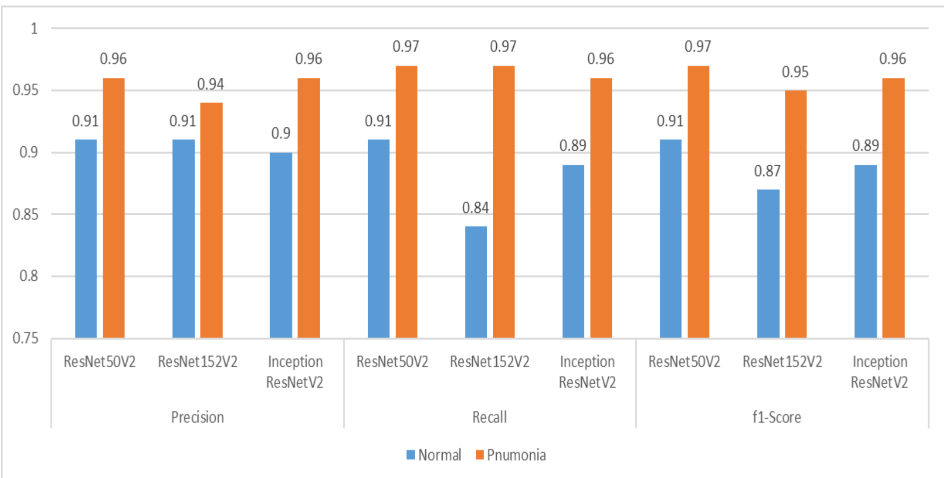


Figure 7: The classification report (Precision, Recall, f1-score and Support) for ResNet50V2, ResNet152V2, and InceptionResNetV2 methods.

Table 2: Accuracy and loss for ResNet50V2, ResNet152V2, and InceptionResNetV2 methods.

Method	Accuracy	Loss
ResNet50V2	0.9625	0.1150
ResNet152V2	0.9283	0.1754
InceptionResNetV2	0.9556	0.1310

V. CONCLUSION

The authors have successfully analyzed 5,856 chest X-ray images with three binary methods (ResNet50V2, ResNet152V2, and InceptionResNetV2). The results (Accuracy and loss) for these three methods have been compared and it is concluded that for pneumonia detection from image analysis, the ResNet50V2 method offers the maximum accuracy with the lowest loss comparing with the other two methods.

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