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Applied Deep Learning Approach For Prediction Of Pneumonia Infection

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Abstract— **In this paper, applied deep learning approach for prediction of pneumonia infection is presented. The pneumonia dataset used was extracted from Kaggle repository which consists of 5247 chest X-ray images selected from group of pediatric patients ranging from one to five years old. About 3906 images were obtained from persons who were affected by pneumonia of which 2561 images were for those affected by bacterial pneumonia and 1345 images were for those affected by viral pneumonia while 1341 images out of the 5247 chest X-ray images were from normal subjects. Convolutional neural networks model was trained to detect pneumonia from chest X-ray images. First, the original X-ray images are transformed and the transformed images were passed to a convolutional neural network, which extracted features from the images. Then fully connected layer network was then used to classify the images, and thereby identify pneumonia infection from the chest X-ray images. The training and validation results for the Pneumonia classification deep learning model includes training loss of 0.0797, training accuracy of 96.65%, and training precision of 0.9786 and training recall of 0.9764. The validation loss was 0.2754, validation accuracy of 93.24%, validation precision was 0.9324, and validation recall of 0.9698. The results showed that the trained model presented in this paper can classify pneumonia from frontal view chest X-ray images with high accuracy that is above 96%.**

Keywords— Deep Learning, Bacterial Pneumonia, Convolutional Neural Network, Kaggle Repository, Viral Pneumonia, Data Augmentation, Chest X-ray Images

1. Introduction

Pneumonia is a popular disease that manifests in the form of inflammation of the lung tissues [1,2,3,4,5,6,7,8,9,10]. The causes of Pneumonia includes pathogenic microorganisms and immunologic injury as well as other pharmaceuticals [11,12,13,14,15,16,17,18,19,20]. Pneumonia can be classified as either infectious or non-infectious [21,22,23,24,25,26,27,28,29,30]. It can also be classified as bacteria or viral, among other categories based on the different pathogeneses [31,32,33,34,35]. Across the globe, Pneumonia has been responsible for several millions of death. In any case, with the use of certain antibiotics and antiviral drugs, pneumonia can be managed [36,37,38,39,40,41]. However, management of pneumonia is more effective when early detection and treatment is adopted as it forestalls complications that may result due to escalation in the infection.

Generally, the most popular clinical approach for diagnosing pneumonia is the use of Chest X-ray images [42,43,44,45]. However, experience has shown that it is quite difficult for experts to effectively detect pneumonia infection from Chest X-ray images; the results are quite subjective. As such, the use of modern technology to enhance the accuracy of the diagnosis of pneumonia based on Chest X-ray images has drawn the attention of many researchers. As such in this paper, applied deep learning approach for prediction of pneumonia infection is presented [46,47,48,49,50]. Particularly, deep learning model was trained to detect pneumonia from dataset of chest X-ray images. The prediction performance of the model was ascertain using test dataset of chest X-ray images.

2. METHODOLOGY

2.1 Dataset

In this paper, the pneumonia dataset used was extracted from Kaggle repository which they obtained from Guangzhou Women and Children's Medical Center, Guangzhou [51,52,53,54,55,56]. The Kaggle pneumonia dataset consists of 5247 chest X-ray images which were selected from group of pediatric patients ranging from one to five years old. According to Kaggle repository portal, the chest X-ray imaging was obtained during the patients' routine clinical care. In respect of the 5247 chest X-ray images, about 3906 images (Table 1 and Figure 1) were obtained from different persons who were affected by pneumonia of which 2561 images were for those affected by bacterial pneumonia (Figure 2) while 1345 images were for those affected by viral pneumonia (Figure 3). Similarly, about 1341 images out of the 5247 chest X-ray images were from normal subjects (shown in Table 1 , Figure 1 and Figure 4). It was also noted that there were cases of mixed viral and bacterial infection in some of the pneumonia cases. However, the mixed viral and bacterial infection dataset were not used in this study. Before the dataset was used, it was first segmented into training dataset and test dataset.

Table 1: Total number of images in Pneumonia dataset

Category	No of images in the dataset
Bacterial & Viral Pneumonia	3906
Normal	1345

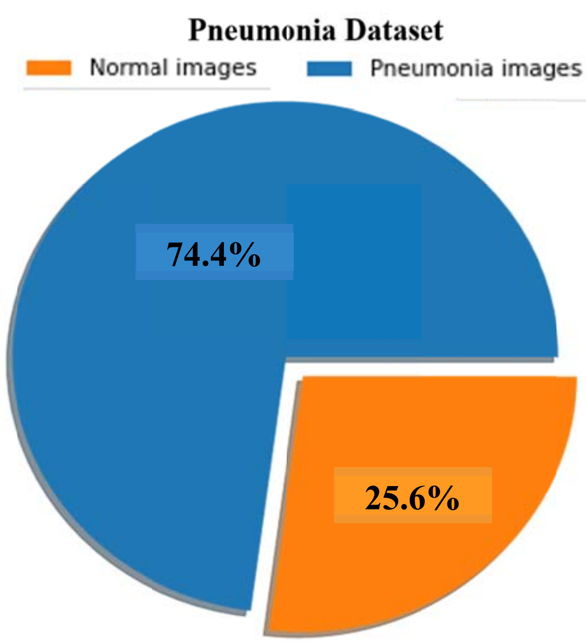

Figure 1: Pie Chart of Pneumonia dataset

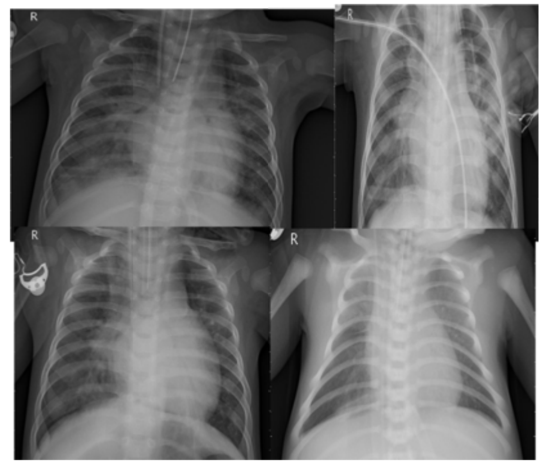

Figure 2: Bacterial Pneumonia Chest X-ray Scan

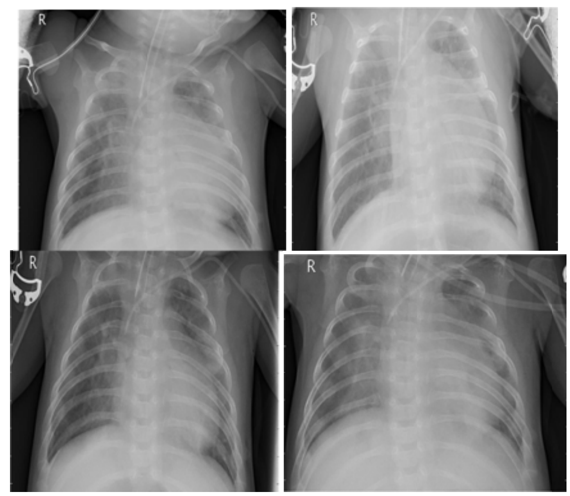

Figure 3: Viral Pneumonia Chest X-ray Scan

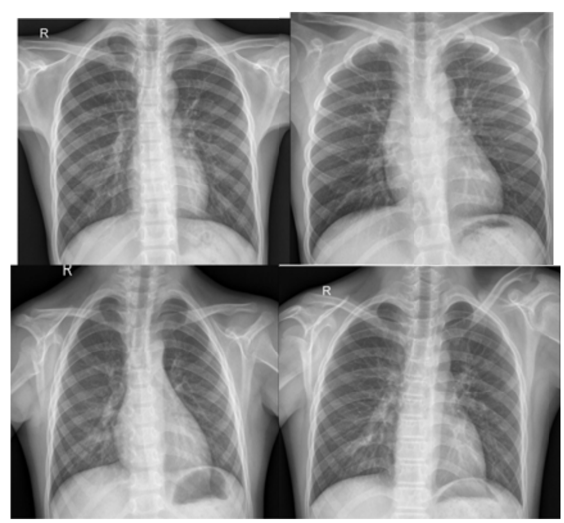

Figure 4: Normal Chest X-ray Scan

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2.2 Data Pre-processing

Data augmentation was applied to help address the problem of overfitting and increase the number of images used in the model training. The data augmentations employed in this case included horizontal flip and zoom. The settings for the image augmentation are shown in Table 2. In addition, data normalization is another important step that was performed before the model training in the deep learning approach adopted in this paper. Notably, all the images used in both the training set and also for the test dataset were normalized. Generally, data normalization help to reduce model training time. In this paper, the images in the dataset were resized to 200 x 200. A batch size of 32 was adopted and binary class model was also adopted.

Table 2: Settings for the image augmentation

Method	Setting
Rescale	1/255
Zoom range	0.2
Horizontal Flip	True

The architecture for the Pneumonia classification model is made up of convolutional block with convolutional layer that has 32 filters, 3 stride and adopted Relu activation function. A max-pooling layer with a pool size of 2 was added. The second convolutional block consists of a 64 filters convolutional layer with a stride of 3, and relu activation was also used. A max-pooling layer with a pool size of 2 was added. The third block consists of a 128 filters convolutional layer with a stride of 3, and a relu activation was also used. A max-pooling layer with a pool size of 2 was added. The fourth block consists of a 128 filters convolutional layer with a stride of 3, and a relu activation was also used. A max-pooling layer with a pool size of 2 was added. A flattening layer was added along with a dropout layer. Also added was a fully connected layer with 512 nodes. The output layer has a sigmoid activation function-based node. The Convolutional Neural Network (CNN) model architecture for Pneumonia classification is shown in Figure 5 and the CNN model summary for Pneumonia classification is given in Figure 6. The CNN model was compiled with an Adam optimizer with binary cross-entropy loss function as well as accuracy metric. The hyper-parameters used for the Pneumonia model compilation is shown in Table 3.

2.3 The Pneumonia Classification Model Architecture

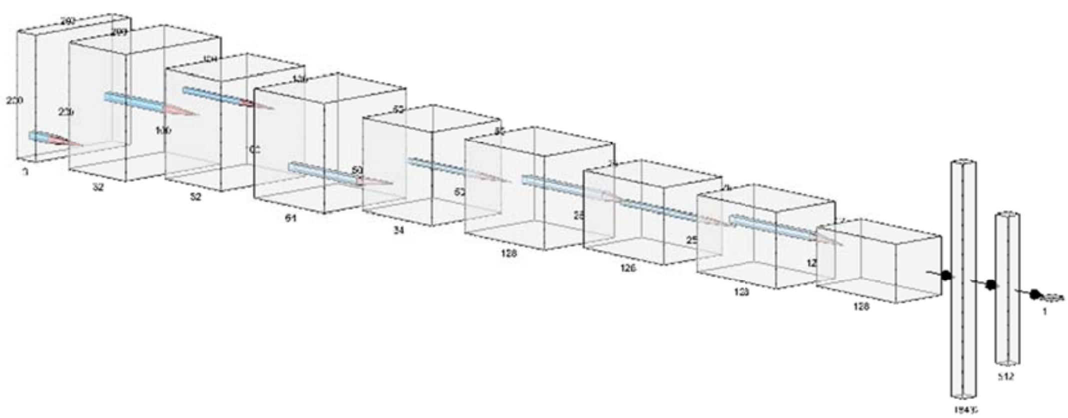

Figure 5: CNN Model Architecture for Pneumonia classification

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 200, 200, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 100, 100, 32)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 100, 100, 64)      18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 50, 50, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 50, 50, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 25, 25, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 25, 25, 128)       147584
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 12, 12, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 18432)             0
_________________________________________________________________
dropout (Dropout)            (None, 18432)             0
_________________________________________________________________
dense (Dense)                (None, 512)               9437696
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 9,679,041
Trainable params: 9,679,041
Non-trainable params: 0
```

Figure 6: CNN Model Summary for Pneumonia classification

Table 3: Pneumonia model Hyper-parameters settings

Optimizer	***Adam***
Loss function	***Binary cross-entropy***
Metrics	***Accuracy, Recall, Precision***

3. Results and Discussion

The Pneumonia model was trained using a Graphics processing unit (GPU) from Google Colab. It took about 3 hours to train the model for 70 epochs. The parameters and hyper-parameters were fine-tuned to improve the performance of the model.

3.1 Training and Validation Results for the Pneumonia Model

The training and validation results for the Pneumonia model are shown in Table 4. The main results obtained are training loss of 0.0797, training accuracy of 96.65%, training precision of 0.9786 and training recall of 0.9764. The validation loss was 0.2754, validation accuracy of 93.24%, validation precision was 0.9324, and validation recall of 0.9698. Furthermore, the various performance parameters for the results on the Pneumonia classification model are plotted in the graphs presented in Figure 7, Figure 8, Figure 19, Figure 10, Figure 11 and Figure 12.

In all, the accuracy of each of the model is over 96.6%. This means that out of every 100 chest X-ray images passed to the models as input, the model will correctly identify over 96 pneumonia cases from the images. Only less than 4 out of the 100 chest X-ray images may be wrongly classified by the model.

Table 4: Training and Validation Results for the Pneumonia Classification Model and the COVID-19 Classification Model

Final Result	Pneumonia Model
Training Accuracy	96.65%
Validation Accuracy	93.24%
Training Loss	0.0797
Validation Loss	0.3844
Training Precision	0.9786
Validation Precision	0.9324
Training Recall	0.9764
Validation Recall	0.9698

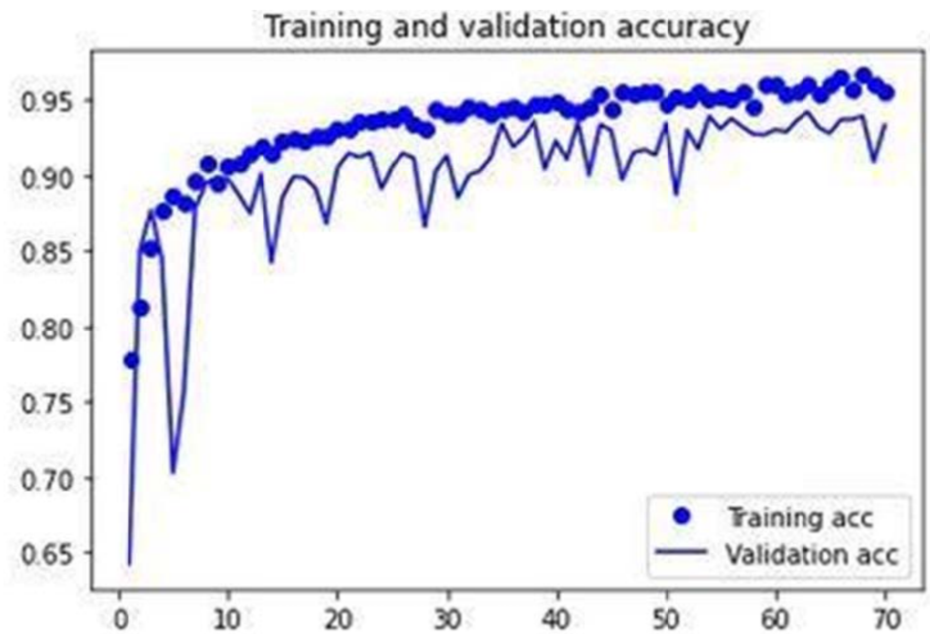

Figure 7: Training and Validation Accuracy Results for the Pneumonia Classification Model

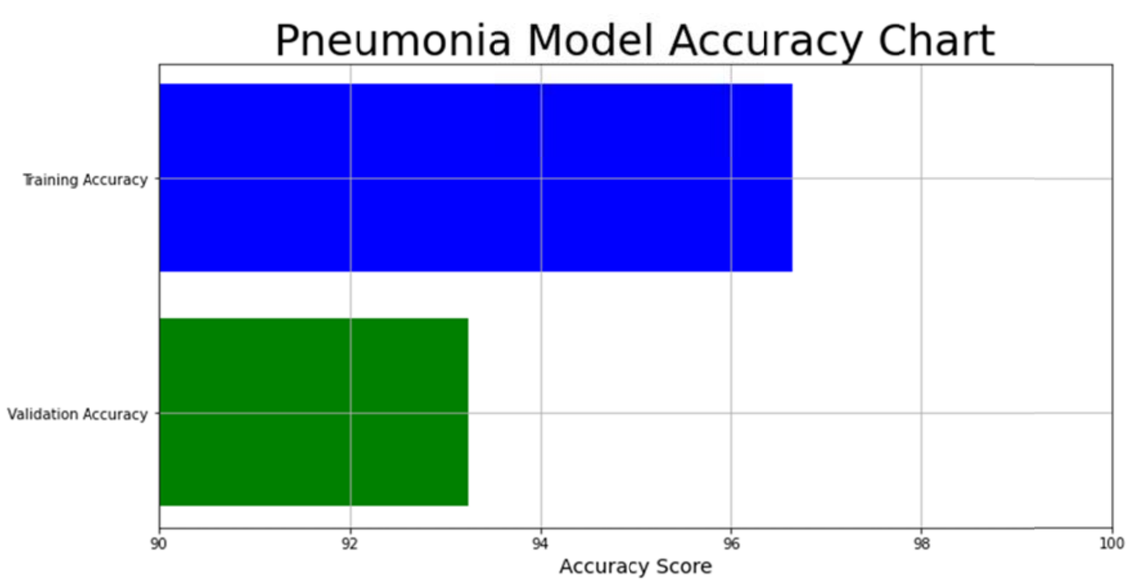

Figure 8: Pneumonia Classification Model Accuracy Chart

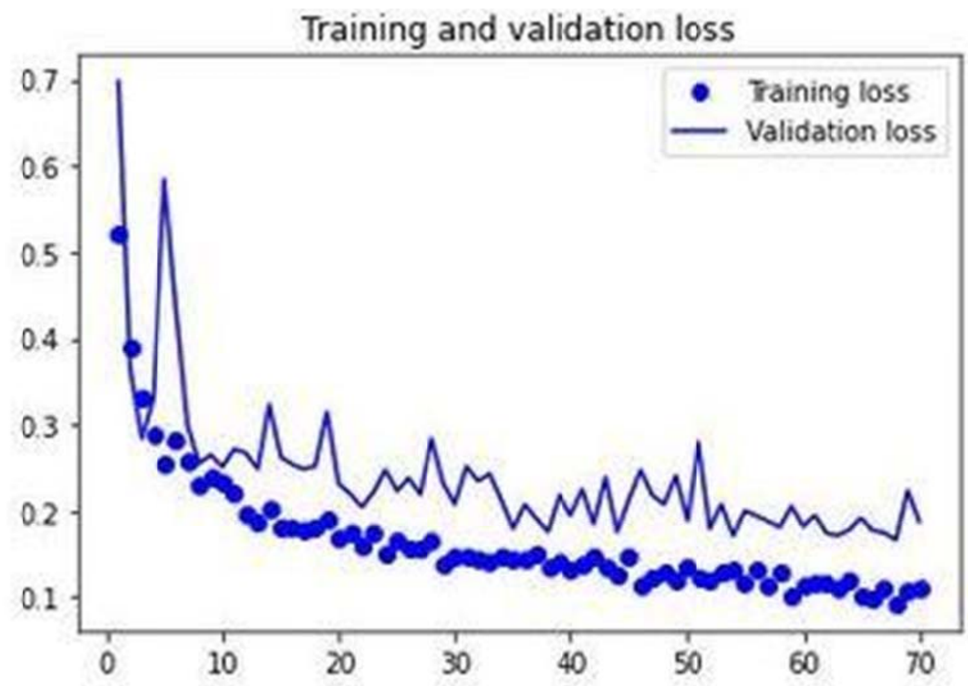

Figure 9: Training and Validation Loss Results for the Pneumonia Classification Model

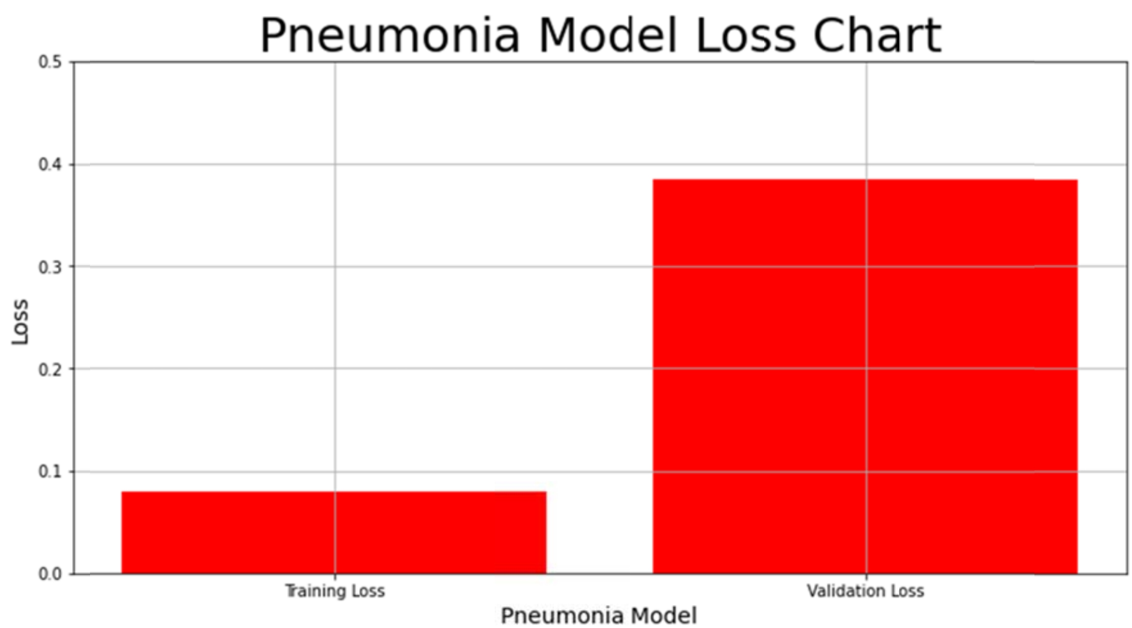

Figure 10: Pneumonia Classification Model Loss Chart

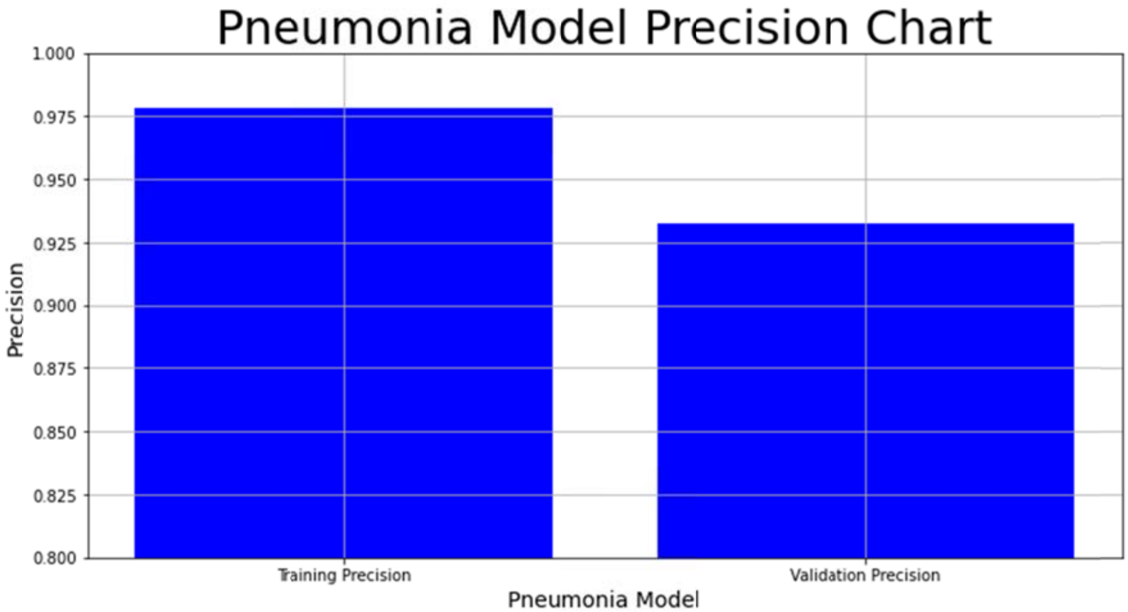

Figure 11: Pneumonia Classification Model Precision Chart

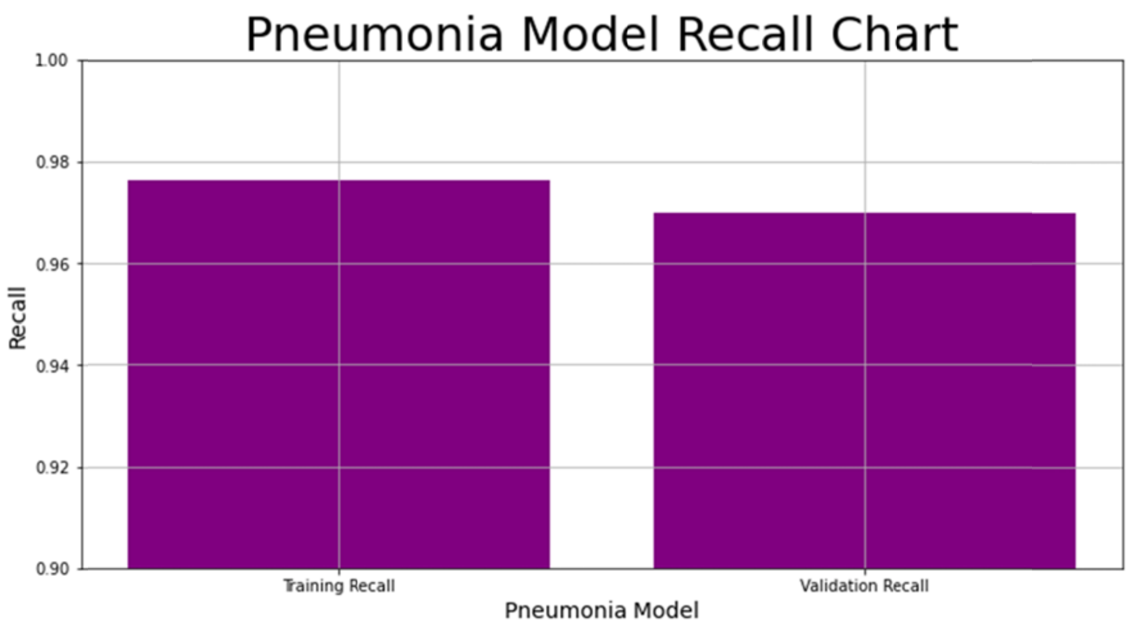

Figure 12: Pneumonia Classification Model Recall Chart

4. Conclusion

In this paper, a deep learning mechanism that can be used to quickly diagnose pneumonia is presented. Convolutional neural networks model was trained to detect pneumonia from chest X-ray images. First, the original X-ray images are transformed and the transformed images were passed to a convolutional neural network which extracted relevant features from the images. Then fully connected layer network was then employed to classify the images, and thereby identify pneumonia infection from the chest X-ray images. The results showed that the trained model presented in this paper can classify pneumonia from frontal view chest X-ray images with high accuracy.

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