



## NEURAL NETWORK BASED REAL TIME PNEUMONIA DETECTION USING TRANSFER LEARNING AND IMAGE AUGMENTATION

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KUS: ICSTEM4IR-22/0093

Manuscript submitted: June 20, 2022

Accepted: September 25, 2022

### Abstract

This paper aims to identify the detection of pneumonia disease using chest x-ray images by applying deep learning methods. Deep learning methods have tracked down their applications in different areas, and they are in effect broadly utilized in clinical medicines and diagnostics. To analyze viral/bacterial infections such as pneumonia, the assessment of chest X-ray images is frequently used, and the productivity of diagnosis can be altogether improved with the utilization of Computer-Aided Diagnostic (CAD) frameworks. Deep learning method such as Convolutional Neural Network (CNN) architecture is utilized in this paper for the characterization of chest X-ray images to analyze pneumonia. We have used the chest X-ray image dataset from Kaggle consisting of 4110 images. Image augmentations were performed on the dataset to oversample the dataset for the model to perform better. Then, at that point, we have built a custom CNN model and, also, we have utilized the transfer learning mechanism with CNN by using MobileNetV2 as the base model for the image classification problems. The average classification accuracy for our proposed CNN and MobileNetV2 based transfer learning method was 97%, and 97% for unbalanced and 97%, and 97%, for balanced datasets respectively. The satisfactory outcome of both models can significantly improve the accuracy and speed of pneumonia diagnosis. This would be very helpful in this pandemic situation in developing countries with limited resources and capabilities in the healthcare sector.

**Keywords:** Pneumonia, Deep Learning, CNN, X-ray, Transfer Learning, Augmentation, Machine Learning

### Introduction

For the diagnosis of lung infections, a commonly used mechanism that is also cheap and simple is chest x-ray (CXR) (Wang et al., 2017). From CXR images, only experienced radiologist can identify

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DOI: <https://doi.org/10.53808/KUS.2022.ICSTEM4IR.0093-se>

Paul, A. K. et al. (2022). Neural network based real time pneumonia detection using transfer learning and image augmentation. *Khulna University Studies*, Special Issue (ICSTEM4IR): 70-82.

whether there exists any symptoms of diseases such as lung cancer, tuberculosis (TB), or pneumonia. Pneumonia is one of the lung disease caused by various viruses (including Covid-19), bacteria, or fungi and is already proved to be a fatal disease in many situations if not treated timely and properly (Kermany et al., 2018). Pneumonia caused by viruses specially by covid-19 is a life-threatening disease for older adults, patients with asthma and even for infants. Also, for developing countries where medical facilities are mostly inaccessible to general people, pneumonia can be a fatal disease. A survey result published by World Health Organization (WHO) depicts that each year around the world 14% of all deaths of children under 5 years old are caused by pneumonia (“Pneumonia”, n.d.). Among the three categories of causes of pneumonia, viral pneumonia is usually mild but bacterial pneumonia is life threatening for children under 5 years old and fungal pneumonia is deadly for patients with weak immune system. Diagnosis of pneumonia from CXR images are usually recommended by doctors because of it’s low cost as compared to other diagnosis tools such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) images (Mardani et al., 2019). Due to its immense demand for diagnosis, thousands of CXR readings are necessary per year but the number of expertise radiologist are not sufficient specially in developing or even in developed countries (Oates et al., 2019).

The key to reduce the death rates from lung disease is to diagnose and treat a patient timely. However, diagnosis and treatments can be affected due to massive imbalance between the number of doctors and the number of patients in an area. In addition, the resolution of CXR image is often not good enough as compared to MRI or CT images and thus hinders the accurate diagnosis by a radiologist. The expertise knowledge by the radiologist can be further supplemented by Computer Aided Diagnostic (CAD) tool that can automatically detect pneumonia from CXR images with the help of Machine Learning (ML) or Deep Learning (DL) by extracting useful features related to pneumonia (Khan et al., 2021). The most popular DL model for image processing is Convolutional Neural Network (CNN). CNN takes image as input, perform convolution operation with input image by a filter of arbitrary size, extract useful features from it and finally classify the input image based on those extracted features (Abbas et al., 2021; Minaee et al., 2020).

Most of the pneumonia dataset available publicly are highly class imbalanced. That means, in one class more images are available as compared to other classes. As an example, the author in (Kermany et al., 2018) used a dataset consisting of 5856 images in total. Among those images 4273 images belong to the pneumonia category and the rest of 1583 images belong to normal category. This class imbalance problem can affect the accuracy (specially the sensitivity value) of a DL based classification system. Therefore, simple techniques that can be used to overcome the class imbalance problem is to increase the image samples for minority class by duplicating the image samples or under-sample the majority class by deleting some of the images to make it balance with the minority class. This sampling method of balancing the dataset exhibits limited variance and thus limited generalization (Kotsiantis et al., 2006). If the dataset is small, then avoiding the problem of overfitting of the model on the small dataset is done by expanding of dataset using data augmentation technique or more recently by generating the dataset in an artificial way using Generative Adversarial Network (GAN) (Goodfellow et al., 2014; Krizhevsky et al., 2017).

Traditional ML algorithms require handcrafted feature extraction from the input image and then using those features and applying the algorithms to classify the lung diseases (Chandra and Verma, 2020; Rajinikanth et al., 2021). However, their accuracy is low. On the other hand, DL techniques are data driven and automatically achieves end-to-end feature extraction and classifi-

cation without any manual feature extraction (Chhowa et al., 2019; Ma et al., 2020; Zhang et al., 2021). For image classification related task such as pattern recognition, the most prominent technique that achieved outstanding accuracy is CNN. The only requirement is the large dataset, i.e., CNN can produce very high accuracy when the dataset is large. In biomedical image classification or detection related problem, CNN can be trained on the dataset from scratch or using a pretrained CNN on ImageNet dataset and by applying transfer learning strategy, one can achieve prominent result (Anaya-Isaza and Mera-Jiménez, 2022).

In this paper, we have proposed a custom CNN model and train the model from scratch and also we applied transfer learning strategy by using MobileNetV2 model (Sandler et al., 2018). We explored the problem of data imbalance and also we studied the performance of our model when the dataset is balanced.

The rest of the paper is organized as follows: Section focuses on literature review on pneumonia detection and classification. Section depicts the the materials and methods used to classify pneumonia from CXR dataset. Then we presented our experimental results and analysis in section . Finally, we made concluding remarks and possible future directions of our research work in section .

## **Related Work**

Image classification using CXR has drawn considerable interest from researchers for quite a long time, and lately the interest in this research field is further boosted due to COVID-19 pandemic. The author in (Stephen et al., 2019) proposed a custom made CNN architecture consisting of four convolutional layers for feature extraction followed by two dense layers and finally the output layer for image classification. They evaluated the model on different data sizes and perform data augmentation techniques. They reported an average accuracy of 93.01% over all the dataset of various sizes. However, other important performance metrics such as specificity and recall or sensitivity value was absent during evaluation. Thus, their performance evaluation could not be consolidated by only accuracy. Another work (Siddiqi, 2019) proposed an eighteen layer deep CNN architecture and trained their model on the pediatric CXR dataset. The paper reported the classification accuracy of 94.39% and sensitivity is 99% which is quite high. However, the specificity is only 86%. The author in (Verma et al., 2020) proposed a four layer custom CNN architecture to classify among three classes namely TB, viral pneumonia, and bacterial pneumonia from CXR images. They employed data augmentation to overcome the overfitting problem. They have reported an accuracy of 99.01%. However, the detail of the experimental evaluation is missing in their paper.

There are other research works that focus on transfer learning-based pneumonia detection and classification. The author in (Jain et al., 2020) proposed six different models out of which two are custom made CNN and the rest of the four are transfer learning based pretrained model such as VGG16, VGG19, ResNet50, and Inception-V3. Their proposed two custom model architectures consist of 2 layers and 3 layers respectively. With this custom model, they have reported an accuracy of 85.26% and 92.31% respectively. On the other hand, using transfer learning, the reported accuracy for VGG16, VGG19, ResNet50, and Inception-v3 model are 87.28%, 88.46%, 77.56%, and 70.99% respectively. However, their custom model architecture is very simple and effective measures are not taken to enhance the accuracy. Also, specificity and sensitivity are not reported as performance evaluation metric. Another work (Rajasenbagam et al., 2021) utilized a VGG19 model to propose

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Table 1: Dataset and their characteristics

Dataset	Category	Number of Samples	Number of Training Samples	Number of Testing Samples	Type	Depth
Unbalanced	Normal	1265	1012	253	JPG	8
	Pneumonia	2845	2276	569	JPG	8
Balanced	Normal	575	460	115	JPG	8
	Pneumonia	576	460	116	JPG	8

their CNN architecture using transfer learning mechanism. The test accuracy was reported as 99.34%. They also compared with other pretrained model (e.g., AlexNet, VGG16, and Inception) on the same dataset and found that the VGG19 model gives highest accuracy.

CNN is often considered as a black box that does not reveal the inner understanding of the total process. Thus, it may affect decision making adversely. To understand the inner working principle of CNN architecture, the author in (Rajaraman et al., 2019) tried to explain visually how a CNN can predict and classify between different classes. They have presented transfer learning based VGG16 model and a custom built model to train and test on the dataset and presented their outcomes visually. They have reported an accuracy of 96.2% for the classification of normal and pneumonia images, that is almost 4% increase in accuracy as compared to (Kermany et al., 2018). Also, the accuracy of classifying between viral and bacterial pneumonia is reported as 93.6% that is 3% higher in accuracy as compared to (Kermany et al., 2018). However, the specificity of classifying between viral and bacterial pneumonia were reported as only 85.9%.

There are many other prominent works on pneumonia detection and classification from CXR images exist and discussing all of them is the out of scope of this paper. Readers interested more about pneumonia classification and different approaches to model this type of problems can refer to (Khan et al., 2021).

## Materials and Methods

### Dataset

We have used recently published CXR dataset from Kaggle “Chest X-ray (Covid-19 & Pneumonia)”, n.d. contains a total of 6432 CXR images. From the dataset we have created two separate database of images for the training and testing purpose. To make the dataset unbalanced, we have created a total of 1265 normal images and 2845 pneumonia images. For balanced dataset, we have created 574 normal images and 576 pneumonia images. For balanced dataset, we have used data augmentation technique to enhance the number of data. From the total number of samples, we have used 20% images for testing/validation purpose. The details of the dataset and the characteristics are shown in Table. 1.

Fig. 1 shows 6 example pictures from CXR dataset, including 3 normal images (the first row) and 3 pneumonia images (the second row). There is a wide variety of resolution in the dataset. Some are low resolution and some are high resolution images. This could be a positive point for the model if the model can achieve a high accuracy on this variable resolution dataset. Gathering all images in a super-controlled climate that outcomes in high-resolution and super-clean images are

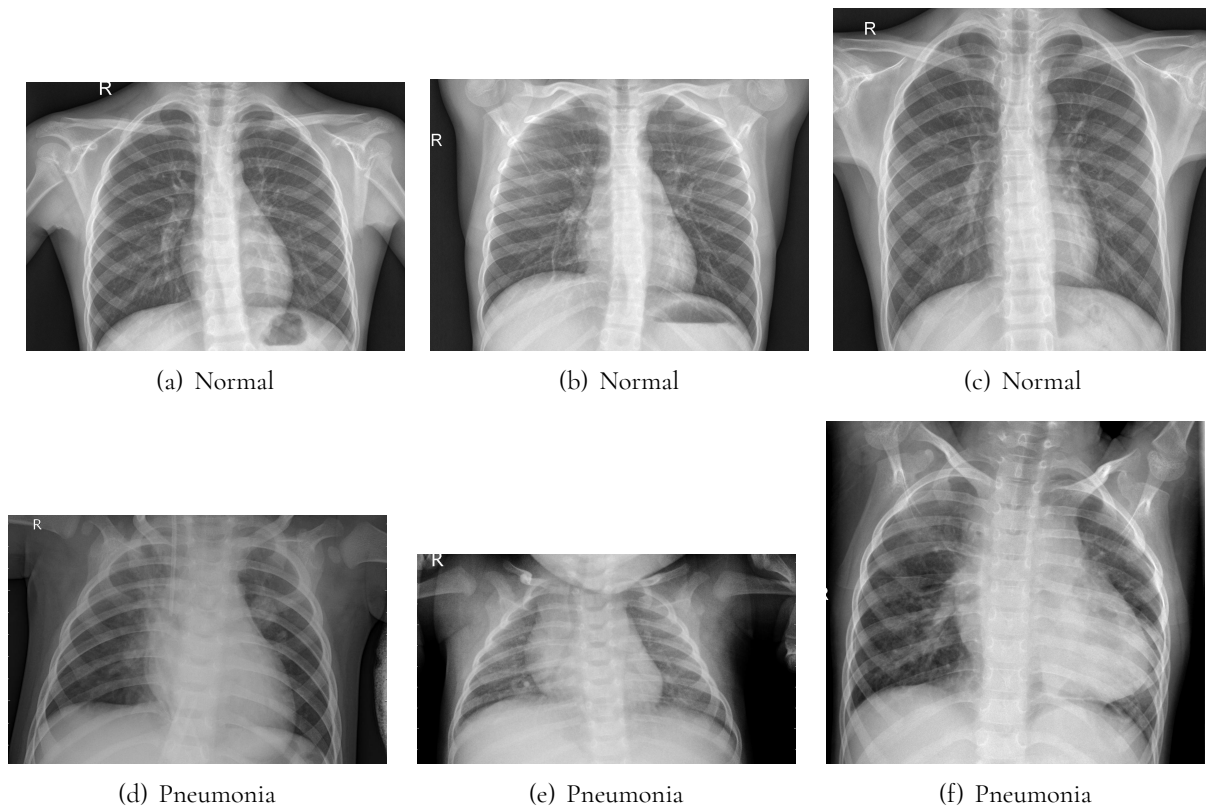


Figure 1: Sample Images from CXR dataset. The images in the first row are normal images without having any symptoms. The second row shows pneumonia images.

expected but isn't generally feasible, and as AI field advances, increasingly more focus is centered toward models and systems that can function effectively on various resolution, quality, and limited scope marked datasets. Additionally some of the images might show various dynamic ranges but during the preprocessing and training all images are standardized to a similar dispersion to make model less delicate to that.

### Data Preprocessing

Before we train the model, a set of preprocessing steps are applied on the image data. Input requirement for MobileNetV2 is (224 x 224) pixels. Thus we have downsampled the images to (224 x 224) pixels. We also rescale the image to restrict the pixels in the range of [0 1] and apply normalization and standardization through mean subtraction and division by standard deviation to ensure equal distribution range for the extracted features.

### Proposed Custom Model and Transfer learning based MobileNetV2 model

Our proposed custom model architecture is shown in Fig. 2. We have created a convolutional neural network architecture which consists of a series of convolutional blocks and dense layer blocks. We have utilized a (3x3) filter size throughout the whole network. By convolutional blocks, we denote a convolutional operation with the filter followed by passing the feature maps to the RELU

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(Rectified Linear Unit) and then the feature map dimension is reduced (half) by passing it to the maxpooling layer. In the first convolutional block, we have performed a convolution operation with stride 1, padding 0 and using 32 filters each of size  $(3 \times 3)$ . After that a  $(2 \times 2)$  Max-pooling layer. Then we have used another convolution block. In every successive convolution block we have increased the number of filters by a factor of two. After two successive convolution blocks we have inserted a dropout layer. The dropout layer is important as they "drop out" certain nodes to reduce the likelihood of the model's over-fitting on the training data. After the dropout layer, we have used two other successive convolution blocks. Then we flatten the last layer and connected with the dense layer consisting of 128 neurons. Then another dropout layer is inserted followed by the output dense layer consisting of 2 neurons to classify between normal images vs. pneumonia images. The layer details and the layer parameters are given in Table 2.

Transfer learning is a technique which is proved to be very effective if the dataset is small. In transfer learning, we used to train a pretrained model on the target dataset. The pretrained model is already trained on a large dataset e.g., on Imagenet (Krizhevsky et al., 2017). Thus all the trainable parameters are optimized to their desired values. So, when we use any such model to train and test on a newly target dataset of the similar kind of problem, higher accuracy is obtained by just fine-tuning the pretrained model. Many examples of pretrained models on Imagenet exist. One such model is MobileNetV2 (Sandler et al., 2018) developed by Google researchers and is used in this paper to classify between normal and pneumonia images. We have kept the CNN layers of MobileNetV2 intact and modify the dense layers of MobileNetV2 to adapt to classify pneumonia from normal CXR images.

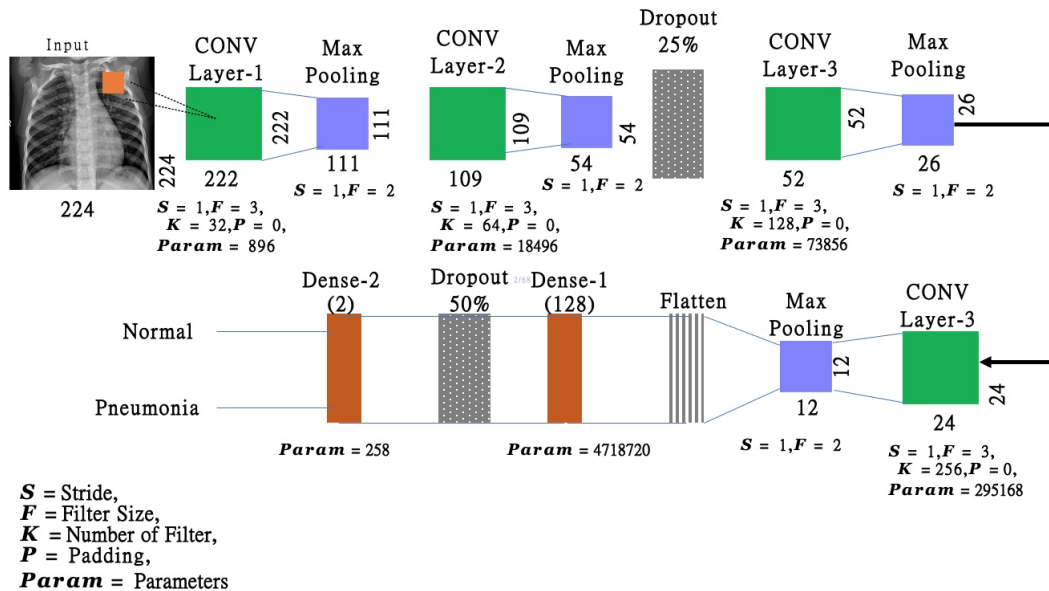


Figure 2: The architecture of the proposed model

Table 2: The Layer Type and Layer Parameters of the Proposed Custom Model.

Layer (Type)	Output Shape (Height, Width, Number of Filters)	Trainable Parameters
Conv2D	(222, 222, 32)	896
MaxPooling2D	(111, 111, 32)	0
Conv2D	(109, 109, 64)	18496
MaxPooling2D	(54, 54, 64)	0
Dropout (25%)	(54, 54, 64)	0
Conv2D	(52, 52, 128)	73856
MaxPooling2D	(26, 26, 128)	0
Conv2D	(24, 24, 256)	295168
MaxPooling2D	(12, 12, 256)	0
Flatten	(None, 36864)	0
Dense	(None, 128)	4718720
Dropout (50%)	(None, 128)	0
Dense	(None, 2)	258

### Experimental Results and Analysis

We have conducted two different experiments in classifying pneumonia and normal CXR images. In one experiment, we have studied the effect of data imbalance problem and in another experiment, we have studied the effect of accuracy on balanced dataset. Both experiments were conducted using our proposed model and the mechanism of transfer learning with a pre-trained CNN model (MobileNetV2). In order to cross validate the performance of our proposed approach, we have utilized the pretrained MobileNetV2 model.

Table 3: Performance Metrics for Proposed Custom Model and MobileNetV2 for Unbalanced Dataset and Balanced Dataset respectively for classification of normal and Pneumonia X-ray Images.

Dataset	CNN Models	Classification Category	Precision	Recall	F1-Score	Accuracy
Unbalanced	Custom Model	Normal	0.98	0.92	0.95	0.97
		Pneumonia	0.97	0.99	0.98	
	Mobile-NetV2	Normal	0.96	0.93	0.95	0.97
		Pneumonia	0.97	0.98	0.98	
Balanced	Custom Model	Normal	0.97	0.96	0.96	0.97
		Pneumonia	0.96	0.97	0.97	
	Mobile-NetV2	Normal	0.99	0.96	0.97	0.97
		Pneumonia	0.96	0.99	0.97	

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### Hyper-parameters of the Model

We fine tuned our proposed model for 50 epochs. The batch size is set to 32 and we have used ADAM optimizer to optimize the loss function with a learning rate of 0.0001 and over the epochs the learning rate is decayed. We have down-sampled all the images to (224 x 224) before being fed to the model. We have implemented our code in Google colab (Bisong, 2019) using TensorFlow (Martín Abadi et al., 2015) and Keras (Chollet et al., 2015).

### Performance Evaluation Metrics

We have used four performance evaluation metrics to evaluate the performance of our proposed custom model and MobileNetV2. The four performance metrics are accuracy, precision (specificity), recall (sensitivity), and F1-score. In order to define the four performance metrics, we have to define the terms "True Positive (TP)", "False Positive (FP)", "True Negative (TN)", and "False Negative (FN)". We assume that, for binary classification problem, the first category (normal) is labeled as true and the second category (pneumonia) is labeled as false. Then TP refers to those examples belong to positive class being correctly classified as positive. FP refers to those examples belong to negative class but falsely classified as being in the positive class. TN refers to those examples belong to negative class being correctly classified as negative. FN refers to those examples belong to positive class but falsely classified as being in the negative class. The mathematical definition of these four metrics are as follows:

$$Accuracy_{class(i)} = \frac{TP_{class(i)} + TN_{class(i)}}{TP_{class(i)} + TN_{class(i)} + FP_{class(i)} + FN_{class(i)}} \quad (1)$$

$$Precision_{class(i)} = \frac{TP_{class(i)}}{TP_{class(i)} + FP_{class(i)}} \quad (2)$$

$$Recall_{class(i)} = \frac{TP_{class(i)}}{TP_{class(i)} + FN_{class(i)}} \quad (3)$$

$$F1 - Score_{class(i)} = \frac{2 \times Precision_{class(i)} \times Sensitivity_{class(i)}}{Precision_{class(i)} + Sensitivity_{class(i)}} \quad (4)$$

### Experimental Results with Unbalanced and balanced dataset

The comparative performance of our proposed custom model and transfer learning based MobileNetV2 with unbalanced data and balanced data is shown in Table 3. The training-loss/accuracy and validation-loss/accuracy curves for unbalanced data and balanced data for our proposed custom model and MobileNetV2 model are shown in Fig. 3. It is obvious from the figure that, our training process with 50 epochs successfully converged to the minimum loss without having any over-fitting or under-fitting issues. Figure 4 depicts the confusion matrix for our proposed model (first column) and the MobileNetV2 model (second column) for unbalanced and balanced dataset. We can see from the figure that for unbalanced dataset, our proposed custom model predicts 20 images out of 253 normal images as pneumonia images (false negative) and 5 images out of 569 pneumonia images was misclassified to normal images (false positive). False negative is further improved (from 20 images for unbalanced dataset to only 5 images for balanced dataset) as the

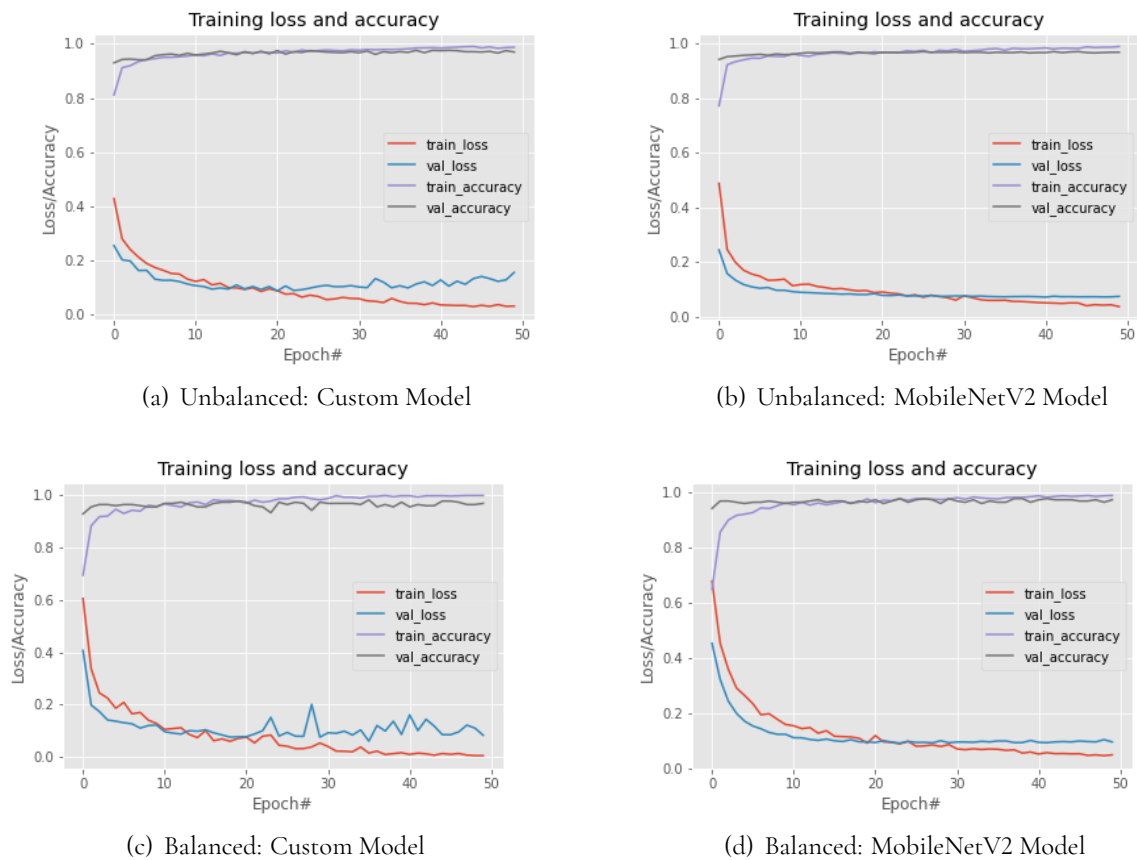


Figure 3: Training loss/accuracy vs validation loss/accuracy curve for unbalanced and balanced dataset. Fig.3(a) and Fig.3(b) shows the curve for custom model and MobileNetV2 model for unbalanced dataset respectively. Fig.3(c) and Fig.3(d) shows the curve for custom model and MobileNetV2 model for Balanced dataset respectively.

dataset is balanced. These statistics reflect the robustness of our proposed model irrespective of unbalanced or balanced dataset. However, we have observed that for balanced dataset our model shows superior performance. On the other hand, MobileNetV2 model performs slightly better than our proposed model. Also from the Table 3, It is perceivable that our proposed custom model performs very well in classifying normal CXR images from pneumonia images with unbalanced and balanced. For unbalanced dataset the performance metrics of our proposed custom model such as the precision, recall, F1-score, and accuracy for detecting normal images are 98%, 92%, 95%, and 97% respectively and for pneumonia images the precision, recall, F1-score and accuracy are 97%, 99%, 98%, and 97% respectively. For MobileNetV2, the precision, recall, F1-score, and accuracy are 96%, 93%, 95%, and 97% respectively for detecting normal images and for pneumonia images they are 97%, 98%, 98%, and 97% respectively. For balanced dataset the performance metrics for our proposed custom model such as the precision, recall, F1-score, and accuracy for detecting normal images are 97%, 96%, 96%, and 97% respectively and for pneumonia images the precision, recall, F1-score and accuracy are 96%, 97%, 97%, and 97% respectively. For MobileNetV2, the precision, recall, F1-score, and accuracy are 99%, 96%, 97%, and 97% respectively for detecting normal images

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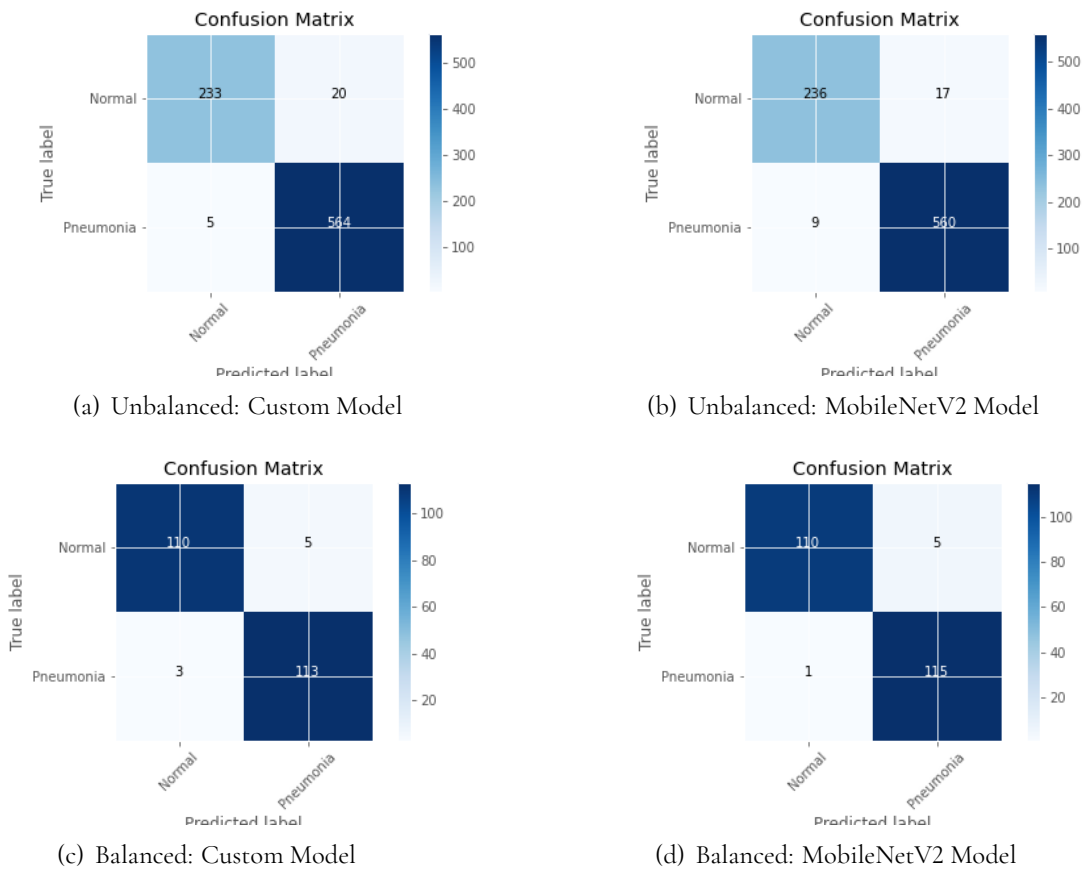


Figure 4: Confusion matrix for unbalanced and balanced dataset. Fig.4(a) and Fig.4(b) shows confusion matrix for custom model and MobileNetV2 model for unbalanced dataset respectively. Fig.4(c) and Fig.4(d) shows confusion matrix for custom model and MobileNetV2 model for balanced dataset respectively.

and for pneumonia images they are 96%, 99%, 97%, and 97% respectively.

It is apparent from the result that our proposed model's recall score for normal images improves as we shifted from unbalanced dataset to balanced dataset. The number of images in normal category was much smaller than the pneumonia category and because of this dissimilarity, the model was more biased toward the majority (pneumonia) class. We can also observe the superiority of MobileNetV2 model over our proposed model. However, there is a slight difference in performance of these two models. Also, MobileNetV2 is a light weight model designed for mobile devices and thus have less number of trainable parameters as compared to our proposed model.

## Conclusion

In this work, we have proposed a custom CNN model and utilized the transfer learning mechanism to train a pretrained model named MobileNetV2 on a large dataset to classify pneumonia and normal CXR images. We have studied the effect of unbalanced dataset and balanced dataset on our proposed model and MobileNetV2 model. For unbalanced dataset, the classification pre-

cision, recall, F1-score, and accuracy of normal and pneumonia images for our proposed custom model were 98%, 92%, 95%, and 97% respectively, and 97%, 99%, 98%, and 97% respectively. For unbalanced dataset, the precision, recall, F1-score, and accuracy of MobileNetV2 are 96%, 93%, 95%, and 97% respectively and 97%, 98%, 98%, and 97% respectively for detecting normal images and for pneumonia images respectively. For balanced dataset, the performance metrics for our proposed custom model such as the precision, recall, F1-score, and accuracy for detecting normal images are 97%, 96%, 96%, and 97% respectively and for pneumonia images they are 96%, 97%, 97%, and 97% respectively. For MobileNetV2, the precision, recall, F1-score, and accuracy are 99%, 96%, 97%, and 97% respectively for detecting normal images and for pneumonia images they are 96%, 99%, 97%, and 97% respectively. For MobileNetV2 model, performance evaluation scores were slightly higher than our proposed model. We also observed that, for unbalanced dataset, the accuracy, precision, and recall values are higher for more dominated dataset (pneumonia images were higher in numbers as compared to normal X-ray images). This effect can be mitigated when we balance the dataset.

However, the total number of trainable parameters of our proposed model is 5107394 which is much higher as compared to the MobileNetV2 model which has a total of 2388098 trainable parameters. In our future work, we will try to optimize our model in terms of total number of trainable parameters while keeping the accuracy to an acceptable level by adding more number of convolutional layers and maxpooling layers with appropriate filter size and with a combination of reduced number of neurons in the dense layer. Also, we have a plan to modify our existing architecture by incorporating attention mechanism to make the model more robust in classifying pneumonia diseases from normal ones.

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