Pneumonia Detection using Convolutional Neural Network(CNN)

By: Temesgen Tesfay

September - 6th, 2021

Key fact:

- Pneumonia accounts for 15% of all deaths of children under 5 years old, killing 808 694 children in 2017.

Description of the Pneumonia Dataset

The dataset is organized into 3 folders (train, test, and validation) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal). Chest X-ray imaging was performed as part of patients' routine clinical care.

- **Source**

  https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

  Description

  - The data has 1.2 GB of images, and files in .jpg containing the respective labels.
  - Classes labels, image is labeled as :
    - Pneumonia
    - Normal

The dataset has 5856 images, the images are classified among train, test, and validation. 89% allotted to train set, 10.6% to test set, and the remaining fraction is to the validation set. There is a data imbalance between the training and test, which might lead to model overfitting.

Data Augmentation

Data augmentation techniques deal with cases where the training data is limited. The techniques allow us to modify or even artificially synthesize more data thereby boosting the performance of a machine by reducing overfitting. The idea is to alter the training data with small transformations to reproduce the variations. These approaches that alter the training data in ways that change the array representation while keeping the label the same are known as data augmentation techniques. Using random rotation and random flip, we increased the model performance on accuracy metric from 0.833 to 0.86.3.

Exploratory Data Analysis(EDA)

The dataset contains over 5000 training images and additional 624 images for testing. Each image is stored in .jpg files The Distribution of the label instances in the training set can be seen in the bar graph below:

The distribution of dataset group between normal and pneumonia classes

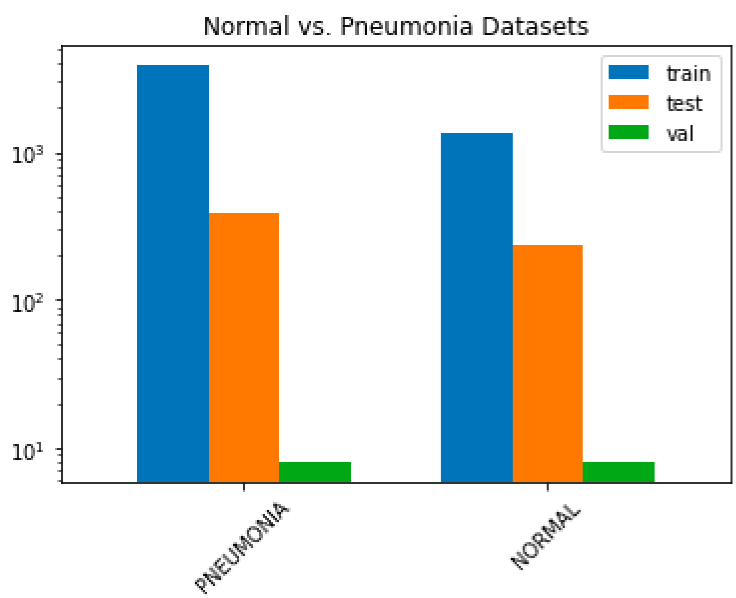

Fig 1.1 dataset proportion between normal and pneumonia

Fig 1.1 the sample size among the group has a huge difference hence, used log distribution to resize the bar graph for visualization. There is a clear indication of data imbalance.

The Distribution of Normal and Pneumonia images

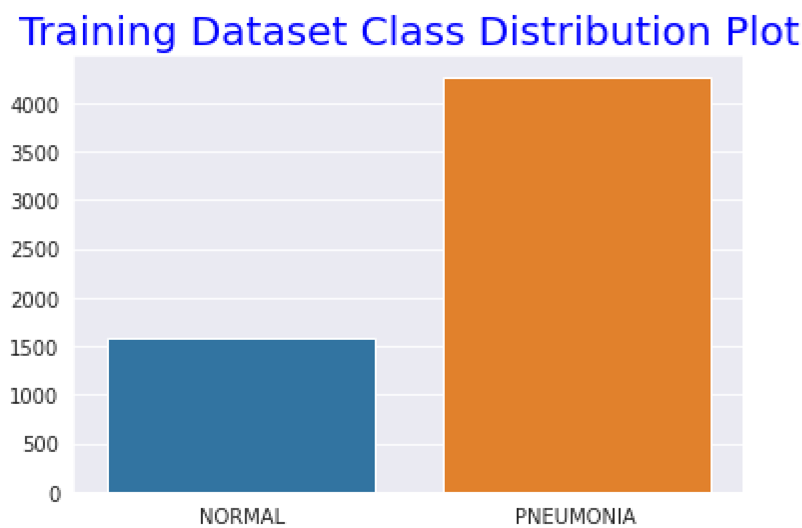

Fig 2.1 normal and pneumonia distribution

In the training dataset, we find that 75% of images show a patient with pneumonia.

A class of pneumonia versus normal lung images

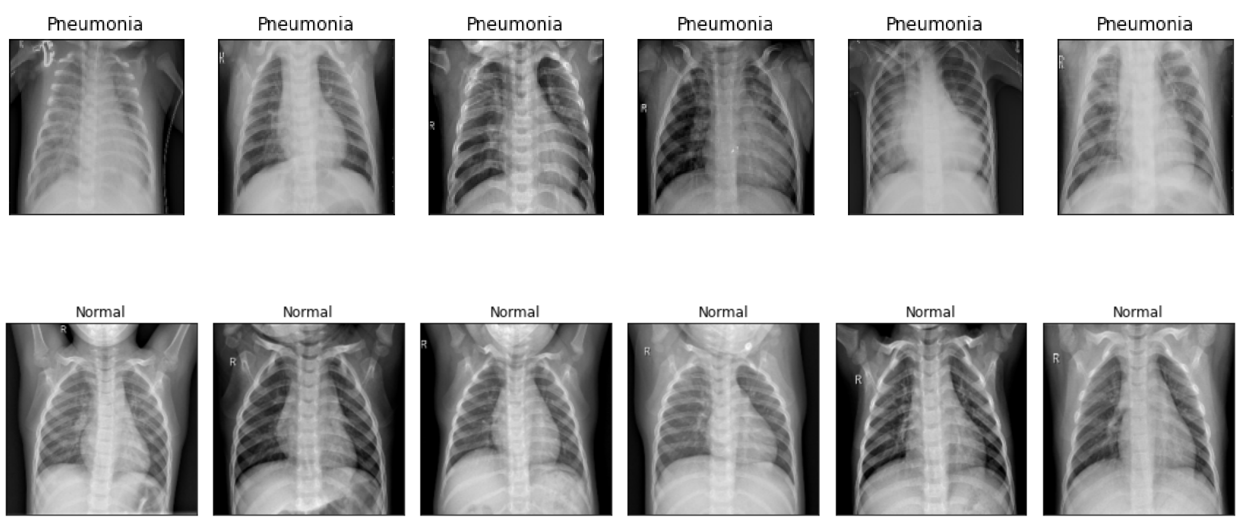

Fig 3.1 Sample images of pneumonia and normal chest-Xray image

Many Of the pneumonia-positive lungs show a wide irregular whitish area versus the normal dark brown regular pattern.

Convolutional Neural Networks(CNN) Model

A fully connected CNN model was created using Keras on top of TensorFlow. The base model of CNN architecture was created using ResNet50V2 Keras applications, and its parameters are as follows:

- Image resolution input shape = (height = 220, width, 220, and 3 channels = (220,220,3)
- Training set size: 5216
- Validation set size: 16
- Test set size: 624
- Batch size = 32
- Metric: Recall or Sensitivity, and F1 score

The model's Training and Validation accuracies and losses plots:

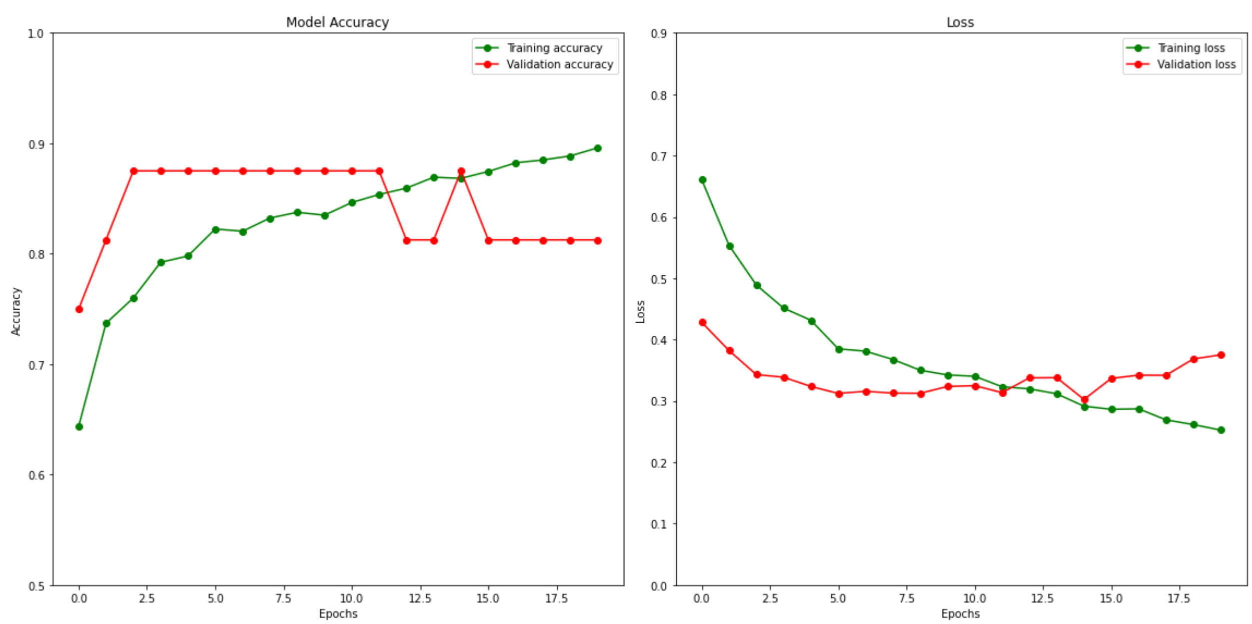

Fig 4.1 Model Accuracy vs Loss Distribution

Confusion Matrix

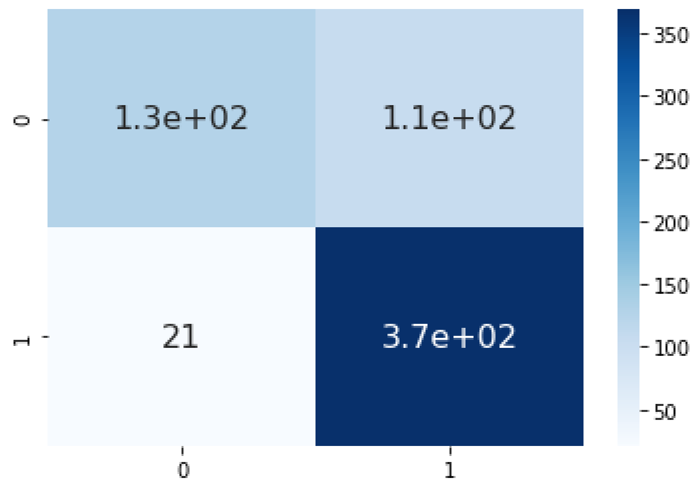

Fig 5.1 Confusion Matrix

The confusion matrix classification report metrics return the following:

	precision	recall	f1-score	support
0	0.86	0.55	0.67	234
1	0.78	0.95	0.85	390
accuracy			0.80	624
macro avg	0.82	0.75	0.76	624
weighted avg	0.81	0.80	0.78	624

The focal point of this project is to minimize false negatives or incorrectly classified pneumonia patients. Therefore, Recall will be prioritized in evaluating model performance. The project did experiments to improve recall outcomes. Some of the experiments implemented:

- Implemented fully connected convolutional neural network
- Executed various regularization techniques
- Transfer Learning from pre-trained data images stored in the file named-imagenet.

Since we want to prioritize recall, we decided to use an F-Beta score to allow us to weigh precision and recall separately. In F-Beta, a Beta score of > 1 weights recall greater than precision, and the opposite is true for F < 1. In our case, we decided to set Beta equal to 3 since we want to highly prioritize recall.

Precision, recall, and F3 score

Fig 6.1 Precision, recall, and F3 score value as a function of model threshold

Several other parameters and models were tested to check model performance to improve baseline CNN classification. Various regularization methods such as relu, batch-normalization, pooling, and dropout techniques were implemented on the subsequent fully connected layer to check the model performance and the sigmoid activation function to the last layer of binary outputs.

Transfer Learning:

Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. For example, knowledge gained while learning to recognize cars could apply when trying to recognize trucks. From a practical standpoint, reusing or transferring information from previously learned tasks for the learning of new tasks has the potential to significantly improve model performance.

For this task, we used the ResNet50V2 model which was previously trained on a subset of ImageNet (a huge database of 14 million images manually labeled with over 22,000 categories) as part of the ImageNet Large Scale Visual Recognition Challenge. While much of this data is very different from our pneumonia data, the abstract features that are created can still be very useful for us. In this case, I froze all the layers and added a new top layer to be trained on these data and output pneumonia predictions.

Conclusion

- The model performs to identify the labeled images. The data used Chest-X Rays images to detect pneumonia symptom images seen on the lung beneath the chest or diaphragm make it impossible to get the pixels from the second deep layer because feature extraction is responsible for collecting pixels from the outermost visible edges, corners, and plane part of the chest and ribs.
- The ResNet50V2 Keras application for transfer learning performs better to image classification.
- The insufficient data sample size coupled with the imbalance to train the model contributed to biases and overfitting; however, the data augmentation technique minimizes the degree of the overfitting problem.
- The model is applied both in deep learning convolutional neural networks and transfer learning by keeping the top layers frozen and feeding the input data to

the base layer with various regularization techniques. Transfer learning from pre-trained images minimized the computational cost and returns reasonable model performance.