Pneumonia Detection using Convolutional Neural Network(CNN)

By: Temesgen Tesfay

Springboard

September, 6th, 2021

Key fact:

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

What is Pneumonia?

Pneumonia is an inflammatory condition of the lung affecting primarily the small air sacs known as alveoli. Symptoms typically include some combination of productive or dry cough, chest pain, fever, and difficulty breathing. The severity of the condition is variable. Pneumonia is usually caused by infection with viruses or bacteria and less commonly by other microorganisms. Diagnosis is often based on symptoms and physical examination. Chest X-ray, blood tests, and culture of the sputum may help confirm the diagnosis. The disease may be classified by where it was acquired, such as community- or hospital-acquired, or healthcare-associated pneumonia.

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. For the analysis of chest x-ray images.

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. Some popular augmentations people use are grayscales, horizontal flips, vertical flips, random crops, color jitters, translations, rotations, and much more. By applying just a couple of these transformations to our training data, we can easily double or triple the number of training examples and create a very robust model.

- **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.

Exploratory Data Analysis(EDA)

Occurrence of Labels

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:

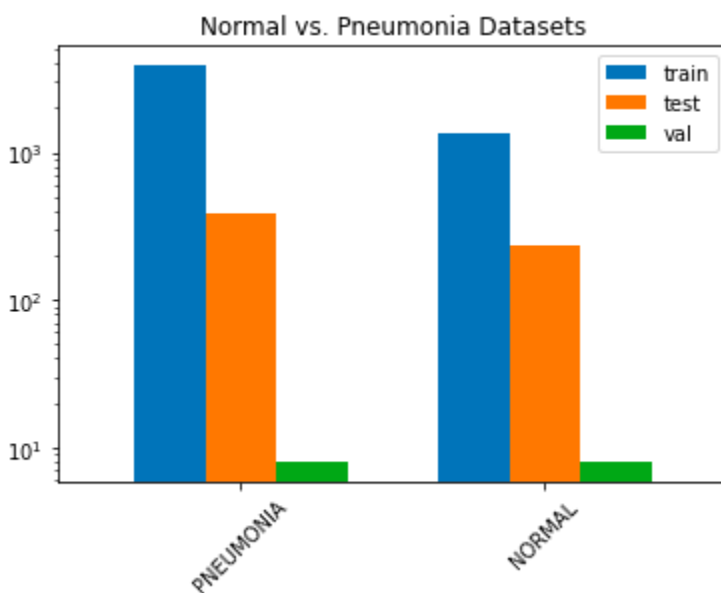**The distribution of dataset group between normal and pneumonia classes**

Fig 1.1 dataset proportion between normal and pneumonia

The Distribution of Normal and Pneumonia images
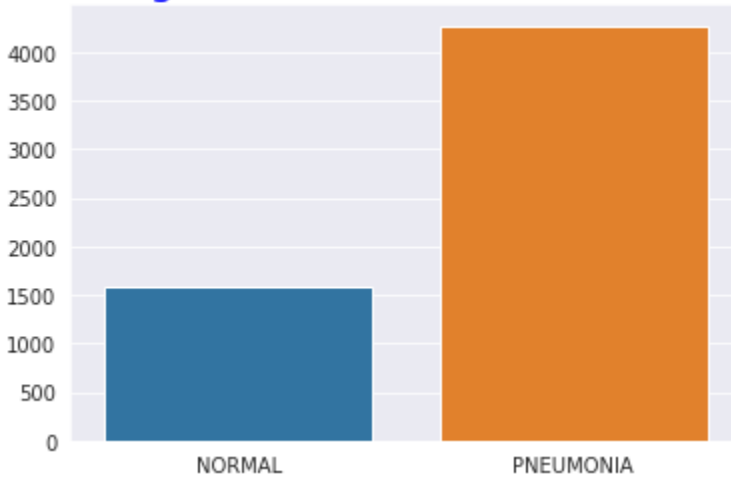

Fig 2.1 normal and pneumonia distribution

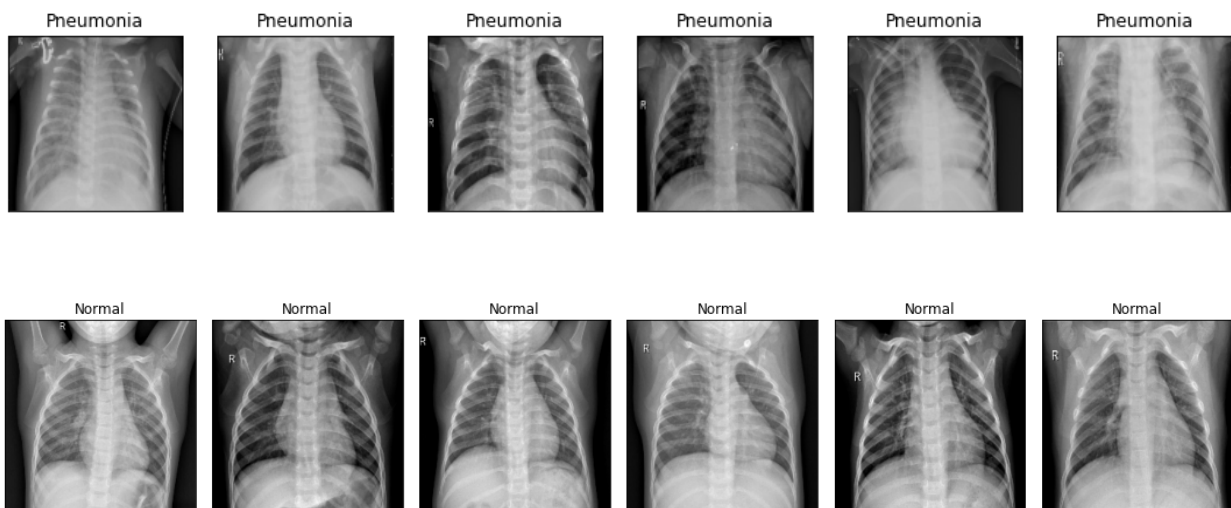## A class of pneumonia versus normal lung images

Fig 3.1 Sample images of pneumonia and normal chest-x-ray imag

Compared to the normal lung, pneumonia infected lung images dominated with a high percent of whitish area depending on the severity of the infection.

Convolutional Neural Networks(CNN) Model

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of artificial neural networks, most commonly applied to analyze visual imagery. They are also known as shift invariant or space invariant artificial neural networks(SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide a translation. Responses are known as feature maps. CNN is used in applications in image and video analysis, natural language processing, brain-computer interfaces, and financial time series.

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 = 224, width, 22, and 3 channels = (220,220,3)
- Training set size: 5216
- Validation set size: 16
- Test set size: 624
- Batch size = 32
- Early Stopping: Monitoring validation loss with the patience of 4
- Metric: Recall or Sensitivity, and F1 score

The model's Training and Validation accuracies and losses during training are shown in the plots below:
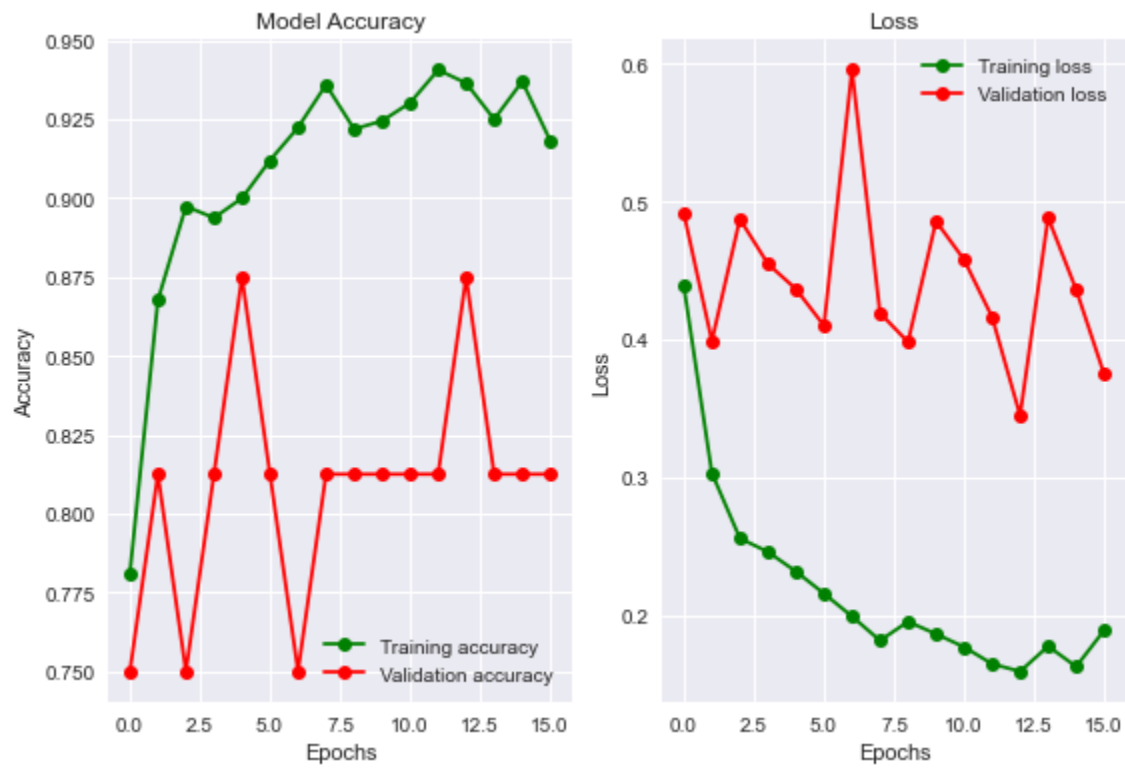

Fig 4.1 Model Accuracy vs Loss Distribution
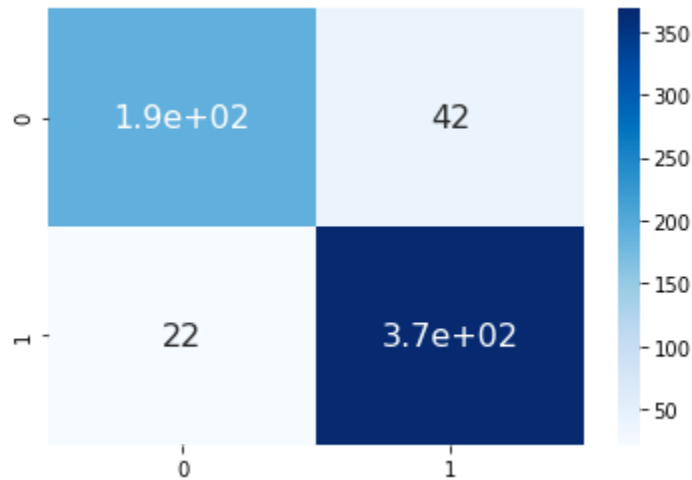
Confusion Matrix

Fig 5.1 Confusion Matrix

The confusion matrix classification report metrics return the following:

	precision	recall	f1-score	support
0	0.90	0.82	0.86	234
1	0.90	0.94	0.92	390
accuracy			0.90	624
macro avg	0.90	0.88	0.89	624
weighted avg	0.90	0.90	0.90	624

From the dataset, we learn there is a data imbalance between training and test datasets which might lead to model overfitting. Under this situation accuracy is not the right metric to measure model performance, instead, the F1 score provides a harmonic mean of Precision and Recall classifiers than accuracy metrics.

This project focuses on the model to minimize False-negative rates to improve model performance on F1 score metrics.
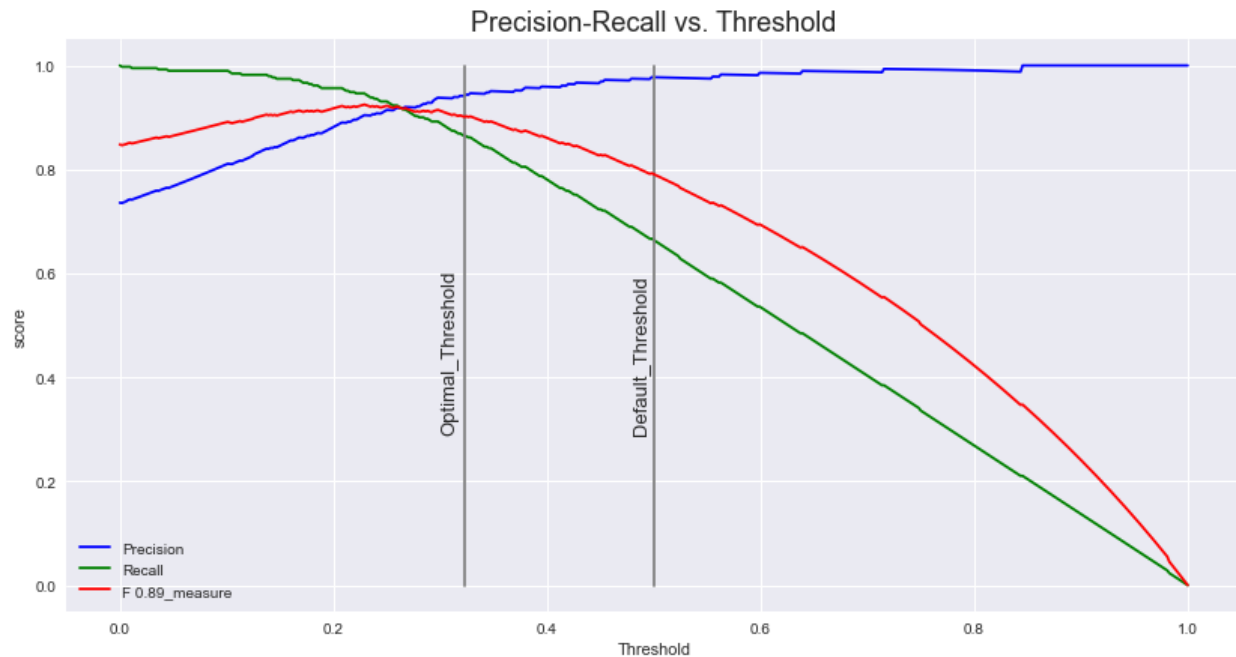
Precision, recall, and F0.89 Measure

Fig 6.1 Precision, recall, and F0.89 measure value as a function of model threshold

Several other parameters and models were tested to check model performance to improve baseline CNN classification performance. Various regularization methods such as relu, batch-normalization, pooling, and dropout techniques are applied on the subsequent fully connected layer to check the model performance. Sigmoid activation function implemented to the last layer 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. This area of research bears some relation to the long history of psychological literature on the transfer of learning, although practical ties between the two fields are limited. From the practical standpoint, reusing or transferring

information from previously learned tasks for the learning of new tasks has the potential to significantly improve the sample efficiency of a reinforcement learning agent.

If the dataset image is a subset of Imagenet, where thousands of images are already pre-trained. Therefore, similar objects efficiently identify with a few layer convolutional network because the most relevant features and their weights are stored in the Imagenet. This reduces the computation cost significantly and performs sometimes better but might depend on the model performance.

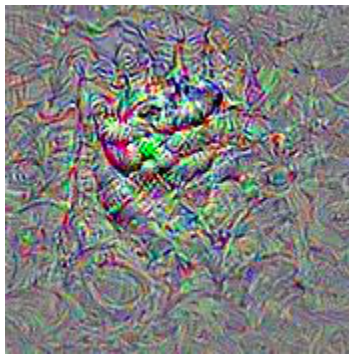The sample of the first filter image in fifth block layers

Fig 7.1 Images from a feature from the first index of the last convolutional layer

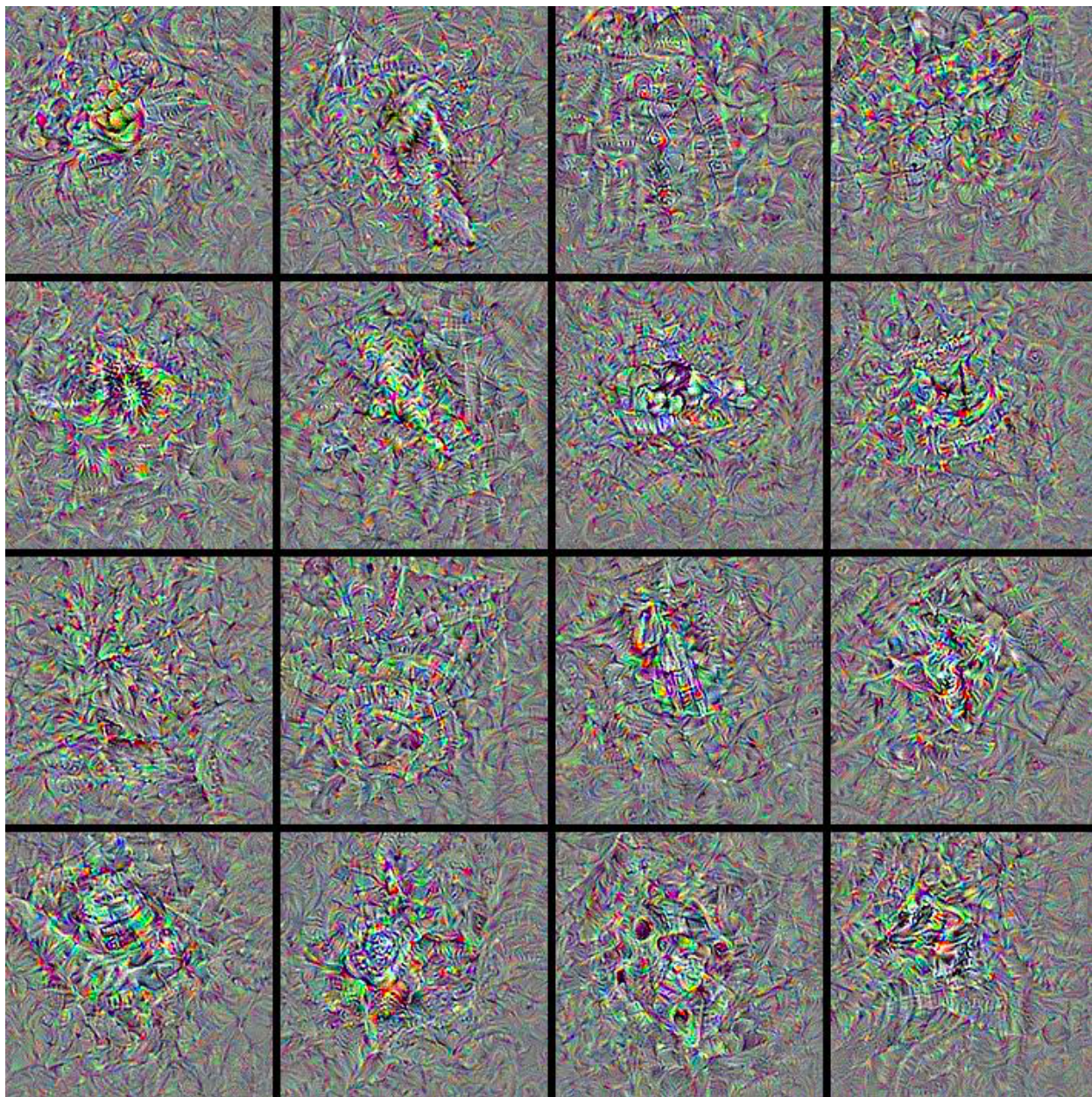# Visualize the last convolutional layer from each filter index

Fig 8. The sample features images from the last convolutional layer

Conclusion

The model performs well 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. ResNet50V2 keras application for transfer learning performs better to image classification.

Due to the insufficient data sample size the score could be better as more data fed to the model to improve model performance as pneumonia is top few killer diseases in the world, to minimize the false negative rate reduces the risk and the death rate from the disease.

The model applied both in deep learning convolutional neural networks and transfer learning using only one top layer from the base model. The pre-trained images from imagenet in transfer learning minimize computational cost.