Pneumonia Detection Using Deep Learning

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Abstract: Pneumonia is one of the top infections that will inflame the air sacs in our one or both lungs. The air sacs can fill with a lot of fluid, causing cough with phlegm, fever, chills, difficulty breathing, and other diseases. A spread of organisms, including bacteria, viruses, and fungi, can cause pneumonia. Pneumonia can home in seriousness from mild to life-threatening. It is mainly seriously affected infants and young children, people older than age 65, and other people with health problems or weakened immune systems. I have suggested a deep learning program for the detection of pneumonia using the concept of sequential model, convolution neural network, transfer learning, pre trained neural network and autoencoder. In those approaches, I used different layers and extract features from images using different neural network pretrained models, which then are fed into a classifier for prediction. I have prepared three different models and analyzed their performance. Thereafter, I proposed combines outputs from all models and last I decided to choose the best model performance in pneumonia recognition. My best model reached an accuracy of 87.17% with a recall of 86.15%.

Keywords: deep learning; transfer learning; tensorflow; medical image processing; computer-aided diagnosis; convolution neutral network; pretrained neural network

1.Introduction

The risk of pneumonia is immense for many, especially in developing nations where billions face energy poverty and rely on polluting forms of energy. The WHO estimates that over 4 million premature deaths occur annually from household air pollution-related diseases including pneumonia. Over 150 million people get infected with pneumonia on an annual basis especially children under 5 years old. In such regions, the problem can be further aggravated due to the dearth of medical resources and personnel. For example, in Africa's 57 nations, a gap of 2.3 million doctors and nurses exists. For these populations, accurate and fast diagnosis means everything. It can guarantee timely access to treatment and save much needed time and money for those already experiencing poverty.

In recent times, CNN motivated deep learning algorithms have become the standard choice for medical image classifications although the state-of-the-art CNN-based classification techniques pose similar fixated network architectures of the trial-and-error system which have been their designing principle. U-Net, SegNet, and CardiacNet are some of the prominent architectures for medical image examination.

CNNs have an edge over DNNs by possessing a visual processing scheme that is equivalent to that of humans and extremely optimized structure for handling images and 2D and 3D shapes, as well as ability to extract abstract 2D features through learning. The max-pooling layer of the convolutional neural network is effective in variant shape absorptions and comprises sparse connections in conjunction with tied weights. When compared with fully connected (FC) networks of equivalent size, CNNs have a considerably smaller number of parameters. Most importantly, gradient-based learning algorithms are employed in training CNNs and they are less prone to diminishing gradient problem. Since the gradient-based algorithm is responsible for training the whole network in order to directly diminish an error criterion, highly optimized weights can be produced by CNNs.

Figure1. Image without Pneumonia

Figure2. Image with Pneumonia

2. Proposed Work

2.1. Dataset Description

The dataset used is ChestX-ray14 released by Wang et al. (2017) also publicly available on the Kaggle platform which consists of 112,120 frontal chest X-ray images from 30,085 patients. Each radiographic image in the dataset is labeled with one or more out of different 14 thoracic diseases. These labels were concluded through Natural Language Processing (NLP) by text-mining disease-classification from the associated radiological reports and are expected to be more than 90% accurate. For the sake of this work, following the approaches from the past, we treat the labels as ground truth for the purpose of pneumonia detection. Prior to the release of this dataset, the largest publicly available dataset of chest radio-graphs was Openi which consisted of roughly 5,232 X-ray images.

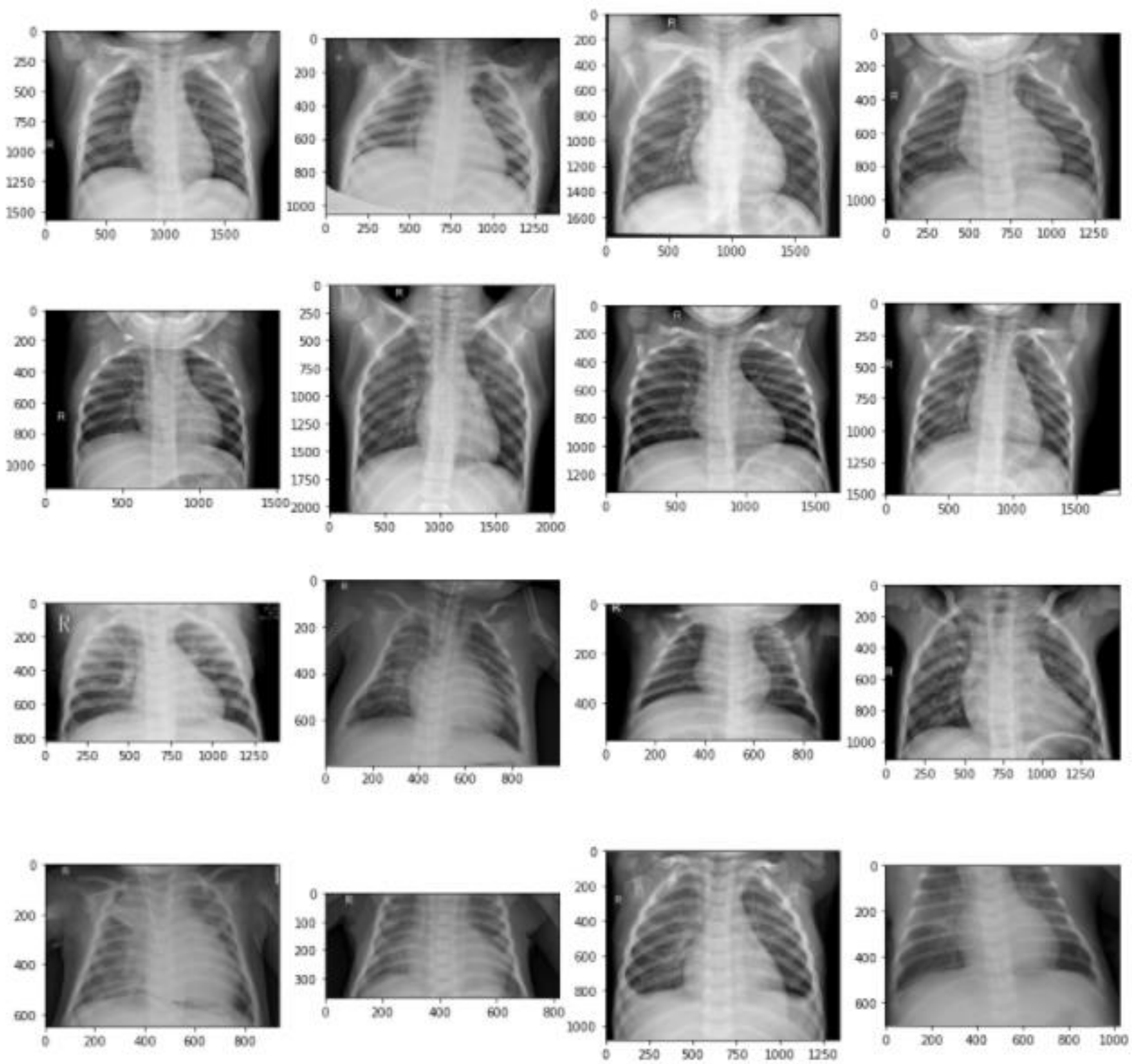

Figure3. First 8 images are normal x-ray images and next 8 images are pneumonia x-ray images

2.2. Preprocessing

Dataset I worked has training, validation and test set, but validation set has only 16 images whereas training set has 5216 images. So first I had created a proper distribution set with 80% as training data and 20% as validation data. Then I merge training and validation set and then split them in the ratio of 80:20 respectively.

After that the number of images in training set is 5216, number of images in validation set is 16 and number of images in testing set is 624. After division of 80:20, the total number of training images is 4185 and the total number of validation images is 1047.

- Making new directories for training set and validation set
- Copying the images in new directories

- Having a look over the dataset after the split
- Setting the path of training directory and validation directory

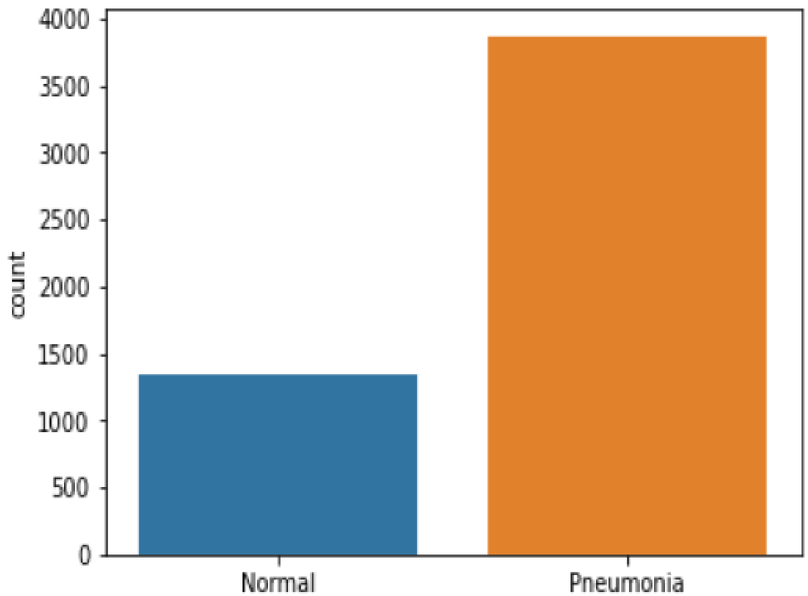

Figure4. Number of Normal and Pneumonia images

2.3. Convolution Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

- The **Keras** Python library makes creating deep learning models fast and easy. The sequential API allows you to create models layer-by-layer for most problems. It is limited in that it does not allow you to create models that share layers or have multiple inputs or outputs.
- Keras **Conv2D** is a 2D Convolution Layer, this layer creates a convolution kernel that is wind with layers input which helps produce a tensor of outputs.
- **MaxPooling2D** from keras.layers, which is used for pooling operation. For building this particular neural network, we are using a Maxpooling function, there exist different types of pooling operations like Min Pooling, Mean Pooling, etc. Here in MaxPooling we need the maximum value pixel from the respective region of interest.
- **Flatten** from keras.layers, which is used for Flattening. Flattening is the process of converting all the resultant 2-dimensional arrays into a single long continuous linear vector.

- **Dense** from keras.layers, which is used to perform the full connection of the neural network

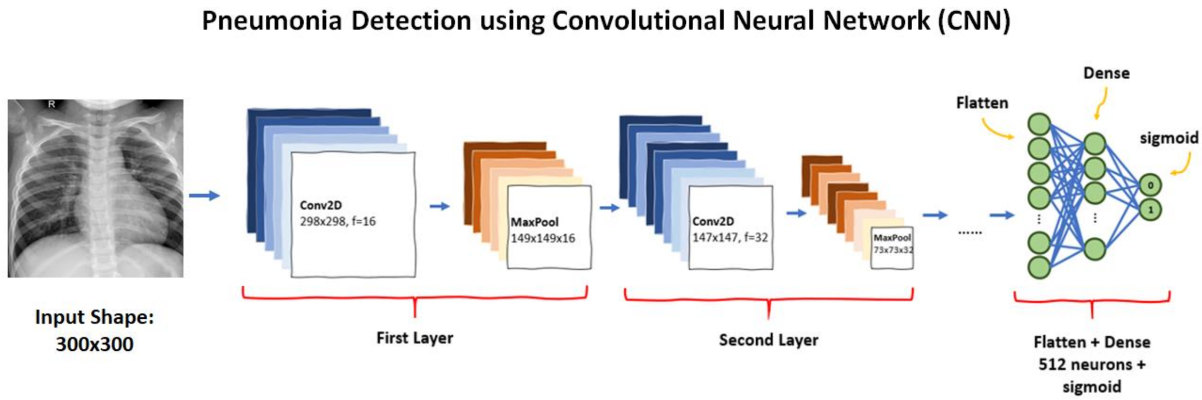

Figure5. Sequential and CNN layers

2.4. Image Data Generator

ImageDataGenerator which Takes a batch of images and applies a series of random transformations to each image in the batch (including random rotation, resizing, shearing, etc.) and then Replacing the original batch with the new, randomly transformed batch for training the CNN.

2.5. Preprocessing and Augmentation

I employed several data augmentation methods to artificially increase the size and quality of the dataset. This process helps in solving overfitting problems and enhances the model's generalization ability during training.

The rescale operation represents image reduction or magnification during the augmentation process. The rotation range denotes the range in which the images were randomly rotated during training, i.e., 30 degrees. Width shift is the horizontal translation of the images by 0.2 percent, and height shift is the vertical translation of the images by 0.2 percent. In addition, a shear range of 0.2 percent clips the image angles in a counterclockwise direction. The zoom range randomly zooms the images to the ratio of 0.2 percent.

2.6. ResNet50

I had used pre-trained model provided by keras and add some layers on the top. The pre-trained ResNet model in keras takes in input of exactly three input channels, but our input image is of grayscale. So, in order to avoid mismatch of shape we'll let our Image data generator use the default color_mode i.e. rgb instead of specifying it to be gray_scale.

ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer visions tasks. This model was the winner of ImageNet challenge in 2015. The fundamental breakthrough with ResNet was it allowed us to train extremely deep neural networks with 150+layers successfully. Prior to ResNet training very deep neural networks was difficult due to the problem of vanishing gradients.

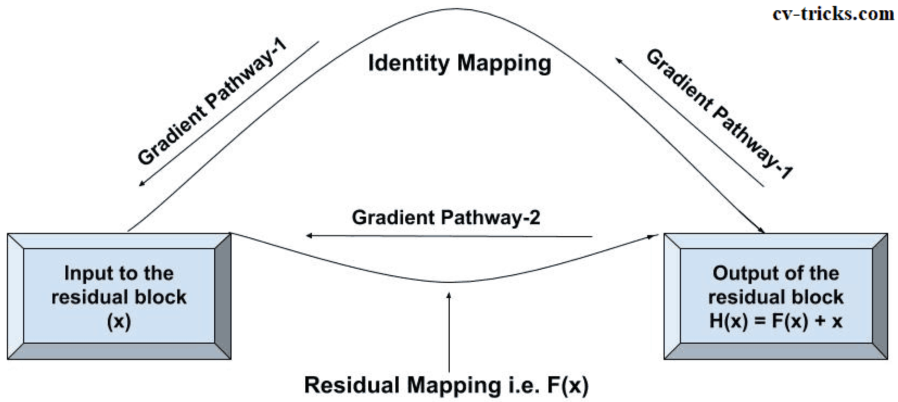

Figure6. Gradient Pathways in ResNet

Key Features of ResNet:

- ResNet uses Batch Normalization at its core. The Batch Normalization adjusts the input layer to increase the performance of the network. The problem of covariate shift is mitigated.
- ResNet makes use of the Identity Connection, which helps to protect the network from vanishing gradient problem.
- Deep Residual Network uses bottleneck residual block design to increase the performance of the network.

3.Result & Discussion

3.1. CNN

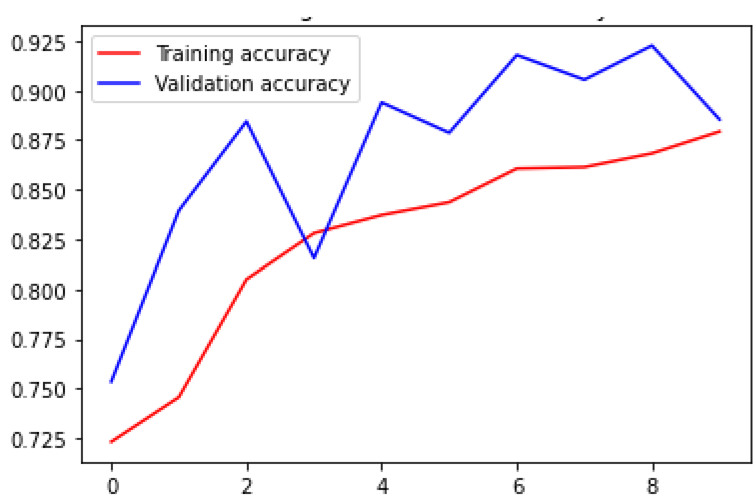

Figure7. Training and validation accuracy

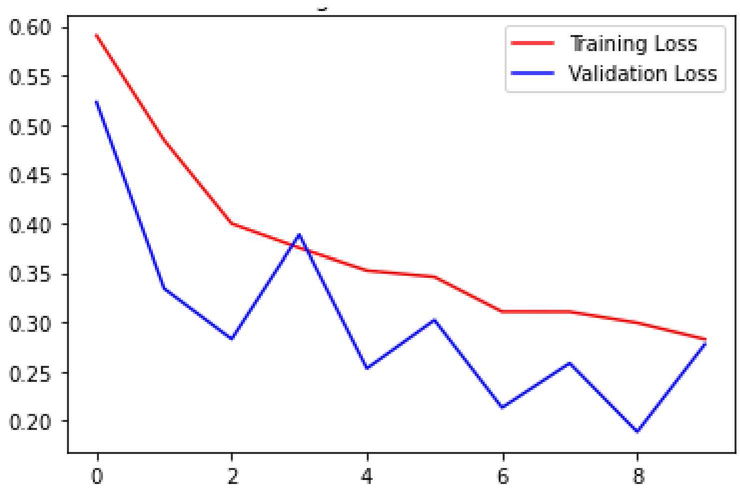

Figure8. Training and validation loss

3.2. ResNet50

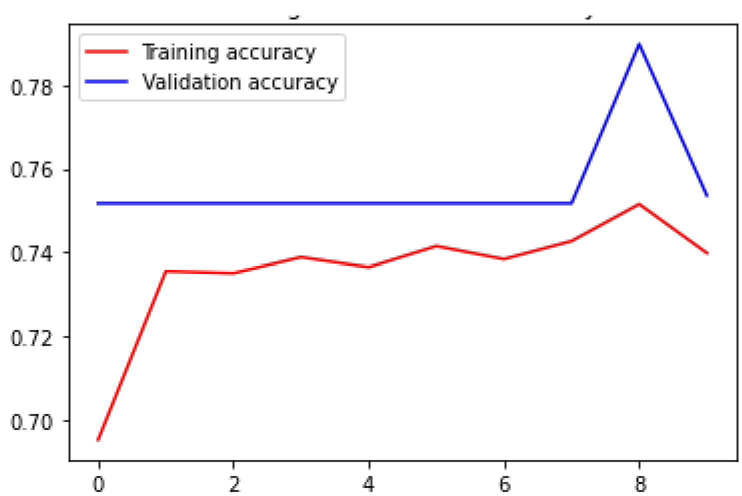

Figure9. Training and validation accuracy

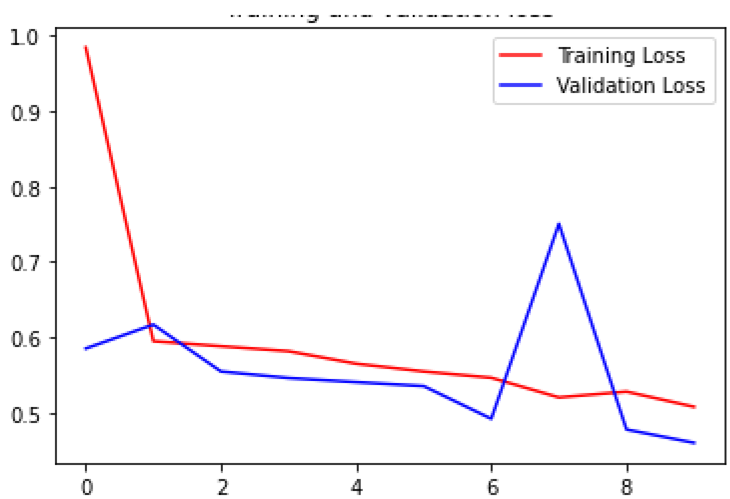

Figure10. Training and validation loss

3.3. Comparison

Model	Accuracy(%)	Loss(%)	Precision(%)	Recall(%)
CNN	87.18	32.63	92.81	86.15
ResNet50	64.1	63.04	63.6	99.48

4.Conclusions

In this article, my goal is to propose a deep learning-based approach to classify pneumonia from chest X-ray images using the concept of sequential model, convolution neural network, transfer learning, pre trained neural network and autoencoder. In this framework, I have used two different approach. One is using Convolution Neural Network. Other is I have adopted the transfer learning approach and used the pretrained architectures, ResNet50 trained on the ImageNet dataset, to extract features. These features were passed to the classifiers of respective models, and the output was collected from individual architectures. I observed that performance could be improved further, by increasing dataset size, using a data augmentation approach, and by using hand-crafted features, in future.

While pneumonia diagnoses are commonly confirmed by a single doctor, allowing for the possibility of error, deep learning methods can be regarded as a two-way confirmation system. In this case, the decision support system provides a diagnosis based on chest X-ray images, which can then be confirmed by the attending physician, drastically minimizing both human and computer error. My results suggest that deep learning methods can be used to improve diagnosis relative to traditional methods, which may improve the quality of treatment.

References

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2. A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images[Link]
3. Deep Learning for Detecting Pneumonia from X-ray Images[Link]
4. An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare[Link]
5. Pneumonia Detection Using CNN based Feature Extraction[Link]

GitHub Link for code: https://github.com/subhadipml/Pneumonia-Detection-Using-Tensorflow