Journal for Research | Volume 06 | Issue 6 | August 2020
ISSN: 2395-7549

Deep Learning for Detecting Pneumonia

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Abstract

In this paper, we present the concept of detecting pneumonia using Deep learning. In today's modern world pneumonia disease is the most lethal one. This disease attacks a person so instantly. So, diagnosis a patient correctly on timely basis is the most challenging task. At the same time cost of treatment is high and not affordable by many people. The goal of this paper is to develop a detecting system for pneumonia using Deep Learning Technologies. Healthcare industry contains a huge amount of healthcare data (Image data) and these healthcare data contain hidden information. This hidden information is useful for making effective detection using different Deep Learning techniques. We can develop efficient Decision-Making for patients who will be suffering from disease and using this we can identify the patients who have pneumonia. So that treatment cost will be affordable by people. In order to learn about deep learning the paper we referenced are mentioned below from [1...13].
Keywords: Lung, Disease, Pneumonia, Object Detection, Feature Extraction. Deep Learning, Convolutional Neural Network

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I. INTRODUCTION

Deep learning is a technology that mimics the functioning of the human brain in data processing and in forming patterns for decision-making. Deep learning is a machine-learning branch of artificial intelligence (AI), which has networks capable of unattended or unmarked data learning. Often referred to as deep neural schooling, or deep neural network.

This paper analyzes how to predict a pneumonia disease. The risk of pneumonia is massive for many, especially in developing countries where trillions are facing energy deprivation and dependent on polluting forms of energy. WHO reports that air pollution-related household diseases, including pneumonia, are causing more than four million premature deaths per year. Every year, more than 150 million people get infected with pneumonia, particularly children under the age of 5.

This paper analyzes how decision support systems can be built using Deep Learning techniques. Such methods are used to uncover hidden patterns within health data and these patterns can be identified using Deep Learning. Computer-based information or decision-support systems can also facilitate accurate assessments with reduced costs and improved precision.

A. *Pneumonia:*

The lungs are one of the important organs of our body such as brain, heart and so on. If the work of a lung is not enough, it will affect the other parts of a human body. It is nothing more than a breath, pumping an oxygenated blood all over the body. If the body's supply of oxygen is inadequate for all tissues, the body is short of breath and death occurs.

Pneumonia is an infectious illness caused by an infection in the lung air sacs. Patients with pneumonia may undergo alveoli inflammation, followed by fluid in the air sacs. A radiologist may determine whether or not pneumonia occurs using the severity from Chest x-ray images. Computer-aided detection (CAD) will boost the diagnostic capabilities of radiologists by giving a second opinion to radiologists. Many techniques can be used to design the CAD system including deep convolutional architecture. This paper aims to know the efficiency in classifying and detecting pneumonia by using deep convolutional architecture. Furthermore, the tests are to be measured and evaluated.

There are numbers of factors which increase the chances of lung disease causes due to:
- Virus
- Bacteria
- Fungi

B. Data Sources:

A total of 5840 images have been obtained from Lung Disease dataset. In the dataset we have two categories of images and they are Normal Lungs images and Pneumonia Affected Lungs images.

The whole dataset is splitted into a training set and testing set. Training set consists of 5216 images and the testing set consists of 624 images.

II. LITERATURE REVIEW

The A model developed with the aid of Deep learning techniques such as Neural Network Intelligent Pneumonia Disease Prediction Method. The results showed the strange intensity of each of the methodologies in achieving the goals of the targets listed. Intelligent Lung Disease Prediction System was able to answer questions that could not be addressed by traditional decision-support systems. It facilitated the creation of vital information, e.g. trends, relationships among lung disease-related medical factors.

Another research was dealing with records of patients on a reference database. The Neural Network is tested and equipped with 2 input images such as Regular Lungs X-ray images and Pneumonia affected Lungs X-ray images. In the diagnosis of lung diseases, the coevolutionary network was recommended. Training was done using Deep Learning Algorithm. Whenever the doctor fed unknown data, the machine recognized the unknown data through similarities with the qualified data and detected whether or not the patient has Pneumonia.

While deep learning has been around for more than two decades, it is only now realizing its potential. Deep Learning incorporates statistical analysis, machine learning and database technologies to discover hidden patterns and massive dataset relationships.

By Vangie Beal. Deep learning is a subset of machine learning that processes data and creates patterns for use in decision making. Deep learning techniques teach machines to perform tasks that would otherwise require human intelligence to complete.

Deep learning uses three strategies: Convolutional Neural Network (CNN)[2] , Recursive Neural Network(RNN) ,Recurrent Neural Network(RNN).A Convolutional Neural Network (CNN / ConvNet) is a Deep Learning algorithm capable of capturing an input image, assigning significance (learnable weights and biases) to different aspects / objects in the image and distinguishing them from each other.

There are Pre Trained Convolutional Neural Network which is built by many which can be used by us by removing the last layer with our classifier so that it will be trained with our dataset since it is pre trained models accuracy of the model will be better than our model. These Pre Trained models are suitable for particular datasets alone so we have to keep that in mind before using them.

The name of Pre Trained Models are ImageNet, VGG Net, GoogleNet, and Microsoft ResNet and so on. But out of this model I studied two papers which are on ImageNet[6] and VGG Net[7].

When we use these Pre Trained Model as our model then that is known as Transferable Learning means we will transfer weights of that model to our model to train our dataset to get better accuracy and results [10].

Depending on the modeling objective each deep learning technique serves a different purpose. Classification and prediction are the two most important modeling objectives.

The performance of the models in this study was evaluated using the standard accuracy, precision, recall, and F-measure metrics measured using the Confusion Matrix predictive classification table [9].

The experiments were performed on a complete training dataset that included all the instances used to randomly compare the training and test sets. I have identified a few data generators: one for data training, and the other for data validation. A data generator can load the appropriate amount of data directly from the source folder, convert it to training data (fed to the model) and training targets.

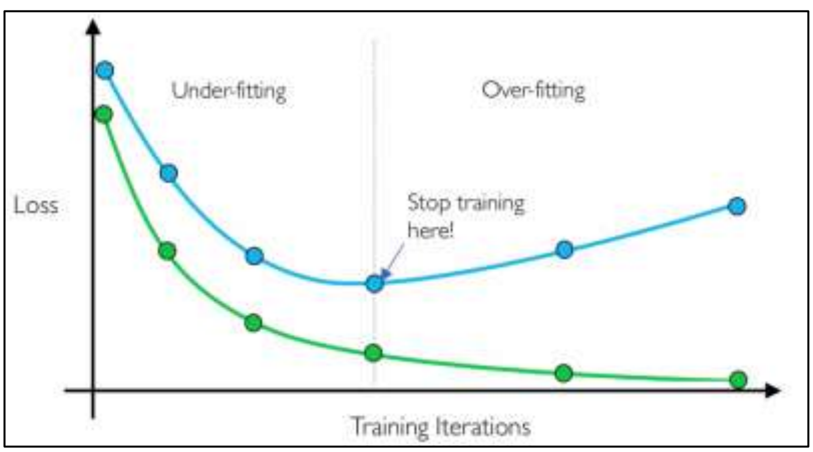

Fig. 1:

In figure 1, we are trying to explain about the concept of overfitting and underfitting while training the model. Overfitting happens when the model gives a good performance on training data and poor performance on other data whereas Underfitting happens when the model gives a poor performance on both training data and the other data.

The graph is drawn with respect to training iterations and loss. In the graph the middle point is where we stop our model to get the best result so that model works perfectly without overfitting and underfitting [3].

I usually set batch size= 64 bit for this experiment; batch size is set to 32. In general, a value should fit well between 32 and 128. Typically, you can increase / decrease the batch size based on the computing resources and the efficiency of the sample. For this experiment we build a model with 4 Convolution layers, Max-Pooling and Batch Normalization and three Fully connected layers.

Convolutional layers are the main building blocks used in convolutional neural networks. Simple application of a filter to an input that results in activation is a convolution. Repeated application of the same filter to an input results in an activation map called a feature map, which indicates the positions and intensity of a detected feature in an input, such as an image.

Max pooling is a method of discretization based on a sample. The aim is to down-sample an input representation (image, hidden-layer output matrix), reduce its dimensionality and allow assumptions about features found in the binned sub-regions to be made.

Batch normalization is a technique used to train very deep neural networks that standardizes the inputs for each mini-batch into a layer. This results in a stabilization of the learning process and a drastic reduction in the number of training epochs needed for deep networks.

Flattening involves converting the entire matrix of the pooled feature map into a single column which is then fed to the processing neural network. Dropout is a technique used to prevent pattern overfitting. Dropout works by randomly setting the outer edges of cached units [1].

Activation functions are mathematical equations, which evaluate a neural network's performance. The role is attached to each neuron in the network, and decides whether or not it should be triggered ("fired") depending on whether the feedback of each neuron is important to the prediction of the model. Activation functions also help to normalize each neuron's output to a range of between 1 and 0 or-1 to 1.

There are totally seven types of Activation function but we used RELU [5]. Activation function was Relu throughout except for the last layer where it was Sigmoid as this is a binary classification problem [8]. Relu refers to the Rectifier Unit, the most widely used activation function for CNN Neuron outputs [9]. Mathematically, it is defined as: Unfortunately, at the root, the ReLu function is not distinguishable which makes it difficult to use with backpropagation training[8].

We used Stochastic Gradient Descent for optimizer.It is a simple yet very effective approach to the discriminative learning of linear classifiers under convex loss functions, such as (linear) supporting vector machines and logistic regression.

Fully connected layers are an essential component of the Convolutional Neural Networks (CNNs), which have proven to be very effective in the identification and classification of computer vision photos. The CNN process begins with convolution and pooling, the image is broken down into features and analyzed independently [2].

After all the layers are created, the model is run on a full training set containing 5216 images with two types of images. It took 1 hour to build the model and the model generated a neural network with four layers. It gave us
30,738,978 trainable parameters and 960[11] non trainable parameters. The top most layer of the layer is flattening and the remaining layers are fully connected layers which are dense layers. The model is trained using 10 epochs with batch size of 32.

A dense layer is just a regular layer of neurons in a neural network. Each neuron receives input from all the neurons[13] the previous layer, thus densely connected. The layer has a weight matrix W, a bias vector b, and the activations of previous layer a.

In order to save the best model weights, we have used Model Checkpoint and Early Stopping so that we can save the best model.

Model Checkpoint: Several iterations are often needed because training takes a great deal of time to achieve a good result. In this case, it is safer to only save a copy of the best performing model when an epoch ends which improves metrics.

Early Stopping: often during training we may find that the distance in generalization (i.e., the difference between training and validation error) is beginning to increase, rather than decrease. This is an overfitting symptom that can be addressed in many ways (reduction of model power, increased training data, data augmentation, regularization, dropout, etc.[12]). The Accuracy of model after we compiled is 91.025 and F1-Score is 93.084.

After the model is built, the model is compiled in order to extract features from images to identify whether the patient has pneumonia or not. Feature Extraction means every image has a uniqueness about them that only helps us to differ from other images [4].The model captures that uniqueness and calls it a feature.

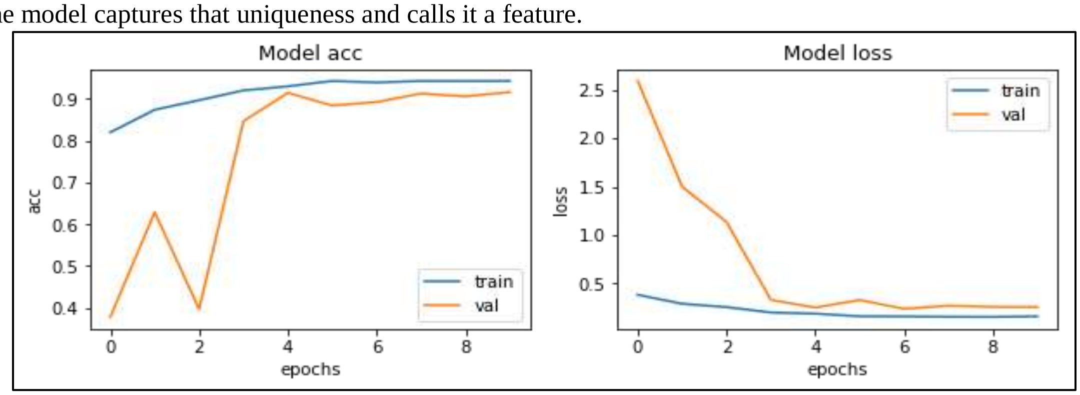

Fig. 2

In figure 2 we compare our model accuracy and loss with respective to epochs. For this model we used 10 epochs which gives us better accuracy and better loss. In the graph of model accuracy vs epochs step by step the model accuracy increases after each epoch is completed, same for the graph between model loss vs epochs in which the model loss decreases in each epoch. So the graph explains the model accuracy and loss is related to epochs.

A confusion matrix summarizes a classifier's classification performance relative to some test data [9]. It's a two-dimensional matrix, indexed by the true class of an entity in one dimension and by the class given by the classifier in the other. Table 1 provides an example of ambiguity matrix for a classification assignment of three classes, with classes A, B, and C.

Confusion Matrix		
Model	***Yes***	***No***
Four Layer	***191***	***43***
	13	***377***

III. Conclusion

The model correctly identified 480 patients out of 624 patients with lung disease and the remaining 144 patients were incorrectly identified as being free of the disease while they were actually having the disease. As for the model's precision ranking, 89.76 percent of patients labeled as class Yes do belong to class Yes, while 89.32 percent of patients labeled as class No do belong to class No. Although this paper is far from complete, the success of deep learning in such diverse real-world problems is remarkable. I've shown how to distinguish data on positive and negative pneumonia from X-ray image collection. The model was made from scratch, which distinguishes it from other methods which rely heavily on the approach to transfer learning. To identify and diagnose X-ray images consisting of lung cancer and pneumonia, this study could be expanded in the future. In recent times, separating X-ray images that contain lung cancer and pneumonia has been a major issue and our next step should be to tackle this problem.

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