Development of a Novel Deep Learning Approach for Efficient Detection of Pneumonia from Chest X-ray Images

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Abstract. This paper proposes Deep Learning based prediction model for building an algorithm which automatically identifies whether a patient is suffering from pneumonia or not by visualising chest X-ray images. The algorithm had to be extremely accurate because misclassification can impact people's wellbeing.

1 Introduction

Access to comprehensive, quality healthcare services is important for promoting and maintain health, preventing and managing the disease, reducing unnecessary disability and premature death, and achieving health equity for all. Pneumonia is a lung infection that can range from mild to so severe, it happens when an infection causes the air sacks in your lungs to fill with fluid or pus that can make it hard for you to breathe enough oxygen to reach your bloodstream. 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, an 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.

Deep learning has evolved together with the digital era, which has brought about an explosion of data in all forms and from every region of the world. This data, known simply as big data, is drawn from sources like social media, internet search engines, e-commerce platforms, and online cinemas, among others. However, the data, which normally is unstructured, is so vast that it could take decades for humans to comprehend it and extract relevant information. Companies realise the incredible potential that can result from unravelling this wealth of information and are increasingly adapting to AI systems for automated support. Deep learning learns from vast amounts of unstructured data that would normally take humans decades to understand and process. Demonstration of the efficacy of the proposed method with the minimisation of the computational cost as the focal point was conducted and compared with the exiting state-of-the-art pneumonia classification networks

A specific kind of such a deep neural network is the convolutional network, which is commonly referred to as CNN. It's a deep, feed-forward artificial neural network. Remember that feed-forward neural networks are also called multi-layer perceptron's(MLPs), which are the quintessential deep learning models. The models are called "feed-forward" because information flows right through the model. There are no feedback connections in which outputs of the model are fed back into itself. CNN's specifically are inspired by the biological visual cortex. The cortex has small regions of cells that are sensitive to the specific areas of the visual field.

2. Related Works

Today's deep learning models can reach human-level accuracy in analysing and segmenting an image. Latest improvements in deep learning models and the availability of huge datasets have assisted algorithms to outperform medical personnel in numerous medical imaging tasks such as skin cancer classification, haemorrhage identification, arrhythmia detection, and diabetic retinopathy detection's algorithms are increasingly being used for conducting lung nodule detection and pulmonary tuberculosis classification. Performance of several convolutional models on diverse abnormalities relying on the publicly available Chest X-Ray Images (Pneumonia) dataset from Kaggle.

3. Literature Survey

Recently a lot of research work has been carried out on the prediction and classification of Pneumonia. Korfiatis et al. have presented a paper [1] on segmentation of lung which is affected by interstitial Pneumonia. The authors have proposed a two-dimensional lung field segmentation algorithm. It employs a K-Means Clustering followed by a filtering operation. The results obtained by this method are compared with the other two methods and the authors have claimed that the proposed method is superior. In another interesting paper, automated volumetric quantification of interstitial pneumonia patterns is presented [2]. After identification, the patterns are classified into three categories using the k-nearest neighbour classification technique. It is reported that the classification performance is quite satisfactory. A molecular test is developed [3] that differentiates usual interstitial pneumonia from other lung diseases. This paper proposes a method to diagnose idiopathic pulmonary without surgery of the patient. It is reported that specificity is 92% and sensitivity is of 82% is achieved by the proposed classifier. For the detection of radiologist level pneumonia from chest X-rays, a deep learning-based method is suggested [4] in which all 14 diseases are correctly classified. A classifier for identification of usual interstitial pneumonia pattern from RNA-sequence is suggested in [5]. A logistic regression model is employed for this purpose which provides specificity of 88% in the test set. For the efficient prediction of pneumonia a deep convolution neural network is proposed [6]. The results obtained are compared with those obtained by SVM and random forest method. In an interesting paper, the authors have developed a CNN model to classify pneumonia from chest X-ray image samples [7]. In another work, the diagnosis of pneumonia from chest X-ray images is reported using the deep learning-based approach. A diagnosis accuracy of 87% is reported in this paper [8]. Using the concept of transfer learning a deep neural network model is developed for the detection of pneumonia from chest X-ray images. An ensemble model is also suggested which combines the outputs of many pre-trained models. An accuracy of 96.4% is reported by using the ensemble-based approach [9].

4. Methods and Materials

We propose a convolutional neural network model trained from scratch to classify and detect the presence of pneumonia from a collection of chest X-ray image samples. The datasets collected here initially consisted of three subsets that are for training, testing and validation. In order to balance the proportion of data assigned to the training and validation set, the datasets were rearranged into training and validation set only. Data augmentation were done in order to avoid overfitting and artificially increasing the datasets. Rescaling is done for magnification of images during the augmentation process. The overall architecture is of the CNN model which consists of feature extractors and classifier. The proposed architecture consists of a combination of convolution pooling and classification layers. There is a use of RELU as an activation layer present between two dense layers and a sigmoid activation function that performs classification tasks. The classification layer contains a flattened layer and a dropout of size 0.5. The results obtained are training loss = 0.1288, training accuracy = 95.31%, validation loss= 0.1835, and validation accuracy = 93.73%.

All experiments can be conducted on a standard PC with macOS Sierra, Windows10, Ubuntu16.04 or higher. We used the system with specs having Ubuntu18.04 LTS, 16GB RAM, Intel core i7, 8th gen.Software used Python3.7, TensorFlow(Version 2.0.0a0), Keras(Version 2.3.1), Numpy(Version 1.17.2), Mlxtend(Version 0.17.0), OpenCV(Version 4.1.2.30), Tqdm(Version 4.36.1), SciPy(Version 1.4.1), Pandas(Version 0.25.1), Pillow(Version 6.2.0), ImageIO(Version 2.6.1).

4.1. Dataset.

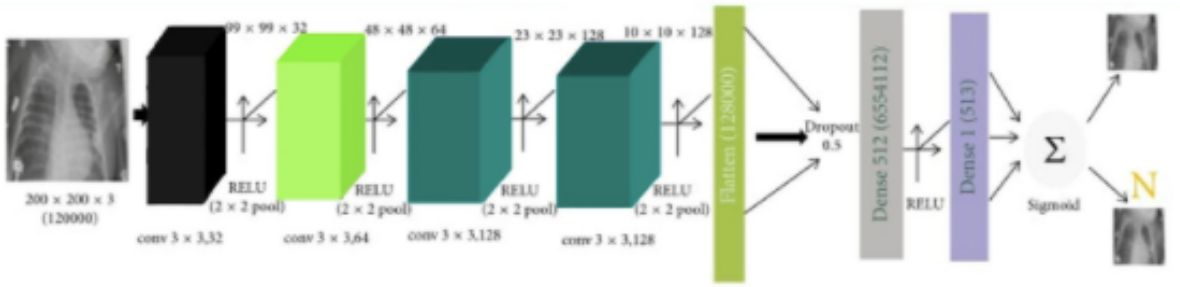
The original dataset consists of three main folders (i.e., training, testing, and validation folders) and two subfolders containing Pneumonia (P) and Normal (N) chest X-ray images, respectively. A total of 5,856 X-ray images of anterior-posterior chests were carefully chosen from retrospective paediatric patients between 1 and 5 years old. .e entire chest X-ray imaging was conducted as part of patients' routine medical care. To balance the proportion of data assigned to the training and validation set, the original data category was modified. We rearranged the entire data into training and validation set only. A total of 3,722 images were allocated to the training set and 2,134 images were assigned to the validation set to improve validation accuracy.

4.2. Data Preprocessing.

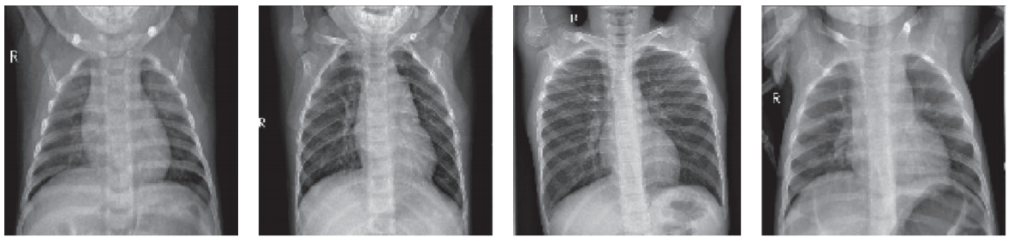
We employed one of the data augmentation method, i.e. scaling. We called the image from its original size to an image of 150*150 and fed it into the neural network.

4.3. Model.

The overall proposed architecture of the Convolutional Neural Network model contains two major parts: 1. Feature extractor, 2. Classifier. Each layer in the feature extraction layer takes its immediate preceding layer's output as input, and its output is passed as an input to the succeeding layers, i.e. we have proposed a sequential model. The architecture consists of convolution, max pooling and classification layer combined together.The feature extractor comprises of conv3*3, 32; maxplooing2*2; conv3*3, 32; maxpooling2*2; conv3*3, 64; maxpooling2*2. The output of the feature extractor layer is then flattened and given input to the classification layer. The classification layer consists of 64 densely connected hidden neutrons with randomly dropping the 50% of the neutron to value 0, and is fed to the ReLU activation function to generate the output class.

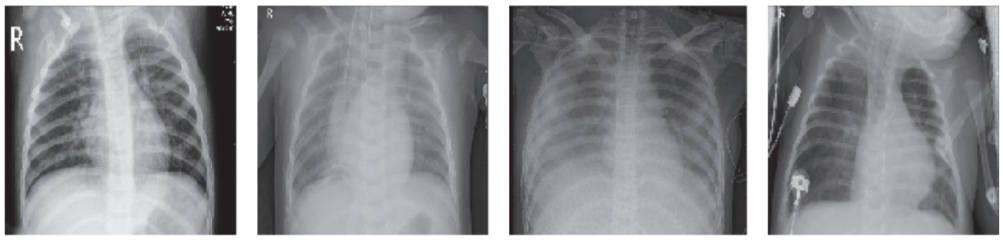


```
Found 5216 images belonging to 2 classes.
Found 16 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_16 (Conv2D)           (None, 148, 148, 32)      896
_________________________________________________________________
activation_26 (Activation)   (None, 148, 148, 32)      0
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_17 (Conv2D)           (None, 72, 72, 32)        9248
_________________________________________________________________
activation_27 (Activation)   (None, 72, 72, 32)        0
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 36, 36, 32)        0
_________________________________________________________________
conv2d_18 (Conv2D)           (None, 34, 34, 64)        18496
_________________________________________________________________
activation_28 (Activation)   (None, 34, 34, 64)        0
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 17, 17, 64)        0
_________________________________________________________________
flatten_6 (Flatten)          (None, 18496)             0
_________________________________________________________________
dense_11 (Dense)             (None, 64)                1183808
_________________________________________________________________
activation_29 (Activation)   (None, 64)                0
_________________________________________________________________
dropout_6 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 65
_________________________________________________________________
activation_30 (Activation)   (None, 1)                 0
=================================================================
Total params: 1,212,513
Trainable params: 1,212,513
Non-trainable params: 0
_________________________________________________________________
```



(a) (b) (c) (d)

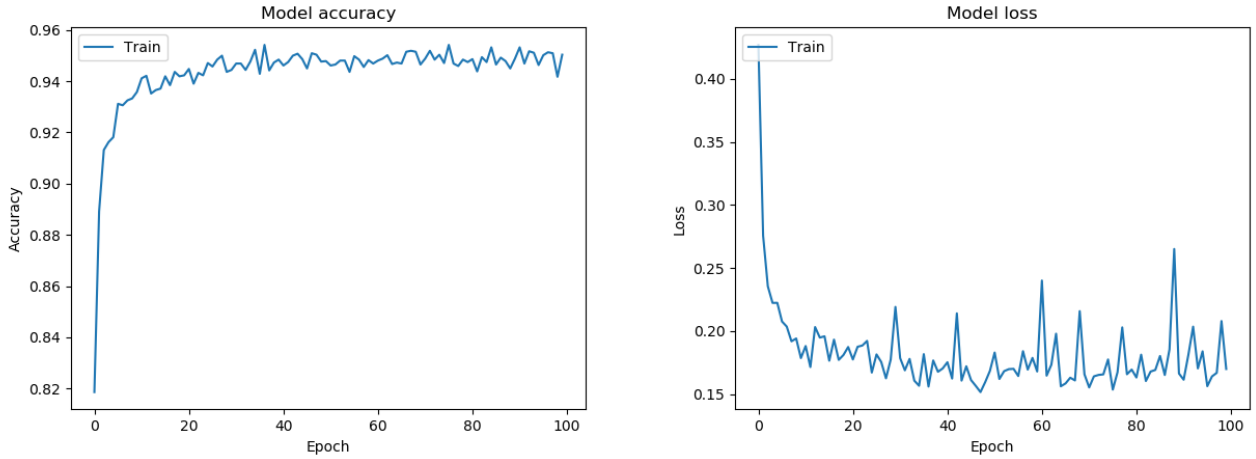
FIGURE 1: Sample images without pneumonia.



(a) (b) (c) (d)

FIGURE 2: Sample images with pneumonia [10].

5. Results



To evaluate and validate the effectiveness of the proposed approach, we conducted the experiments. Different results were obtained, but this study reports only the most valid. As explained above, methods such as batch size and the number of hidden layers were changed and were deployed to assist in fitting the dataset into the deep convolutional neural network architecture. It was in order to obtain substantial results as shown in Figure 4. i.e final results obtained are training loss = 0.1288, training accuracy = 95.31%, validation loss= 0.1835, and validation accuracy = 93.73%. CNN frameworks always require images of fixed sizes during training used to demonstrate the validation performance of our model on variant input data, we reshaped the X-ray images into 150 ×150 × 3 sizes, and trained

them with batch sizes of 4, 8, 16, 32 and number of the hidden layer as 1, 2, 3, 4 and obtained their overall performance as shown below i.e a batch size of 16 and with 2 hides layers, the best validation accuracy is obtained.

Batch Size	Training Accuracy	Validation Accuracy
4	93.72	89.47
8	94.22	91.64
16	**95.31**	**93.73**
32	91.75	87.21

Number of hidden layers	Training Accuracy	Validation Accuracy
1	92.41	90.42
2	**95.31**	**93.73**
3	91.75	86.56
4	88.27	84.72

6. Conclusions

We demonstrated how to classify a chest X-Ray image into two classes, i.e. Normal and Pneumonia. We build our model using Convolutional neural network from scratch which separates it from other transfer learning techniques used nowadays. In the future, this work will be extended to a web app, which can be used by doctors to easily predict whether the patient has Pneumonia or not.

7. References

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