Scientific Voyage
Vol. 1, No. 4,
Page 28-33 (2020)

SCIENTIFIC VOYAGE

ISSN: 2395-5546

GCECT
Publication
Oct.-Dec.

Pneumonia Detection based on X-ray image classification using Convolutional Neural Network based Deep Learning Model

Subrata Sarkar [a1], Alok Mukherjee [a2], Kingshuk Chatterjee [a3],
Partha Haldar [a4]

[a] *Government College of Engineering and Ceramic Technology, Kolkata 700010, West Bengal, India*

Abstract. Pneumonia is a disease that threat humanity to this day. Even though we have developed vaccines and medicines, many lives are still lost every year due to this disease. So we have made an effort to develop an algorithm which would be able to detect this disease in an early stage to help people with the diagnosis. We have developed a Convolutional Neural Network (CNN) based Deep Learning (DL) model that detects pneumonia from the X-ray image of patients. This helps in classifying a given image, which, in turn, helps the physicians and other medical persons for easier diagnosis. In this study we have compared the outputs from two CNN based DL models: a 3 layered model and another 10 layered model. We have taken the chest x-ray images of different patients for developing and testing the proposed algorithm in Python platform.

Keywords: Pneumonia, X-ray image, Convolutional Neural Network (CNN), Deep Learning, Image classification.

1. Introduction

Pneumonia is an infection that inflames the alveoli in one or both lungs. These may be filling up with fluid or pus, causing cough with phlegm or pus; causing fever and difficulty breathing. Tuberculosis is a potentially infectious disease usually caused by Mycobacterium tuberculosis bacteria. Tuberculosis generally affects the lungs, but can also affect other parts of the body. Accurate diagnosing of pneumonia is thus extremely important. Chest radiograph (CXR) or chest X-ray is usually examined by trained specialists. Handling of the huge number of patients every day in the hospitals and clinics would greatly be assisted by a technique, which would perform a basic screening for Pneumonia detection.

Machine learning based solutions are developing every day for helping the clinicians and physicians more efficiently in correct prediction. So we have tried to develop two deep learning based models. These two designed Convolutional Neural Network (CNN) based models are found to predict pneumonia with a high accuracy of 90% approximately. This proposed method is intended to enable technicians to increase their efficiency, as well as, reduce their effort. At the same time, this would enable fast initial prediction of the disease and allow patients to consult with a physician immediately on detecting any positive result from the algorithm. We have used Keras with tensorflow backend to create the proposed convolutional neural network model. This is followed by training the proposed deep learning model using the open source image data from Kaggle. Finally, the model is validated using images from the same source. We have tried to develop a model which doesn't possess any addition computational intricacy apart from the CNN based deep learning method, which is used as the basic computational tool. Simultaneously, we have tried to retain an acceptable accuracy level, with high specificity so that it can be used as a everyday computation devices or can be handled by weaker computers very easily. These would also help diagnosis in the rural areas especially, where deficiency of computers with superior computational features or high level medical facility is a major hindrance to medical treatment.

---

[1] E-mail: *subrotosarkar32@gmail.com*
[2] E-mail: *alokmukherjee.ju@gmail.com*
[3] E-mail: *kingshukchaterjee@gmail.com*
[4] E-mail: *partha.jumech@gmail.com*

There have been initiatives to develop openly available databases of medical image with the ever increasing demand of medical support, as well as, increasing numbers of patient in the recent few years. OpenI [1] holds one of such open datasets, particularly for chest X-rays. This contains 3,955 (nearly four thousand) radiology reports from the Indiana Network for Patient Care and 7,470 (more than seven thousand) number of chest x-rays from the different hospitals in their picture archiving and communication system (PACS). Pneumonia is usually diagnosed using the increased opacity on CXR [2]. CXRs are the most usual tool used for the diagnostic imaging study by the physicians. But this imaging technique has several influencing factors; like the positioning of the patient during the X-ray imaging, or the depth of inspiration causing variation in the air volume inside lungs are responsible for altering the image quality of the CXR [3]. This further complicates the interpretation of the image, especially with naked eye. In the proposed work, we have used images from the Cell Press [4] on kaggle and images compiled by Kevin Mader [5] on kaggle. CheXnet is one of the recently developed state-of-the-art methods which has a very high level of accuracy of disease detection [6]. Recent advances in the field of deep learning incorporating features of convolutional neural network, especially using activation maximization and other techniques, have given a new direction to the studies, as well as, a new dimension of application of the neural networks.

2. Methodology

We have developed two neural network models in the proposed work. One of the models is a shallow 3 layered network and the other is a 10 layered network. We have described the structure of each of the networks and visualized their filters and class activation mappings in the following sections.

2.1 Algorithm of the proposed models

Model 1: This is a 10 layered CNN model. We have used data sets from kaggle for training our model. We have used 80:20 split for training and testing. The architecture of the model is briefly described here:

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 98, 98, 32)	896
batch_normalization_1 (Batch	(None, 98, 98, 32)	128
conv2d_2 (Conv2D)	(None, 96, 96, 32)	9248
batch_normalization_2 (Batch	(None, 96, 96, 32)	128
conv2d_3 (Conv2D)	(None, 48, 48, 32)	25632
batch_normalization_3 (Batch	(None, 48, 48, 32)	128
dropout_1 (Dropout)	(None, 48, 48, 32)	0
conv2d_4 (Conv2D)	(None, 46, 46, 64)	18496
batch_normalization_4 (Batch	(None, 46, 46, 64)	256
conv2d_5 (Conv2D)	(None, 44, 44, 64)	36928
batch_normalization_5 (Batch	(None, 44, 44, 64)	256
conv2d_6 (Conv2D)	(None, 22, 22, 64)	102464
batch_normalization_6 (Batch	(None, 22, 22, 64)	256
dropout_2 (Dropout)	(None, 22, 22, 64)	0
conv2d_7 (Conv2D)	(None, 20, 20, 128)	73856
batch_normalization_7 (Batch	(None, 20, 20, 128)	512
conv2d_8 (Conv2D)	(None, 18, 18, 128)	147584
batch_normalization_8 (Batch	(None, 18, 18, 128)	512
conv2d_9 (Conv2D)	(None, 9, 9, 128)	409728
batch_normalization_9 (Batch	(None, 9, 9, 128)	512
dropout_3 (Dropout)	(None, 9, 9, 128)	0
conv2d_10 (Conv2D)	(None, 6, 6, 256)	524544
batch_normalization_10 (Batch	(None, 6, 6, 256)	1024
flatten_1 (Flatten)	(None, 9216)	0

```
dropout_4 (Dropout)           (None, 9216)          0
dense_1 (Dense)               (None, 2)             18434
=================================================================
Total params: 1,371,522
Trainable params: 1,369,666
Non-trainable params: 1,856
```

Model 2: This is a 3 layered CNN model. We used data-sets from kaggle for training our model. We have used 80:20 split for training and testing. Here is the architecture of the model:

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 98, 98, 32)        896
batch_normalization_1 (Batch (None, 98, 98, 32)        128
conv2d_2 (Conv2D)            (None, 49, 49, 32)        25632
batch_normalization_2 (Batch (None, 49, 49, 32)        128
dropout_1 (Dropout)          (None, 49, 49, 32)        0
conv2d_3 (Conv2D)            (None, 25, 25, 64)        51264
batch_normalization_3 (Batch (None, 25, 25, 64)        256
dropout_2 (Dropout)          (None, 25, 25, 64)        0
flatten_1 (Flatten)          (None, 40000)             0
predictions (Dense)          (None, 2)                 80002
=================================================================
Total params: 158,306
Trainable params: 158,050
Non-trainable params: 256
```

The proposed models are next tested to identify its accuracy, specificity, f1-score and Mathew's Correlation Coefficient (MCC). Testing is carried out for both the 3 layered and 10 layered CNN models. A comparison is carried out between the two models by judging the outputs. We have used Keras with tensorflow backend in python domain as the major computational tool to carry out the algorithm design.

3. Results and Discussion

3.1 Results for pneumonia detection

The outcomes of the proposed models are described in Table 1. A comparative analysis of the two proposed models could also be obtained from this table. It shows that the 10 layered CNN architecture produces much higher accuracy and sensitivity compared to the 3 layered model.

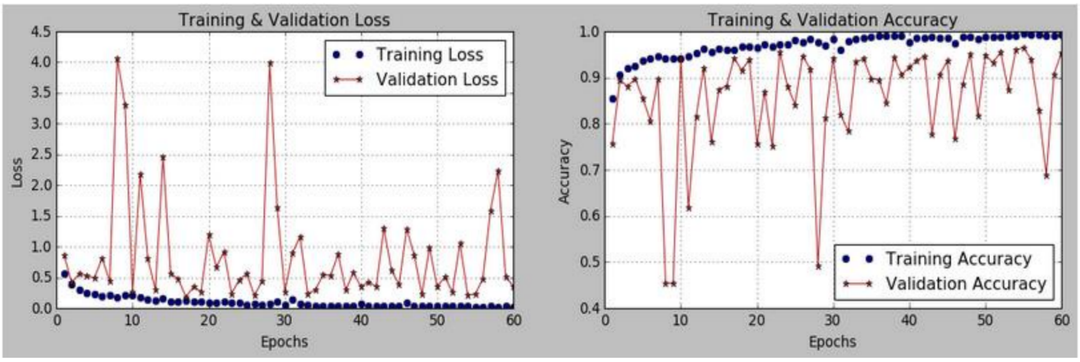
Table 1. Comparative analysis of the two proposed CNN models

Models	*Accuracy*	*Sensitivity*	*Specificity*	*F1-score*	*MCC*
Custom model 10 layers	0.9539	0.9713	0.9037	0.9691	0.8788
Custom model 3 layers	0.9283	0.9311	0.9203	0.9508	0.8218

The metrics for training the models are explained next. Apart from that, the metrics on how the models performed on test data is also discussed. Training of the 10 layered model has been carried out for 60 epochs and the 3 layered model has been trained for 30 epochs.

3.2 Custom model of 10 layers

The outcomes of the custom model of the 10 layer CNN architecture is shown graphically in Fig. 1, which illustrate the variation in loss and accuracy of the model for the 60 epochs, obtained for both validation and testing the model. The results are also represented in table 2. It is also observed that the accuracy of the model increases almost monotonically with increase in the number of epochs.



(a) (b)

Fig. 1: Outcomes of the 10 layer CNN architecture showing (a) Loss and (b) Accuracy

Table 2. Outcomes of the 10 layers CNN model

Test Accuracy = 0.954				
	precision	***recall***	***f1-score***	***support***
class 0 (abnormal)	0.97	0.97	0.97	871
class 1 (normal)	0.92	0.9	0.91	301
Accuracy			0.95	1172
Macro average	0.94	0.94	0.94	1172
Weighted average	0.95	0.95	0.95	1172

The confusion matrix, without normalization, is also found as: $\begin{bmatrix} 846 & 25 \\ 29 & 272 \end{bmatrix}$. This is also shown in Fig. 2

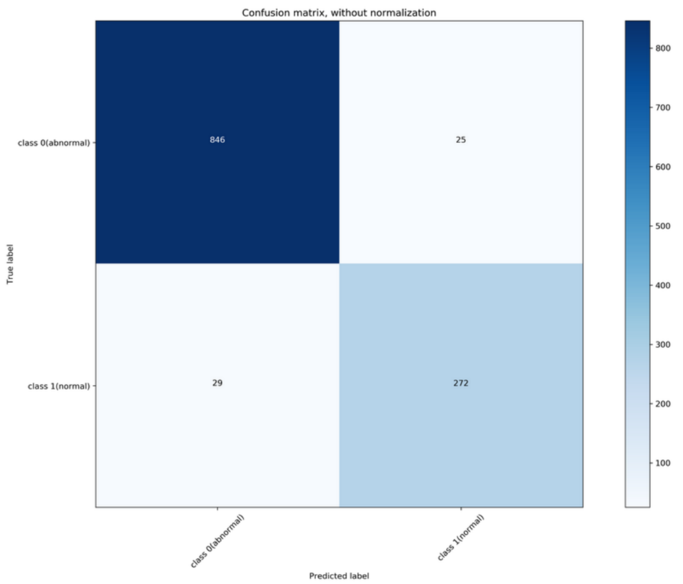
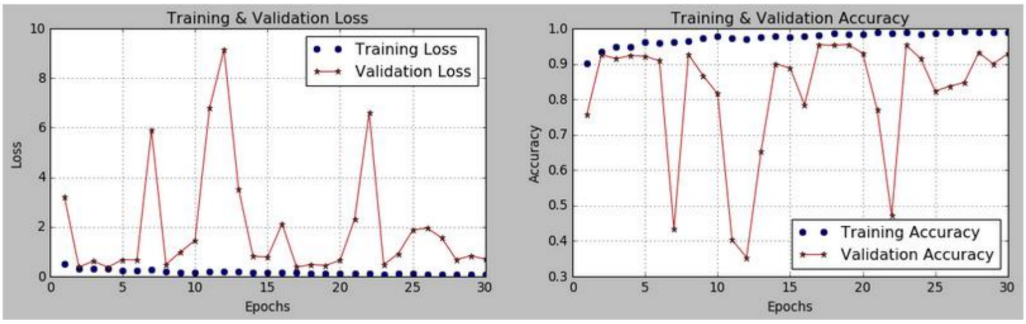


Fig. 2: Confusion matrix of the custom model of 10 layers

3.3 Custom model of 3 layers

The outcomes of the custom model of the proposed 3 layer CNN architecture is shown graphically in Fig. 3. These figures again illustrate the variation in loss and accuracy of the model, but this time for 30 epochs only.

These are again obtained for both validation and testing the model. The results are again represented in tabular form in table 3. Again it is observed that the accuracy of the model increases almost monotonically, like that of the proposed 10 layer model, with increase in the number of epochs.



(a) (b)
Fig. 3. Outcomes of the 3 layer CNN architecture showing (a) Loss and (b) Accuracy

Table 2. Outcomes of the 10 layers CNN model

Test Accuracy = 0.923				
	precision	***recall***	***f1-score***	***support***
class 0 (abnormal)	0.97	0.93	0.95	871
class 1 (normal)	0.82	0.92	0.87	301
Accuracy			0.93	1172
Macro average	0.90	0.93	0.91	1172
Weighted average	0.93	0.93	0.93	1172

It is clearly observed by comparing Table 1 and Table 2 that the proposed 10 layer model outperforms the 3 layer model in most of the fields. This easily explains the superiority of the proposed 10 layer model over the 3 layer model. The confusion matrix, without normalization, is also found as: $\begin{bmatrix} 811 & 60 \\ 24 & 277 \end{bmatrix}$.
This is again shown in Fig. 4.

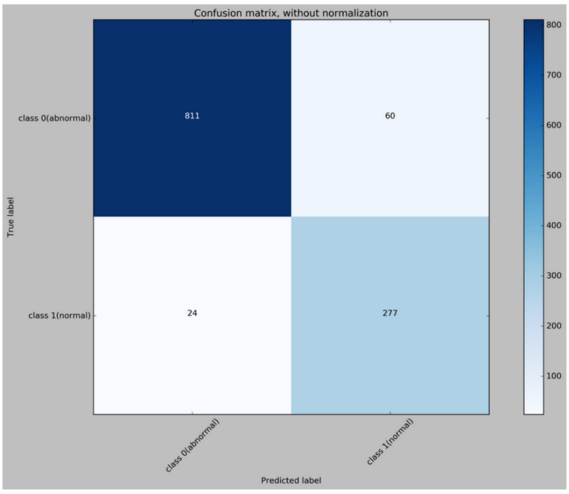


Fig. 4. Confusion matrix of the custom model of 3 layers

4. Conclusion

Two Convolutional Neural Network (CNN) models are proposed in this work to develop an algorithm for the detection of Pneumonia, using the Chest radiograph (CXR) or chest X-ray images. Results show that both the proposed CNN models perform satisfactorily; although, the superiority of the 10 layer CNN architecture is well established. The metrics for the test dataset again prove that both the CNN models are effective for image classification. Both of the custom models have been tested using Flask locally. The present work shows a good prosperity for easy implementation in medical field, especially where low computational analysis is the most important factor. Easy, fast and efficient detection of pneumonia disease using the proposed models would help in an efficient initial screening; thereby faster diagnosis of patients. Thus the model shows good prosperity for implementation in real world.

References:

1. X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, R.M. Summers, ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks onWeakly-Supervised Classification and Localization of Common Thorax Diseases; http://openaccess.thecvf.com/content_cvpr_2017/papers/Wang_ChestX-ray8_Hospital-Scale_Chest_CVPR_2017_paper.pdf.

2. T. Franquet, Imaging of community-acquired pneumonia (J. Thorac Imaging 2018, epub ahead of print, PMID 30036297.

3. B. Kelly, The Chest Radiograph, *Ulster Med. J.* **81** (2012) 143.

4. D.S. Kermany et al., Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning; https://www.cell.com/cell/fulltext/S0092-8674(18)30154-5.

5. K. Mader, Pulmonary Chest X-Ray Abnormalities; https://www.kaggle.com/kmader/pulmonary-chest-xray-abnormalities.

6. P. Rajpurkar et al., CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning; https://arxiv.org/abs/1711.05225.