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# Large Scale Chest X-Ray Analysis and Pneumonia Classification using Convolutional Deep Neural Network

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**Abstract -** *Pneumonia or acute respiratory infection is the most common reason for child death; nearly 16% of all deaths of children under 5 years old happen due to Pneumonia. In adults, it is one of the most common causes for hospital admission. The dataset consisted of 5863 X-Ray images where the chest X-rays were categorized into normal and pneumonia classes. After performing data augmentation in the pre-processing stage, 2D-Convolutional deep neural network is being used to train the classifier that can identify Pneumonia chest x-rays efficiently. Data augmentation method is being used to handle imbalanced data and avoid over-fitting. Overall accuracy achieved is 92%.*

***Key Words*: Chest x-ray classification, CNN in healthcare field, convolutional neural network, image classification, Pneumonia classification.**

## 1. INTRODUCTION

Pneumonia or acute respiratory infection is the most common reason for child death; nearly 16% of all deaths of children under 5 years old happen due to Pneumonia [1]. In adults, it is one of the most common causes for hospital admission. These facts unmistakably demonstrate that it is so critical to manage Pneumonia at a beginning phrase to lessen the death rate. With the help of artificial intelligence (AI) and machine learning (ML) it is possible to gather clinical decision help applications that will allow clinical specialists to separate the diseases at the fundamental stages and give better treatment to the patients.

Streptococcus pneumonia is the most common cause of bacterial pneumonia in children. The lungs are comprised of little sacs called alveoli, which load up with air when a sound individual breaths. At the point when an individual has pneumonia, the alveoli are loaded up with pus and fluid, which makes breathing difficult and limits oxygen consumption [2].

In today's era, convolutional neural network (CNN) has become a very obvious choice for researchers in medical images classification problem. In this work, we focused on classifying large scale chest X-ray images of pneumonia patients and normal chest X-rays to train and build an efficient classifier that can classify Pneumonia with higher precision utilizing 2D CNN.

The major contributions of the paper can be summarized as follows-

- The model is focused on developing and training the CNN algorithm which results in an overall accuracy of 92%.
- To handle highly imbalanced data set, augmentation is performed for increasing the size of the training set and balancing the dataset.
- Batch normalization technique is also performed for standardizing the inputs to a layer for each mini batch.
- Lastly the corrected predicted class is categorized on the basis of normal chest X-rays and pneumonia chest X-rays.

This paper summarizes as follows- Section 2 reports the literature survey done by other researchers in this field, section 3 reports data set distribution followed by methodology and proposed model in section 4. The results and discussions are found in section 5 followed by conclusion in section 6.

## 2. LITERATURE SURVEY

Several research works are present in the field of pneumonia classification. Some of the related works are stated below.

Okeke et al. [3] proposed a CNN model trained from scratch to classify and detect presence of pneumonia from a collection of chest X-ray image samples. Data augmentation was performed as the dataset was highly imbalanced and achieved remarkable validation accuracy. Verma et al. [4] used CNN algorithm with different data augmentation techniques for improving the classification accuracies. The overall accuracy was reported as 94%. Varshni et al. [5] appraised the functionality of pre-trained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. Saraiva et al. [6] evaluated the generalization capacity of the models and used cross-validation of k-fold. The classification models proved to be efficient compared to the work of which obtained 92.8 % and the present work had an average accuracy of 95.30 %. Urey et al. [7] proposed a deep learning architecture for the classification task, which was trained with modified images, through multiple steps of preprocessing. The classification method used CNN and residual network architecture for classifying the images. The findings yielded an accuracy of 78.73% and surpassed the previously top scoring accuracy of 76.8%. Waman et al. [8] used CNN algorithm to detect pneumonia disease. Hashmi et al. [9] used a novel approach based on a weighted classifier which combines the weighted predictions from the state-of-the-art deep learning models such as ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3 in an optimal way. The proposed weighted classifier model achieved a test accuracy of 98.43% and an AUC score of 99.76 on the unseen data from the Guangzhou Women and Children's Medical Center pneumonia dataset. Correa et al. [10] presented a method for automatic classification of pneumonia using ultrasound imaging of the lungs and pattern recognition. The approach presented in the paper was based on the analysis of brightness distribution patterns present in rectangular segments from the ultrasound digital images and achieved sensitivity of 90.9% and 100% specificity.

## 3. DATASET DISTRIBUTION

The dataset is obtained from the Chest X-Ray Images (Pneumonia) dataset [11]. Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. The dataset consisted of 5863 X-Ray images where the chest X-rays were categorized into normal and pneumonia. The dataset distribution is shown in Fig -1 below.

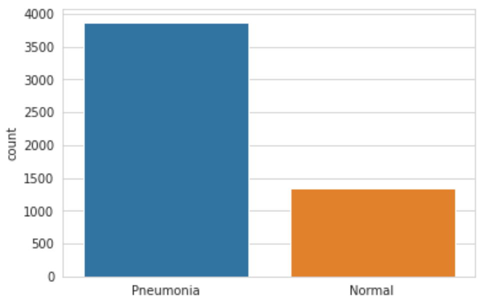


**Fig -1**: Dataset distribution

## 4. METHODOLOGY AND PROPOSED MODEL

### 4.1 Data Augmentation

The dataset was highly imbalanced; maximum X-Ray images were of Pneumonia category. So data augmentation was performed which artificially increases the size of the training set by generating many realistic variants (like- randomly shifting images horizontally by 20% of the width, randomly zooming by 30% of some training images, etc.) of each training instance. This reduces over fitting, making this a regularization technique. The generated instances should be realistic as possible. The images obtained after data augmentation are shown below. Fig -2 shows the normal X-rays and Fig -3 shows the pneumonia X-rays.

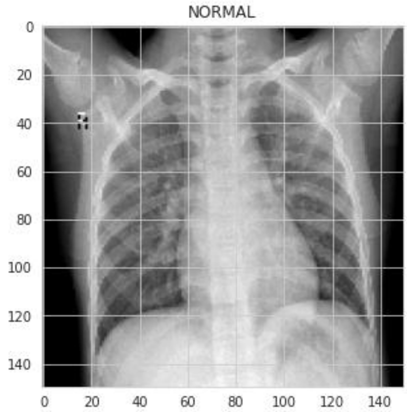


**Fig -2**: Normal X-Ray

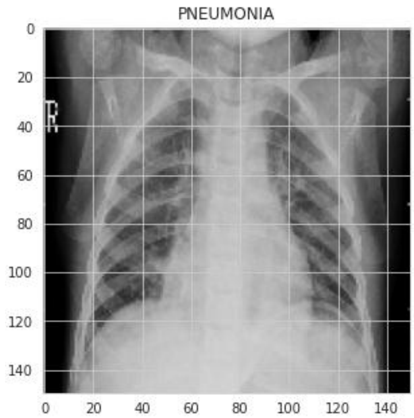


**Fig -3**: Pneumonia X-Ray

### 4.2 Implementation of CNN

The proposed model of binary classification is presented by CNN. The most important building block of a CNN is the convolutional layer: neurons in the first convolutional layer are not connected to every single pixel in the input image, but only to pixels in their receptive fields. In turn, each neuron in the second convolutional layer is connected only to neurons located in the first layer.

The proposed model also uses pooling layers in which their goal is to subsample the input image in order to reduce the computational load, the memory usage, and the number of parameters. Just like in convolutional layers, each neuron in a pooling layer is connected to the outputs of a limited number of neurons in the previous layer, located within a small rectangular receptive field. The max pooling layers preserves only the strongest features, getting rid of all the meaningless ones, so the next layers get a cleaner signal to work with. Moreover, max pooling offers stronger translation invariance and it requires slightly less computations. The activation function used here is ReLu. Rectified linear unit (ReLu) is used as an activation function in each convolutional layer to introduce non-linearity from the input to the output

The first layer uses 32 fairly large filters (3×3) and a stride as the input images are not very large. It also sets the input shape (150, 150, 1). Then batch normalization was done for reducing the parameters. Next we have a max pooling layer which uses a pool size of 2, so it divides each spatial dimension by a factor of 2. The number of filters grows up as we climb up the CNN towards the output layer (it is initially 32, then 64, then 128 and 256). Batch normalization layers are present in the middle. The fully connected network composed of two hidden layers and two dense output layers. The inputs are flattened since a dense network expects a 1D array of features for each instance. Four dropout layers are added with a dropout rate of 50% each to reduce over fitting.

The overall architecture of CNN is provided in the Table-1 below.

**Table -1:** Architecture of CNN

| Layer | Output Shape | Parameters |
|---|---|---|
| Conv2d_1 | (150, 150, 32) | 320 |
| Batch_nomalization_1 | (150,150, 32) | 128 |
| Max_Pooling_2d_1 | (75, 75, 32) | 0 |
| Conv2d_2 | (75,75, 64) | 18496 |
| Dropout_1 | (75, 75, 64) | 0 |
| Batch_nomalization_2 | (75, 75, 64) | 256 |
| Max_Pooling_2d_2 | (38, 38, 64) | 0 |
| Conv2d_3 | (38, 38, 64) | 36928 |
| Batch_nomalization_3 | (38, 38, 64) | 256 |
| Max_Pooling_2d_3 | (38, 38, 64) | 0 |
| Conv2d_4 | (19, 19, 64) | 73856 |
| Dropout_2 | (19, 19,128) | 0 |
| Batch_nomalization_4 | (19, 19, 128) | 512 |
| Max_Pooling_2d_4 | (10, 10, 128) | 0 |
| Conv_2d_5 | (10, 10, 256) | 295168 |
| Dropout_3 | (10, 10, 256) | 0 |
| Batch_nomalization_5 | (10, 10, 256) | 1024 |
| Max_Pooling_2d_5 | (5, 5, 256) | 0 |
| Flatten_1 | (6400) | 0 |
| Dense_1 | (128) | 819328 |
| Dropout_4 | (128) | 0 |
| Dense_2 | (1) | 129 |

## 5. RESULTS AND DISCUSSIONS

### 5.1 Metrics

Confusion matrix is performance estimation for machine learning statistical classification problem where output can be at least two classes. It is a table with 4 distinct blends of predicted and actual classes. The confusion matrix of the proposed model is shown in Fig – 4 below.

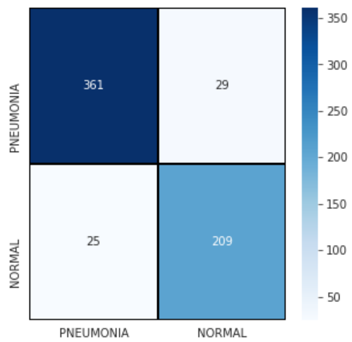


**Fig -4**: Confusion matrix of Pneumonia classifier

### 5.2 Accuracy and other Parameters

The mathematical equations of accuracy, recall and precision are shown below. Depending upon these parameters, the overall accuracy of the classifier is determined.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1 - Score = 2 \times \left[\frac{Precision \times Recall}{Precision + Recall}\right]$$

From the above equations; TP is the number of true positives, FP is the number of false positives, FP is the number of false positive and FN is the number of false negative. All the parameters mentioned in the above equations are presented in the Table-3 below.

The model was trained for 12 epochs with the batch size of 32. The result obtained is given in the table below.

**Table -2:** Accuracy and other Parameters

| Epochs | Optimizer | Loss | Accuracy |
|---|---|---|---|
| 12 | RMSProp | 0.24 | 0.92 |

### 5.3 Classification Results

The classification results comprising of Precision, Recall and F1 score is stated below in the table.

**Table -3:** Classification Results

| Category | Precision | Recall | F1 Score |
|---|---|---|---|
| Pneumonia | 0.94 | 0.93 | 0.93 |
| Normal | 0.88 | 0.89 | 0.89 |

### 5.4 Correct Predicted classes

The correctly predicted classes are predicted on the basis of the pneumonia classifier. The classes which were correctly predicted are shown in Fig. -5.

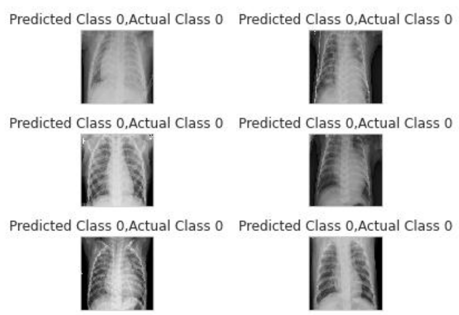


**Fig -5**: Correctly Predicted Classes

## 6. CONCLUSION

In this work, large scale child chest X-Ray is being used. One of the most efficient methods for handling imbalanced dataset, data augmentation is performed to increase the number of training data set. Deep learning algorithm is applied in the domain of healthcare with a vision to develop early fatal disease prediction system that can be used in both clinical and non clinical environment. Overall accuracy achieved is 92%. This result proves that our method is more cutthroat and constructive in large scale chest X-Ray classification.

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