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Chest X-ray Pneumonia Classification using AlexNet

Hafizudin Jamil[1], Masnani Mohamed[1*], Ariffuddin Joret[1]

[1]Faculty of Electrical and Electronics Engineering,
Universiti Tun Hussien Onn Malaysia, Batu Pahat, 86400, MALAYSIA

*Corresponding Author Designation

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Abstract: Pneumonia is caused by infected alveoli inside the human lungs, if the tissue inside the human lungs has inflammation, it may occur pus inside it. In order to detect that a patient has pneumonia, a medical professional has to diagnose their chest X-ray and do physical exams towards the patient. Nowadays, deep learning has been widely used in a lot of industries that have helped a lot of humans to speed up their work. Therefore, this project aims to determine the chest X-ray that is affected by pneumonia. In order to determine the result, a Convolutional Neural Network (CNN) was used with architecture design of AlexNet. The result obtained was more than 95% which is very good in terms of its accuracy in detecting disease.

Keywords: Pneumonia, CNN, AlexNet

1. Introduction

The X-ray is an electromagnetic radiation wave that can penetrate the human body [1]. X-ray can penetrate the human body and are widely used in medical diagnosis, which are [2], [3], [4], the term 'X-ray' itself is common in the medical field because of its widely used in the medical industry.

A chest X-ray of a person is usually used to determine any diseases that are extremely harmful to humans. Medical doctors will do medical diagnosis towards patients by reading their chest X-ray to detect any abnormalities. Research shows that patients with abnormal chest X-rays were rated about 40% had a postoperative complication but only 9% occurred to a patient with normal chest X-ray [5].

A patient will have to queue to meet a doctor due to the environment of the hospitals that are always overcrowded with patients especially in the emergency department (ED) [6]. The overcrowding in the emergency room (ER) can cause a lot of problems such as increase of waiting times, escalating the period of patients to stay in the ER and the worst part is the increasing of medical errors [7]. Therefore, the project aims to help the doctors to analyse the abnormalities in the chest X-ray images faster. An automatic detection will be implemented using MATLAB by comparing between the sample images with the database images to determine a chest X-ray of a patient with pneumonia. The MATLAB feature that is used for this project is the Convolutional Neural Network (CNN) that is able to classify the two

**Corresponding author: masnani@uthm.edu.my*

different classes of X-ray images after going through some processes that will be explained in section 2.1.

1.1 Convolutional Neural Network

The CNN able to do pattern recognition because of a hidden layer in the network called the convolutional layer [8]. The convolutional layer is a crucial component for the CNN, without its convolution layer it cannot function as it should. The convolution layer function is to perform feature extraction. The features extraction will consist of linear and non-linear features that are combined to do the convolution operation and activation function [9]. Figure 1 shows the images of the convolutional neural network system.

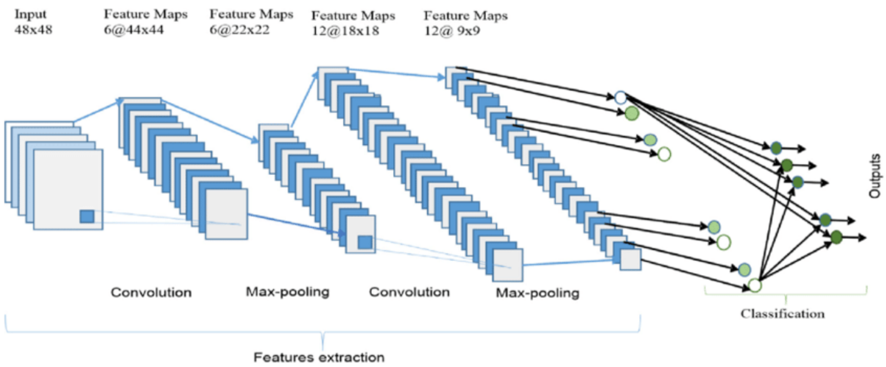


Figure 1: Convolutional Neural Network

1.2 AlexNet

The architecture design that applied in the network is AlexNet. It consists of 8 layers as shown in Figure 2. The layers start with convolution layers and a max-pooling with Local Response Normalization (LRN). The features have 96 different filters in 11×11 in size and the max pooling has 3×3 filters with a size of 2. The second layers will perform the same operations but with 5×5 filters, 3×3 in third to fifth layers of the convolutional layers. Two layers of Fully Connected (FC) used with dropout followed by a Softmax layer at the end of the architecture design. LRN functions are to square-normalize the pixel values in the feature map so that the system can achieve a lateral inhibition [10].

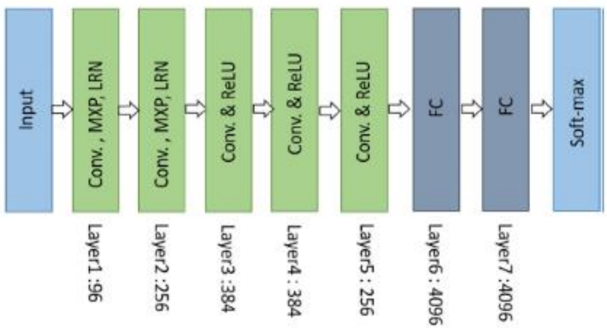


Figure 2. The architecture of AlexNet: Conv = convolution, MXP = max-pooling, LRN = Local Response Normalization and FC = fully connected [11]

2. Materials and Methods

The feature that was used in this project is CNN, that was provided in Deep Learning Toolbox by MATLAB where various architecture designs from it. The CNN is able to conclude any finding if the user created the network and provided enough data to conclude their finding then there should not be a problem to obtain an accurate result. There are 800 chest X-ray images used for the network; 350 normal and 450 for abnormal Chest X-ray images. All of the chest X-ray image files in both categories are uploaded in the same folder in order to make it much more convenient for the network to read the files. Figure 3 shows some of the chest X-ray images that are used as the input of the network divided in 2 classes, the 'IN' named files is for normal image and 'IP' named files is for pneumonia image.

Figure 3: The sample images from both categories

2.1 Methods

In order to classify the chest X-ray image, the chest X-ray image will go through a process that is shown in Figure 4. First step is the collection of input data which is the chest X-ray images of pneumonia and normal. The second step is to set up the AlexNet as the architecture design for the network. The third step is to resize as the AlexNet require a specific size of the images to do the processing. Step 4 is to train the images with classification so that the network can classify between normal and pneumonia chest X-ray images. Lastly, testing and plotting the result that have been obtained by the neural network, it will show the accuracy of the network and its percentage of error.

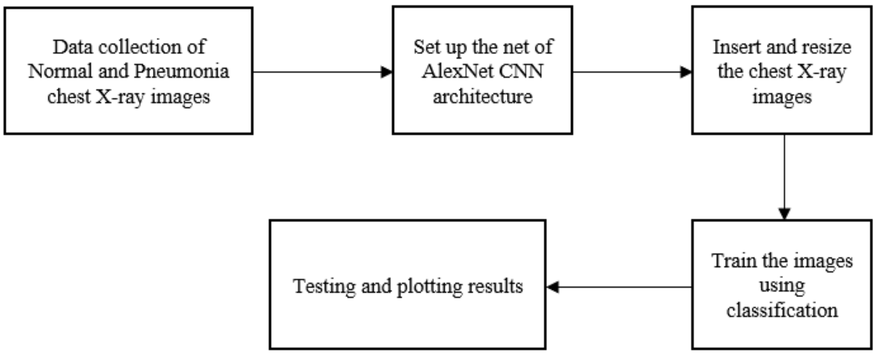


Figure 4: The block diagram of the project

There are 800 chest X-ray images used for the network; 350 normal and 450 for abnormal Chest X-ray images. The total images used for training, testing, validation and overall are 560, 120 and 120 therefore the overall images are 800. The AlexNet consists of layers to determine the desired output. For this project, the layers in the network are shown in Figure 5. The images size is set to 277 × 277 as the AlexNet requires the images to be in that size. A different architecture design requires a different size of images but the images must be in fixed size according to the architecture as the AlexNet required the size of 277 × 277.

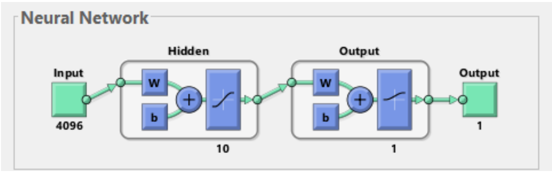
1	*1x1 ImageInputLayer*	9	*1x1 MaxPooling2DLayer*	17	*1x1 FullyConnectedLayer*
2	*1x1 Convolution2DLayer*	10	*1x1 Convolution2DLayer*	18	*1x1 ReLULayer*
3	*1x1 ReLULayer*	11	*1x1 ReLULayer*	19	*1x1 DropoutLayer*
4	*1x1 CrossChannelNormalizationLayer*	12	*1x1 GroupedConvolution2DLayer*	20	*1x1 FullyConnectedLayer*
5	*1x1 MaxPooling2DLayer*	13	*1x1 ReLULayer*	21	*1x1 ReLULayer*
6	*1x1 GroupedConvolution2DLayer*	14	*1x1 GroupedConvolution2DLayer*	22	*1x1 DropoutLayer*
7	*1x1 ReLULayer*	15	*1x1 ReLULayer*	23	*1x1 FullyConnectedLayer*
8	*1x1 CrossChannelNormalizationLayer*	16	*1x1 MaxPooling2DLayer*	24	*1x1 SoftmaxLayer*
				25	*1x1 ClassificationOutputLayer*

Figure 5: The layers of the system

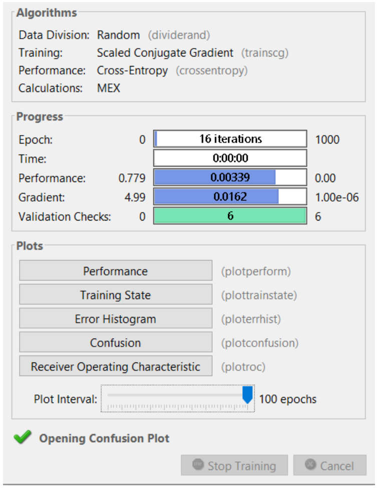
As the AlexNet required the size of 277 × 277 to make the images fixed in its size and cause a less shrinking. A less shrinking image will make a less deformation of features inside the images [12]. The inserted images in the classification system will be according to the disease or class that occurs in the chest X-ray images. After inserting all of the images according to its class, the network will be able to learn by the train features of the neural network. The image classification is very important because it will determine the result that the network will produce.

3. Results and Discussion

Figure 6(a) shows the generated Neural Network Training that takes about 16 iterations of epochs by using AlexNet as its architecture model for the network. The network generated 4096 input neurons with 1 hidden layer that had 12 neurons in it. The results for this project will be shown in a form of a confusion plot divided by 4, which are Training, Validation, Testing and Overall. The classified images from the AlexNet architecture are implemented in the Neural Network Training or nntraintools. Figure 6(b) shows the image of Neural Network Training provided by MATLAB that was used to produce the output of the project.



(a)



(b)

Figure 6:(a) The model of Neural Network, (b)The Neural Network Training tool

3.1 Performance

The performance plot is really important to indicate if the training, test and validation had encountered a problem or not. For this project the performance plot is shown in Figure 7. From the graph, the best performance is at epoch 9 where it was taken because of the lowest error in validation. Epoch is a cycle of training and it usually will take more than a few epochs to obtain the result.

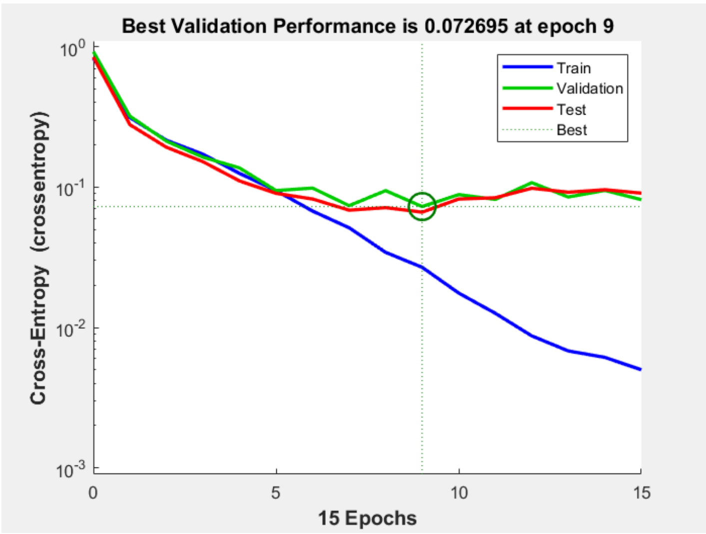


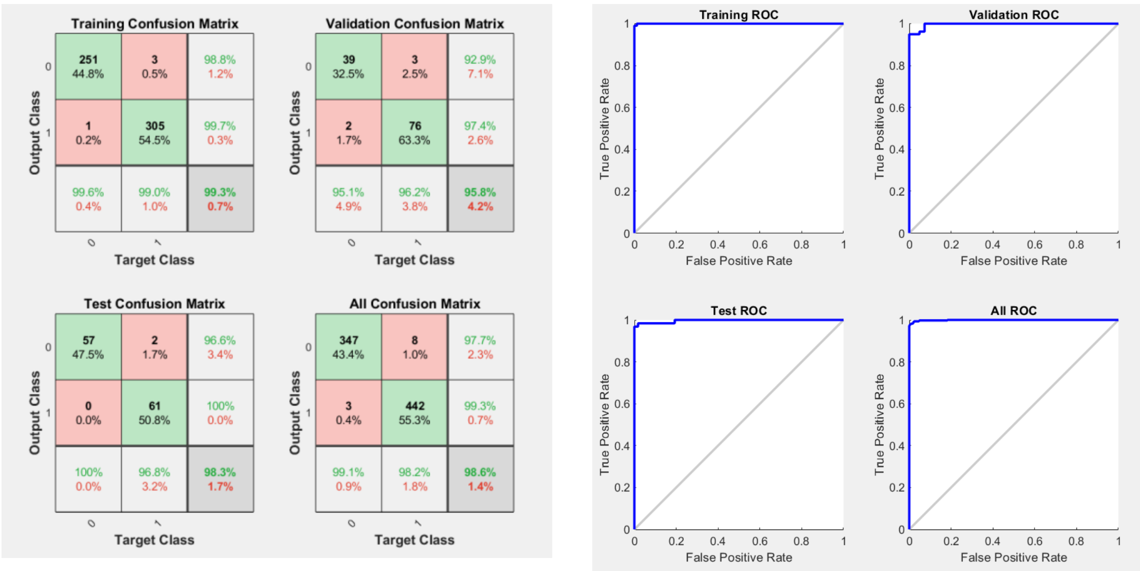
Figure 7. The Performance Plot of the network

3.2 Results

3.2.1 Confusion plot and Receiver operating Characteristic

The confusion plot was generated to summarize the classification output of the neural network performance. The confusion plot was also used to evaluate the performance of the CNN model created. Figure 8 shows the image of the confusion plot generated by using MATLAB. The confusion plot generates clear results of the accuracy among both of the image classes.

The neural network Receiver Operating Characteristic was carried out to show the quality of the classifiers from the network. For this project, the Training, Validation, Test and Overall had a result that was more to True Positive Rate but with minimum error. In Figure 9, it shows that the curves in the graph are at the left top edges of the plot, hence showing that the Neural Network classification has a high percentage of accuracy. The percentage error for this project is very minimal and more than 90% of the Dataset are successfully classified.



(a) (b)

Figure 8: (a) The confusion plot of the results, (b): The image of Receiver Operating Characteristic

3.3 Discussions

The rows of the confusion matrix correspond to the output class and columns correspond to the target class. Figure 8 shows the graph plot of the confusion plot. The diagonal cells are correctly classified and off-diagonal cells are incorrectly classified. The total images from the Dataset are 800 chest X-ray images. The summary for all the details is included in Table 1, Table 2, Table 3 and Table 4. The rows of the confusion matrix correspond to the output class and columns correspond to the target class. In the graph plot, the diagonal cells are correctly classified and off-diagonal cells are incorrectly classified.

For training, the images taken from the Dataset are 560 chest X-ray images. The true positive rate in the table below represents the chest X-ray normal images classification and it shows that the accuracy is 98.8 %. The false negative rate is the chest X-ray pneumonia images classification and it shows that the accuracy is 99.7 %. The false positive and negative rate shows the incorrectly classified class of the images and the percentage are 1.2% and 0.3% respectively.

Table 1: The training performance

No	Parameter Performance	Percentage Performance %
1	True Positive Rate	98.8
2	False Positive Rate	1.2
3	True Negative Rate	99.7
4	False Negative Rate	0.3
5	Accuracy	99.3

For validation, the images taken from the Dataset are 120 chest X-ray images. The true positive rate in the table below represents the chest X-ray normal images classification and it shows that the accuracy is 92.9 %. The false negative rate is the chest X-ray pneumonia images classification and it shows that the accuracy is 97.4 %. The false positive and negative rate shows the incorrectly classified class of the images and the percentage are 7.1% and 2.6% respectively.

Table 2: The validation performance

No	Parameter Performance	Percentage Performance %
1	True Positive Rate	92.9
2	False Positive Rate	7.1
3	True Negative Rate	97.4
4	False Negative Rate	2.6
5	Accuracy	95.8

For testing, the images taken from the Dataset are 120 chest X-ray images. The true positive rate in the table below represents the chest X-ray normal images classification and it shows that the accuracy is 96.6 %. The false negative rate is the chest X-ray pneumonia images classification and it shows that the accuracy is 100 %. The false positive and negative rate shows the incorrectly classified class of the images and the percentage are 3.4% and 0.0% respectively.

Table 3: The test performance

No	Parameter Performance	Percentage Performance %
1	True Positive Rate	96.6
2	False Positive Rate	3.4
3	True Negative Rate	100
4	False Negative Rate	0.0
5	Accuracy	98.3

Overall, the images from the Dataset are 800 chest X-ray images. The true positive rate in the table below represents the chest X-ray normal images classification and it shows that the accuracy is 97.7 %. The false negative rate is the chest X-ray pneumonia images classification and it shows that the accuracy is 99.3 %. The false positive and negative rate shows the incorrectly classified class of the images and the percentage are 2.3% and 0.7% respectively. A total of 11 images misclassified resulting in 98.6% of accuracy for overall of the classified chest X-ray images. The misclassified image occurs because the chest X-ray images in the network may have appeared a little bit different from its training making the network unable to classify the class of the images.

Table 4: The overall performance

No	Parameter Performance	Percentage Performance %
1	True Positive Rate	97.7
2	False Positive Rate	2.3
3	True Negative Rate	99.3
4	False Negative Rate	0.7
5	Accuracy	98.6

The receiver operating characteristic (ROC) that are shown in Figure 9 are important because it can prove the quality of the neural network's classification. The ROC will have a threshold value where an interval of [0,1] that shown in the graph. There are two values for the result that consists of True Positive Ratio (TPR) and False Positive Ratio (FPR). TPR is the probability of the actual are classified correctly and FPR is for negatively classified. The results show a curve at the left top edge of the plot, it shows that the classification is very accurate.

4. Conclusion

The aim of the study is to determine if the chest X-ray images had pneumonia or normal Chest X-ray images. With the aid of deep learning and the architecture used for this project, it is able to fulfill the aim by producing a higher accuracy of 98.6% for the database created. The use of AlexNet as the architecture of the neural network has produced a good result and medical healthcare should consider using this system because it will benefit their healthcare performance. The created project can be improved by implementing a Graphic User Interface (GUI). A GUI is more convenient to be used by anyone, the user can conveniently use the system and decide the process that user wants to process and obtain a desired result.

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