THE EFFECT OF EPOCH ON THE ACCURACY OF DETECTION OF LUNG CANCER

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Abstract: The purpose of this study was to detect lung cancer from CT-Scan images using the deep learning (DL) method, namely Convolutional Neural Network (CNN). Convolutional Neural Network (CNN) is a deep learning neural network that has mimicked the network functions of the human brain. CNN is one of the deep learning algorithms which is a multi layer perceptron (MLP) development which is designed to process data, so that it can be used to detect and recognize an object in an image. The study was conducted by training the model on 2000 CT-Scan images by varying the epoch three times and giving a learning rate of 0.0001 for each variation. It can be seen that the greater the epoch given, the higher the accuracy obtained but it takes a long time. So that the best results given by the model are found in variation III with an accuracy value of 98.50%.

Keywords: Lung cancer, CT-Scan, Deep Learning, Convolutional Neural Network, ResNet

I. INTRODUCTION

Lung cancer is the most feared type of cancer with a very high mortality rate among all other types of cancer. The main problem is the difficulty in diagnosing and the time needed to identify it, thereby reducing the level of life after being diagnosed. Patient survival rates can increase from 15% to 49% if cancer is detected at an early stage [1]. Smoking is a major cause of lung cancer, where cigarette smoke contains more than 4,000 chemicals of which 63 types are carcinogens and toxic [2]. Lung cancer is divided into two major parts, namely non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC) [3]. NSCLC is a more common type of lung cancer and this research is based on the classification of NSCLC type lung cancer. There are various modalities that can be used to diagnose lung cancer one of which is to use Computed Tomography Scan (CT-Scan). CT-Scan is a diagnostic support modality that has a systematic imaging that uses a combination of X-rays and computer technology to produce images. CT-Scan modalities are more effective than plain chest x-rays in detecting and diagnosing lung cancer because they are able to provide good and clear images in this case have good contrast and can provide precise anatomical information [4]. The images obtained from CT-Scan can be analyzed later using digital image processing techniques on a personal computer.

An extraordinary interest in deep learning (DL) has emerged in recent years and the most established algorithm among DL models is the convolutional neural network (CNN). CNN became the dominant method in object recognition tasks because of the amazing results shown by Alex Krizhevsky in 2012, his CNN research succeeded in winning the object recognition competition namely Image Net Large Scale Visual Recognition Competition (ILSVRC).

The CNN method has proven to be superior to other machine learning methods such as SVM in the case of object classification in images. This study uses the Convolutional Neural Network (CNN) method with Residual Network (ResNet) architecture where this method has many layers and this method includes supervised learning, which means the analysis is done by training so that the results obtained for classification will be more accurate. This architecture was also made to overcome the common problems that occur in the DL training process, namely the use of a long time and limitations on the number of layers [5].

II. METHOD

A. Dataset

This study used the CNN with ResNet architecture to classify lung cancer CT-Scan images with normal lung image criteria, stage I, stage II, stage IIIa and stage IIIb lung cancer images of 400 images each. The data sets of lung cancer images with NSCLC type were taken from the cancer imaging archive (TCIA), and the normal images were obtained from various hospitals.

B. ResNet Architecture

The classification method used is the convolutional neural network (CNN) with ResNet architecture, with a total of 18 convolution layers, known as ResNet-18, installed from the Neural Network Toolbox™. In the ResNet architecture feature extraction and classification are carried out in the same process.

The feature extraction process is carried out at the convolution layer, in addition to the convolution layer a batch norm is applied and then the activation function layer, ReLu. In the pooling layer it is only applied in the initial stages of feature learning, that is after the first convolution that is used is maxpooling and in the last stage of feature learning that is before it is entered into the classification layer that is used average pooling. Within each type of ResNet architecture based on the number of constituent layers there are residual blocks which will divide the convolution layer into five stages. Before the classification process, flatten or reshape is done to change the result matrix from the pooling layer. The results of this flatten are used as input in the next process which is the classification stage.

This classification process is carried out at the fully connected layer or dense and softmax activation function. At the fully connected layer we update the weight and bias to obtain the optimal model. Then the values of the neurons are activated using the softmax activation function. The value of softmax is the probability of each class of lung cancer stage classification on the input data. So the determination of the final results of this classification stage is based on the maximum value of the softmax value.
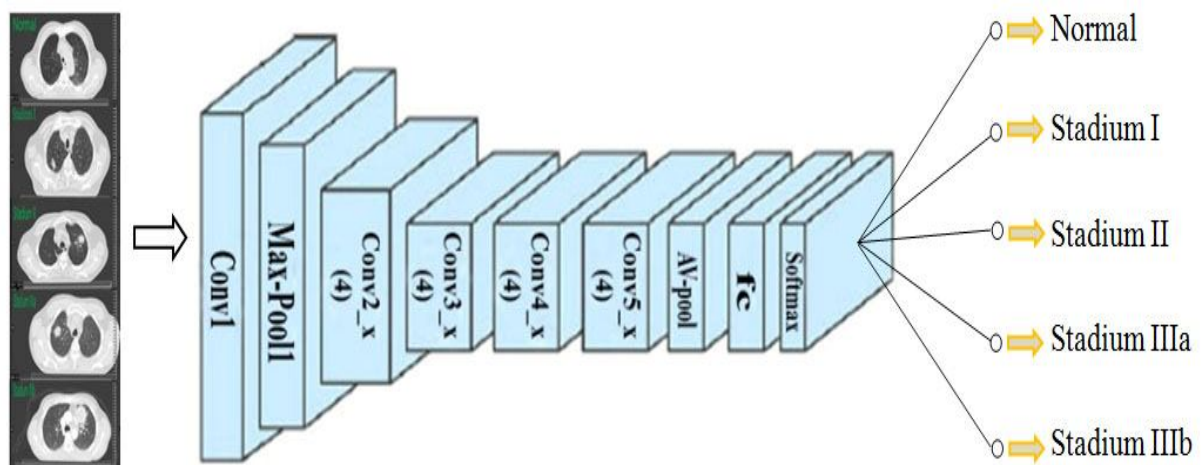

Fig. 1 The procedure for classification of lung cancer images using the ResNet-18 architecture
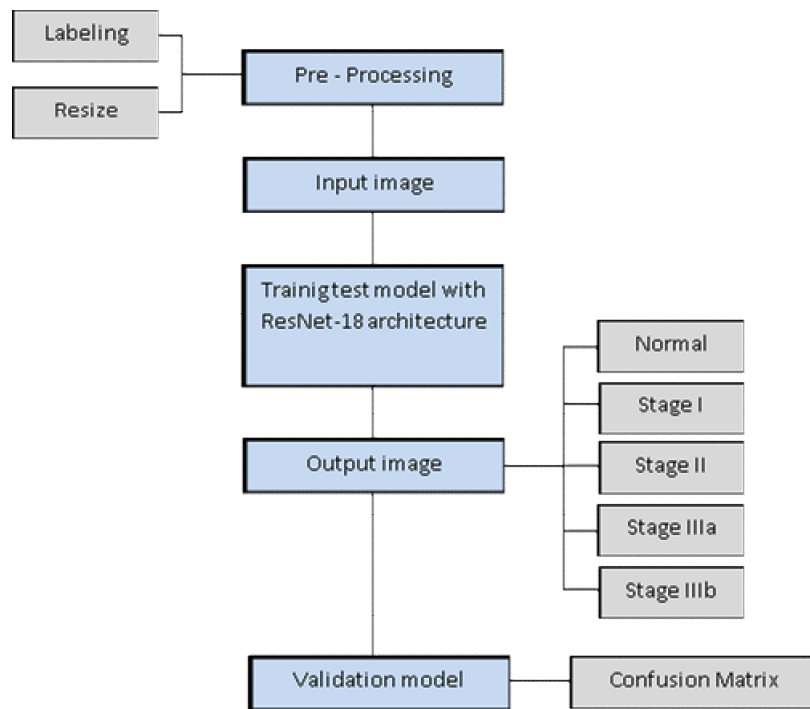
Fig. 2: A Block diagram for the proposed classification of lung cancer

III.   THE TRAINING and TESTING PROCESS

A. Preprocessing

Preprocessing is the proces of labeling and resizing. The process of labeling in each image to introduce the image of normal lung with images of lung cancer stage I, stage II, stage IIIa, and stage IIIb, then the resizing process is done using Matlab software. The function of resize is to resize the dimensions of the image without reducing information from the image and sometimes the size changes to smaller than the original size or larger. In this research resize is applied by changing the pixel size of the image from 512 x 512 pixels to 224 x 224 pixels to match the input size which is the benchmark in the ResNet architecture.
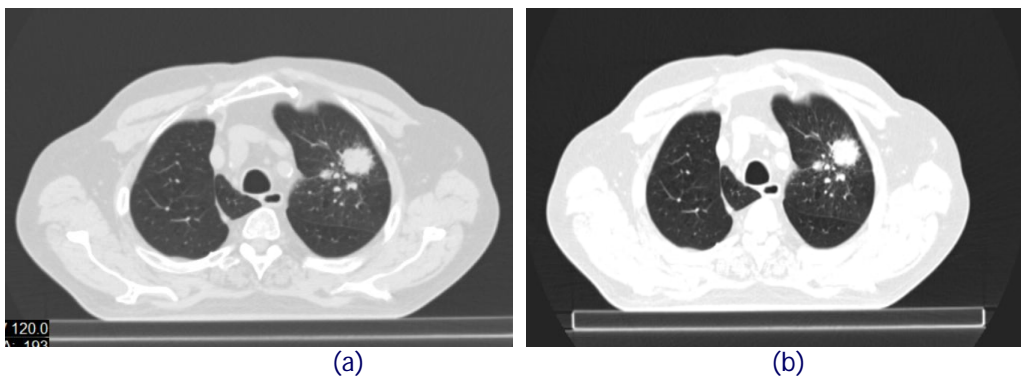

(a)   (b)

Fig. 3 CT-Scan image of a lung cancer patient. (a) original image size of 512×512 pixels,
(b) image with size of 224×224 pixels

B. Training and Testing

This training was conducted several times to get the best acquisition value with a learning rate of 0,0001 for all levels. The network training was carried out around 1-5 epochs with 160 iterations.

C. Classification

This model used 80% data for training data and 20% for testing, with the reason the learning process with more training data will make the CNN model with the ResNet architecture learn more, so that it was expected to produce a good model The confusion matrix was used to measure performance at the classification stage because it contains information that can be compared to the results of classification. The classification performance measurement parameters are shown in table 1.

Table I: Performance of classification measurements on the confusion matrix

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Metrix	Formula	Description
Accuracy	$\dfrac{TP+TN}{TP+TN+FP+FN}$	Accuracy gives us certainty in the prediction or accuracy of the system
Sensitivity	$\dfrac{TP}{TP+FN}$	Sensitivity gives us a measure of how the dataset is ready for classification or a measure of how accurate the information it provides.
Specificity	$\dfrac{TN}{TP+FP}$	Specificity gives us the ratio of how many cancer images are classified as non cancer, against images with other false classifications.

TP (True Positive): positive cases that are correctly classified, TN (True Negative): negative cases that are correctly classified, FN (False Negative): positive cases that are not properly classified, FP (False Positive): negative cases that are classified correctly is wrong.
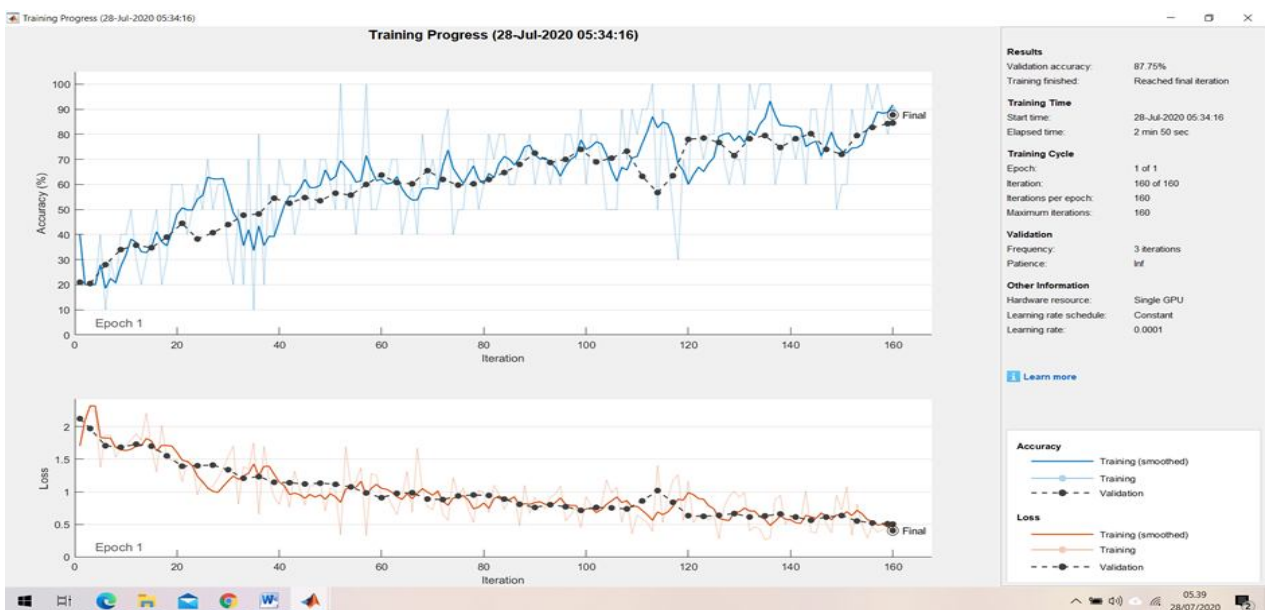
IV.   RESULTS

A. Training results

The ResNet-18 architectural model was trained by varying the epoch three times for variations I, II and III (variations of epoch 1, 3 and 5) where 1 epoch contained 160 iterations. ResNet-18 architecture performance, shown in table 2

Table II: Performance of ResNet-18 Architecture Training

	Variasi I	Variasi II	Variasi III
Epoch	1	3	5
Learning rate	0,0001	0,0001	0,0001
Iterasi	160	160	160
Max Iterasi	160	480	800
Training Accuracy	90%	100%	100%
Validation loss	0,4	0,3	0,2
Validation Accuracy	87,75%	96,25%	98,50%
Time	170 sec	471 sec	783 sec

Table 1 shows the repetition in three trainings. The learning rate is 0,0001 and iteration is 160 for each epoch. The accuracy of the training is 87.75%, 96.25%, and 98.50% for variations I, II and III. The overall results of the training process are shown in Figure 1. The blue graph is accuracy validation and the orange graph is loss validation. The training was carried out three times according to the variation of epoch used.

(a)
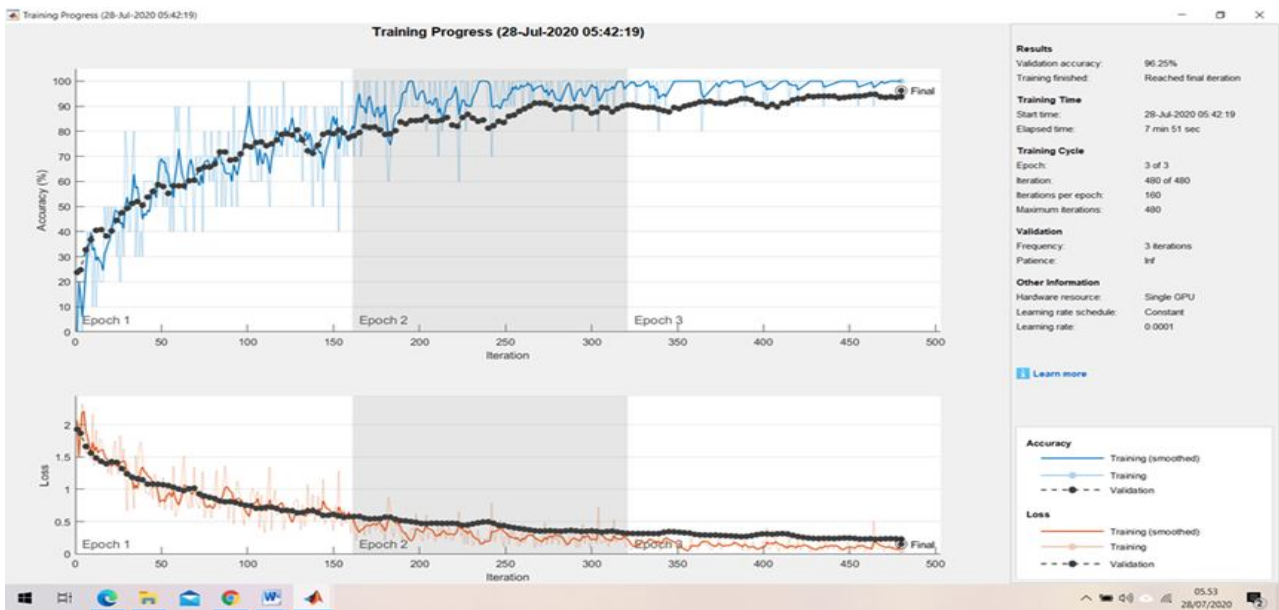
(b)
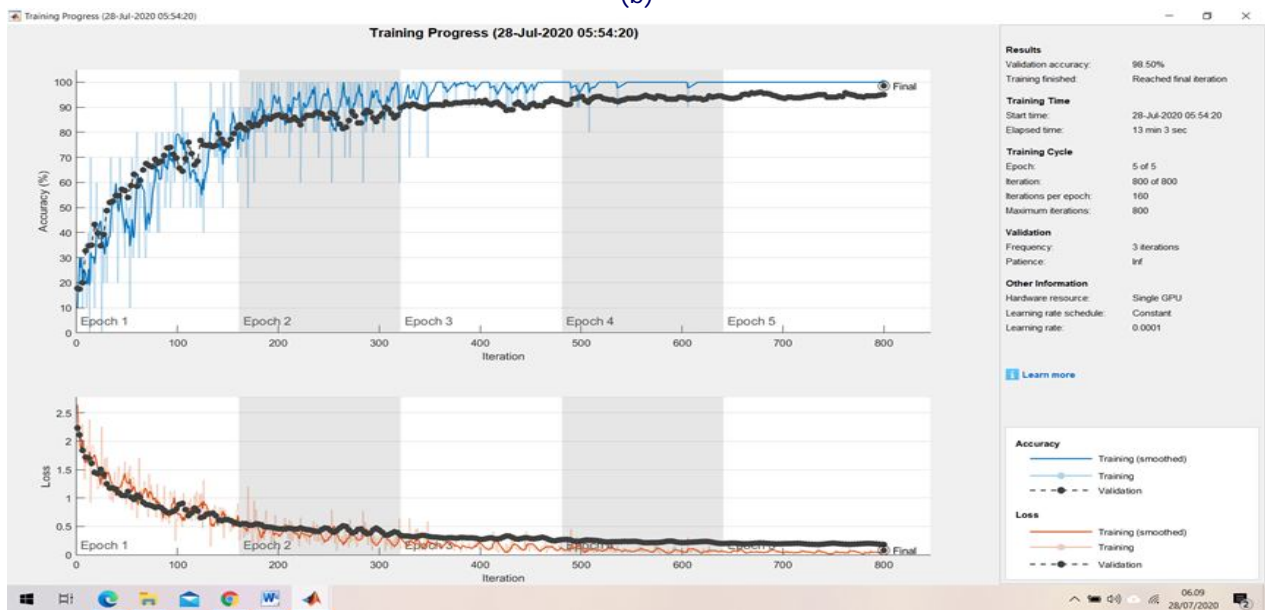
(c)

Fig. 4. The results of the training progress (a) Variation I (b) Variation II (c) Variation III

Figure 1 (a) shows the results of the training for variation I. The accuracy validation results reached 87.75% and the loss validation was 0.4 with a time of 170 seconds. Figure 1 (b) shows the training results for variation II accuracy validation of 96.25% and loss validation of 0.3 with a time 471 seconds. Figure 4 (c) shows the results of the training for variation III. The results of accuracy validation reached 98.50% and loss validation was 0.2 with a time 783 seconds.

B. Test Results

The results of the classification of lung cancer are 80 images for each class or in 20% of the test data with a total of 400 images displayed in a confusion matrix. The green column in the confusion matrix indicates the results of the actual class classification (class correctly classified). The red column indicates the wrong classification results (class classified incorrectly). The column at the right end of the plot shows the percentage of all classes of lung cancer. The bottom row at of the plot shows the percentage of all examples of each class that are classified correctly and incorrectly. The cell in the lower right of the plot shows overall accuracy. The classification results in each class have different levels of accuracy for types of lung cancer. The outputs in this classification are five classes, namely normal, stage I, stage II, stage IIIa, and stage IIIb. The results of the confusion matrix in the ResNet-18 architecture model are shown as shown in Figure 2.

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(a)

(b)

(c)

Fig. 5 Results of classification of lung images as a confusion matrix on Resnet-18.
(b) Variation I (b) Variation II (c) Variation III

From the confusion matrix (Figure 2), we can calculate the accuracy, sensitivity, and specificity of the model in classifying the degree of stagibg of lung cancer shown in table 3 for variations I, II and III.

Table III Measurement of accuracy, sensitivity and specificity of each variation

	Variasi I	Variasi II	Variasi III
Accuracy	87,75%	96,25%	98,50%
Sensivity	87,96%	96,28%	98,56%
Specificity	87,76%	96,26%	98,52%

Table 3 shows that in variation III gave the highest accuracy value among the other variations that was equal to 98.50%. The best value of sensitivity and specificity is also given by variation III with values of 98.56% and 98.52%, respectively.

V. DISCUSSION

The study was conducted by training the ResNet-18 model to classify NSCLC type lung cancer into five classes, namely normal, stage I, stage II, and stage IIIb lung cancer. In this study used CT-Scan images because it is more effective than plain chest x-rays. CT-Scan is able to provide a good and clear image in this case has good contrast and can provide detailed anatomic information precisely so that it can detect and diagnose lung cancer. As with other medical imaging domains, computer system based lung cancer classification study is largely based on machine learning and the artificial intelligence algorithm. The majority of the methods proposed recently use the CNN approach. Several studies related to the model for detection of lung cancer from lung CT Scan images are presented table 4, compares method reviewed using accuracy measures.

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Related work	Methode	Databese	Accuracy
Anthimopoulos et al., 2016	Deep CNN	Swiss University Hospital	85,50%
Gao et al., 2017	CNN	University Hospitalof Geneva	92,80%
Matsuyama and Tsai, 2018	CNN wavelet	Swiss University Hospital	91,90%
Proposed method	ResNet	TCIA	98.50.%

Our model reached 98.50% accuracy and outperformed the models from several other studies. By using ResNet-18 architecture the classification results reached 87.75%, 96.25% and 98.50% accuracy in variations I, II, and III. This shows that the difference in accuracy is obtained from the increase in the number of epochs used in training. The results of the study as shown in table 4 of the ResNet method for variation III provide high accuracy which can be used as a standard or an alternative for detection lung cancer. In subsequent studies, researchers propose the use of this model for use in the detection of other diseases and different imaging modalities. Researchers will try to apply the CNN method with a variety of other in-depth variations of the ResNet architecture to get higher accuracy in the detection of disease will be the direction we plan to pursue.

VI. CONCLUSION

In this study, we implement the CNN method with ResNet-18 architecture for detection NSCLC type lung cancer into five classes namely normal, stage I, stage IIa, stage IIIa and stage IIIb lung cancer. The accuracy results are different for each variation, this is determined by the change in the number of epochs. As shown in table 3 the results of measurements of accuracy, sensitivity and specificity in each variation, namely in variation I the accuracy value was 87.75%, sensitivity 87.96% and specificity 87.76%. In variation II the accuracy value was 96.25%, sensitivity is 96.28% and specificity is 96.26%. And the best results are obtained for variation III accuracy value was 98.50%, sensitivity 98.56% and specificity 98.52%.

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