Journal of Network Communications and Emerging Technologies (JNCET)
Volume 11, Issue 3, March (2021)

Enhanced AlexNet Convolutional Neural Network Based Classification for Identification of Lung Cancer

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Published online: 31 March 2021

ABSTRACT

Lung cancer is a hazardous disease that many deaths were occur in both men and women from this deadly disease. Hence suitable mechanism should be adopted to detect and identify this disease in the initial stage to save the life of large number of peoples suffering from lung cancer. The identification of lung cancer tumor in the early stage, proper prognosis and treatment will decrease the death rate and increase the survival rate. Machine learning technique used to predict, identify and classify this disease however deep learning under machine learning brings a wide way to analyze and evaluate the features of tumor from its CT images. The system proposed in this paper provides an accurate classification AlexNet model and its advanced model where more number of hidden layers was utilized which is an Enhanced AlexNet model. The system developed were trained using LIDC-IDRI CT image dataset and it is evident from the experiments that the classification accuracy of Enhanced AlexNet model is 99% and AlexNet model is 97% with a very less false positive rates of 0.0196 and 0.0392.

Index Terms – Lung cancer, Computed Tomography, AlexNet, Classification.

1. INTRODUCTION

Medical imaging has been continuously evolving with the improvement in technology and the medical images taken in most of the earlier studies comprise of computed tomography (CT), magnetic resonance, and mammography images. The expert doctor of this domain uses these images for analysis and identification of the various levels of lung cancer by using suitable techniques [1]. The different laboratory and clinical steps are being used including chemical treatment to destroy or stop the duplications of malignant cell, targeted therapy and also radiotherapy. All these procedures adopted to identify and detect the cancer diseases are lengthy, costlier and more painful for the patients [5][6]. Thus, to overcome all these problems suitable machine learning techniques for processing these medical images were used which comprise of CT scan images. CT scan images are preferred compared to other images because CT images are less noisy as compared to MRI and X-Ray reports.

The process of tumor classification and identification became more accurate and speedy with minor errors from past years compared to manually done by radiologists. In lung cancer, a Tumor occurs in lung which develops irregularly may cause pain or ineffective to the human body. Hence early identification of tumor into benign (non- cancerous) or malignant (cancerous) and diagnosis of tumor is an important task to save peoples from this deadly disease. Deep learning is a machine learning techniques that provides self-learning techniques for extracting more and features from the images applied at the input stage. An emerging and new CNN architecture which were deeper then LeNet was presented by Alex Krizhevsky, known as AlexNet. AlexNet is one of the popular architecture of CNN which is multilayered, flexible and can be useful to many more classification problems [29-30].

AlexNet is a deep learning technique that needs minimum preprocessing steps in comparable to the other image processing algorithms [9]. The modified and improved version of AlexNet is an enhanced Alexnet developed to achieve better accuracy. Deep learning methods needs minimum preprocessing steps in comparable to the other image processing algorithms. To design and to attain better accuracy of classification in the AlexNet, the parameters used are size of filters, more no of hidden layers and extracted features. As the network layers are deeper, there is high detection level with high level of abstraction of features can be achieved.

Deeper the network leads to increase in computation time due to more number of Convolutional operations. The organization of the paper comprise of section 2 summarizes Related Work, Section 3 describes the architectures used, section 4 describes about results and discussions and section 5 summarizes about conclusion.

2. RELATED WORK

Pouria Moradi et.al [2], has proposed 3D Convolutional Neural Network in detecting lung cancer which provides high sensitivity and reduces false positive rate. Researcher achieved 91.23% accuracy for 3.99 false positive per scan using the method for combining different classifiers. Kim B. et al. have presented a model such that manually segmented tumor has been used by extracting the features from the class labels which then given as an input to the classifier for better classification and identification. Po-Whei Huang et.al [3], proposed a system which achieves an accuracy 0f 83.11% with the ROC area as 0.8437. Here the system classifies malignant tumor and benign tumor from given CT images using support vector classifier based on a number of fractal based features. Kumar D. et al [4], have proposed a model such that features from nodules were extracted and given to classifier input for classification task. The size of the nodules larger then 3mm was applied to classifier where binary decision trees were used for training purpose. Vaishali C.Patil et al [5], have proposed a lung tumor detection using CT images. To detect disease malignancy, the computer aided design system was used. Image processing techniques were used to eliminate noise from CT images. After segmentation, a variety of classifiers such as Artificial Neural Networks and Support vector machine were used to determine different stages of lung cancer to enhance efficiency and to minimize error rate.

Yang et al [8], have presented a deep convolutional neural networks (DCNN) classifier comprise of convolution, max-pooling and fully connected layers to classify the CT images using filters of 3×3 with stride 1×1 for all the convolution layers and in pooling layer. Ryota Shimizu et.al [9], proposed a system to detect malignancy of lung based deep neural network. The learning model uses urine to detect different substances. The model provides an accuracy of 90% while detecting malignancy of lung but it does not determine the category or nature of cancer. Rotem Golan et.al [11], suggested a DCNN which uses back propagation algorithms for extracting features from dataset for effective classification and also the system achieves a sensitivity of 78.9%. Jiang et al [14], has presented a Convolutional Neural Networks which is tested on 1006 samples of LIDC dataset with 90 % training and 10 % testing and achieves sensitivity of 94 %. Pratiksha Hattikatti et al [16] have presented Convolutional Neural Network for finding the range of the lung texture pattern of diseases from computed tomography images. Both SVM classifier and CNN does classification operation but by using CNN, accuracy of about 94% and accuracy of about 86% is achieved by using SVM classifier. So for this problem CNN is the best classifier which gives accurate results for lung cancer classification. Xin-Yu Jin et al [21], have presented a Convolutional neural network classifier for identifying lung nodules which gives an accuracy of about 84.6%. Also sensitivity of 82.5% and specificity of 86.7% are achieved. It is noted that the degree of treating the diseases will be higher as the dataset quantity increases.

From the literature review it is seen that many authors had used many techniques for classification of lung nodules to predict and identify the lung cancer in the early stage. It is evident from the review that one of the most efficient tools to classify the cancerous images is AlexNet with deep learning features. An AlexNet adopted the deep learning features of classification is called as the Enhanced AlexNet and it does more number of computations by utilizing hidden layers, Convolutional layers, softmax layer and fully connected layer. Hence an Enhanced AlexNet does the classification task efficiently with precise computation time.

3. PORPOSED ARCHITECTURE

The most popular architecture used for image classification problem is AlexNet, however AlexNet [29] architectures are used as shown in Figures. 2 and 3 were used to classify benign and malignant. The layer architecture consists of ten layers as shown in Table 1 which dictates about each layer depth, kernel size of pooling filters and strides. Figure 1 given below gives a basic CNN architecture consists of hidden layers and dense layers for feature extraction and classification.

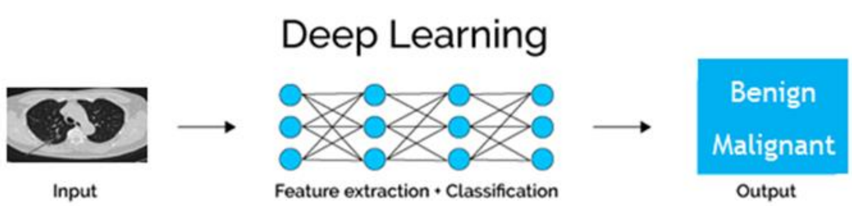


Figure 1 Basic CNN Architecture

The basic CNN architecture consists of following layers.

1. Convolution Layer: These layers have kernels, Stride and Padding.

2. Pooling Layer: it minimizes the dimension of the image that it reduces the parameters involved in computation.

3. Fully Connected Layer: This layer classifies the images of the previous two layers into a label. Since this layer utilizes the sofmax layer to find the probabilities between 0 and 1.

3.1. AlexNet Network Model

An AlexNet architectural model as shown in Figure.2 consists of 12 layers of which five convolution layers, three max- pooling layers and two fully-connected layers with softmax layer. Finally fully connected layer containing softmax layer decides the probability of containing the lung cancer or not.

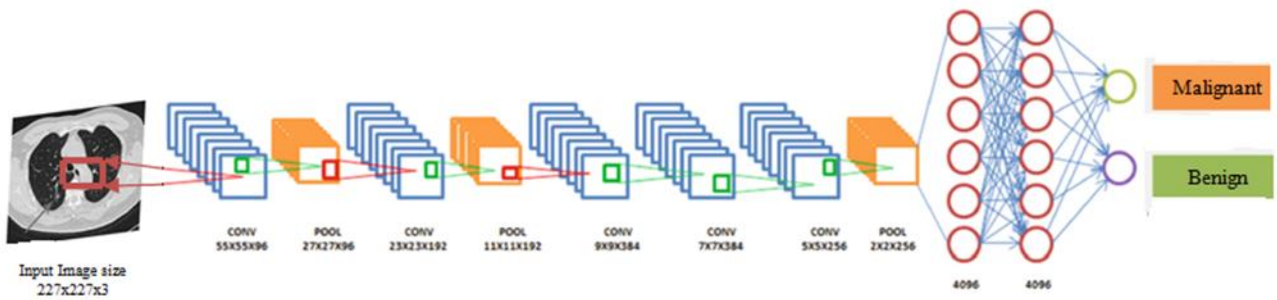


Figure 2 Architecture of AlexNet Model

Layer	Depth	Filter/Pooling AlexNet	Stride
Input	3	-	-
Convolution	96	11 X 11	1 X 1
Max-Pooling	96	3 X 3	2 X 2
Convolution	192	5 X 5	1 X 1
Max-Pooling	192	3 X 3	2 X 2
Convolution	384	3 X 3	1 X 1
Convolution	384	3 X 3	1 X 1
Convolution	256	3 X 3	1 X 1
Max-Pooling	256	3 X 3	2 X 2
Fully connected Layer	4096	-	-
Fully connected Layer	4096	-	-
Output	2	-	-

Table 1 AlexNet Model Architecture

3.2. Enhanced AlexNet Model

The modified and improved version of AlexNet is enhanced Alexnet developed with the objective to achieve better accuracy. For achieving good accuracy of classification, network's depth, kernel size and extracted feature maps are used for the design of Enhanced AlexNet network model shown in Figure 3 which identifies malignant or benign at the output. The proposed lung cancer Identification system is Enhanced AlexNet Model as shown in Figure 3 which identifies the nodule that is used to train to ultimately classify the CT input images as malignant or benign for lung cancer to achieve the result.

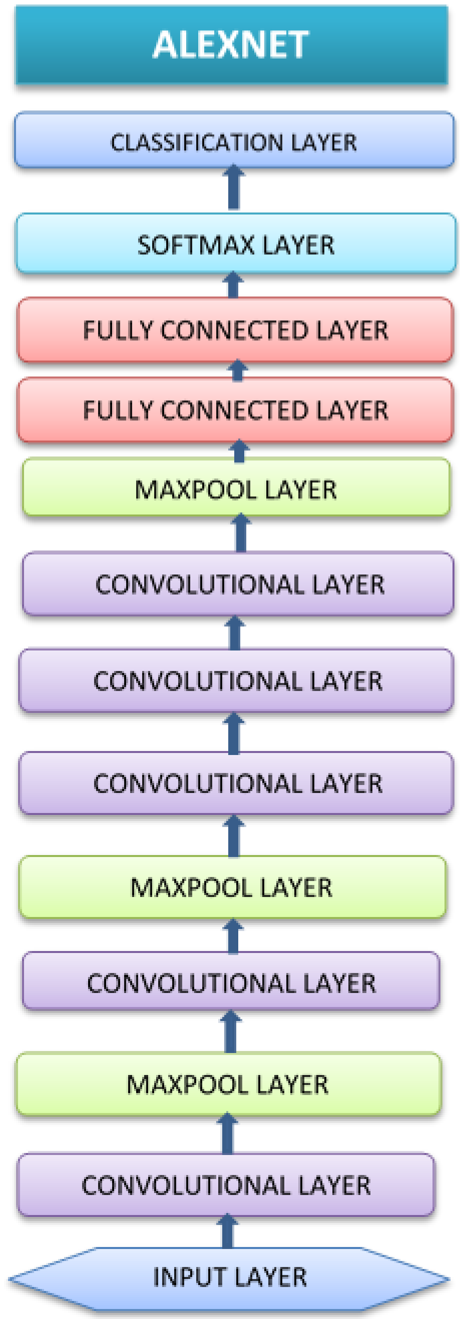


Figure 3 (a) AlexNet Model Architecture

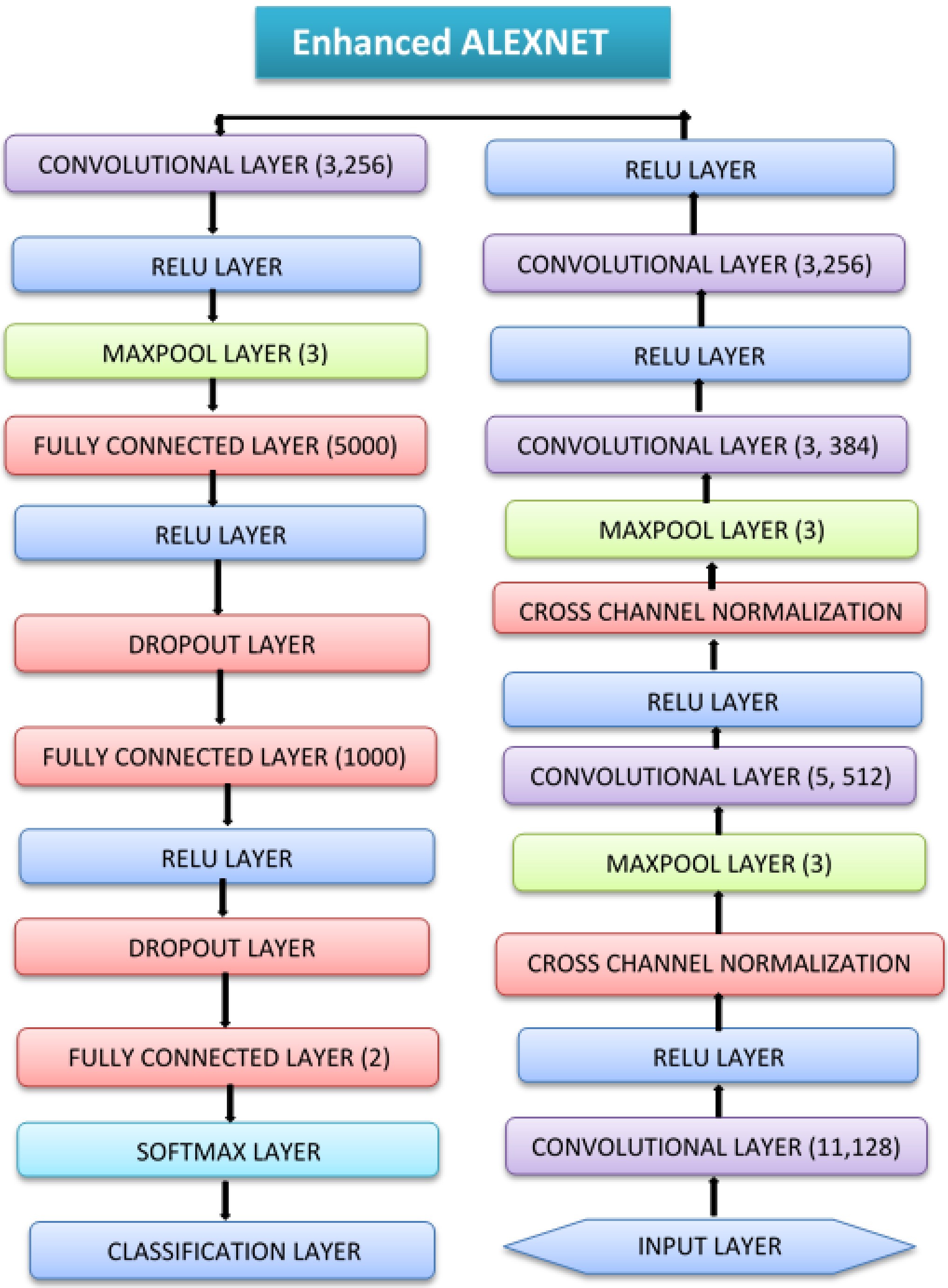


Figure 3(b) Enhanced AlexNet Model Architecture

Algorithm

1. **Acquire the images of lung cancer containing both diseased and non-diseased images using existing LIDC dataset and augmentation technique.**
2. **Preprocess all the images for resize the images to 227 X 227 X 3 based on AlexNet technique used**
3. **Assign the class labels to the images that are benign and malignant.**
4. **Categorize the images among training and testing dataset selecting from all the class labels.**
5. **Train the Enhanced AlexNet with the help of 80 % training images**
6. **Test the Enhanced AlexNet with the help of 20% testing images**
7. **Calculate the various performance measure parameters**
8. **Validate the performance of the proposed model**

Figure 4 Algorithm of Enhanced AlexNet Model

The proposed Enhanced AlexNet architecture as shown in Figure.3 mainly consists 19 layers, from which five convolution layers followed by five ReLu layers, three max- pooling layers, two cross channel normalization layer and two fully-connected layers with softmax layer. The input image of size 227x 227 x 3 is applied to the first convolution layer of the network however at the end the network model decides the probability of containing the lung cancer or not. The sample experimented images of cancerous and non-cancerous are shown in Figure 5.

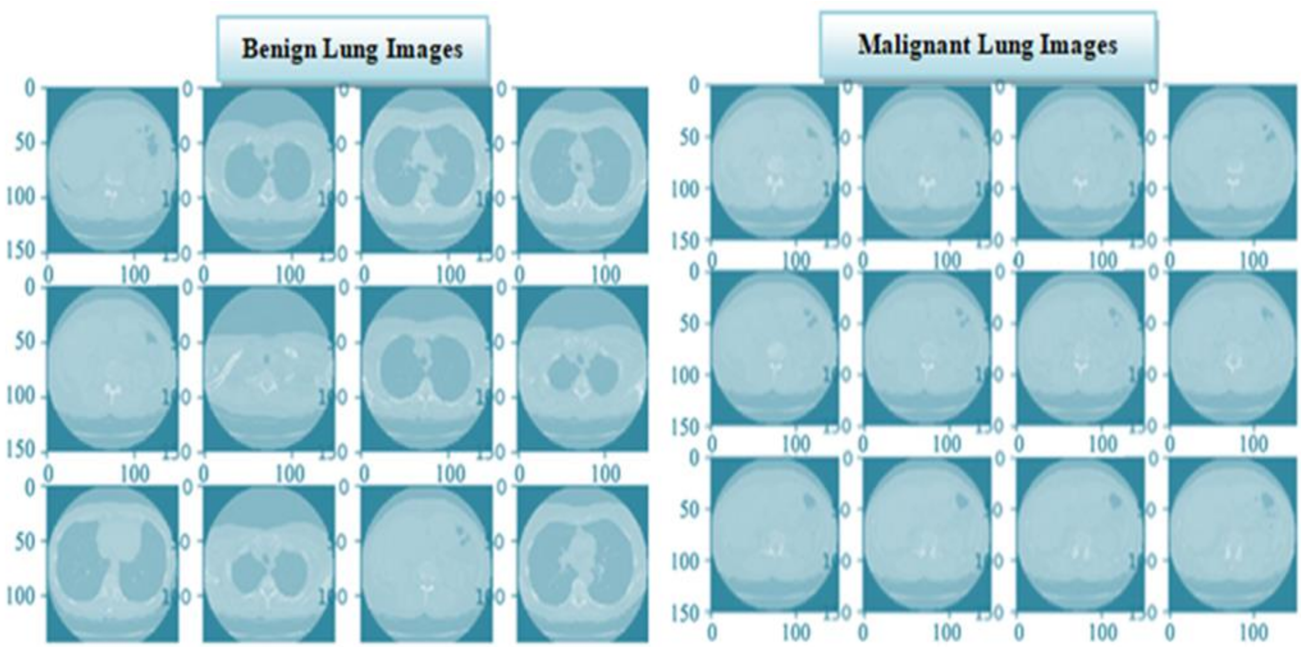


Figure 5 Experimental Images

Layer	Depth	Filter/Pooling Enhanced AlexNet	Stride
Input	3	-	-
Convolution	128	11 X 11	4 X 4
ReLu	-	-	-
Cross Channel Nomalization	5	-	-
Max-Pooling	128	3 X 3	2 X 2
Convolution	512	5 X 5	1 X 1
ReLu	-	-	-
Cross Channel Nomalization	5		
Max-Pooling	512	3 X 3	2 X 2
Convolution	384	3 X 3	1 X 1
ReLu	-	-	-
Convolution	256	3 X 3	1 X 1
ReLu	-	-	-
Convolution	256	3 X 3	1 X 1
ReLu	-	-	-
Max-Pooling	256	3 X 3	2 X 2
Fully connected Layer	5000	-	-
Fully connected Layer	1000	-	-
Output	2	-	-

Table 2 Details of Enhanced AlexNet Architecture Used

3.3. Training of Enhanced AlexNet

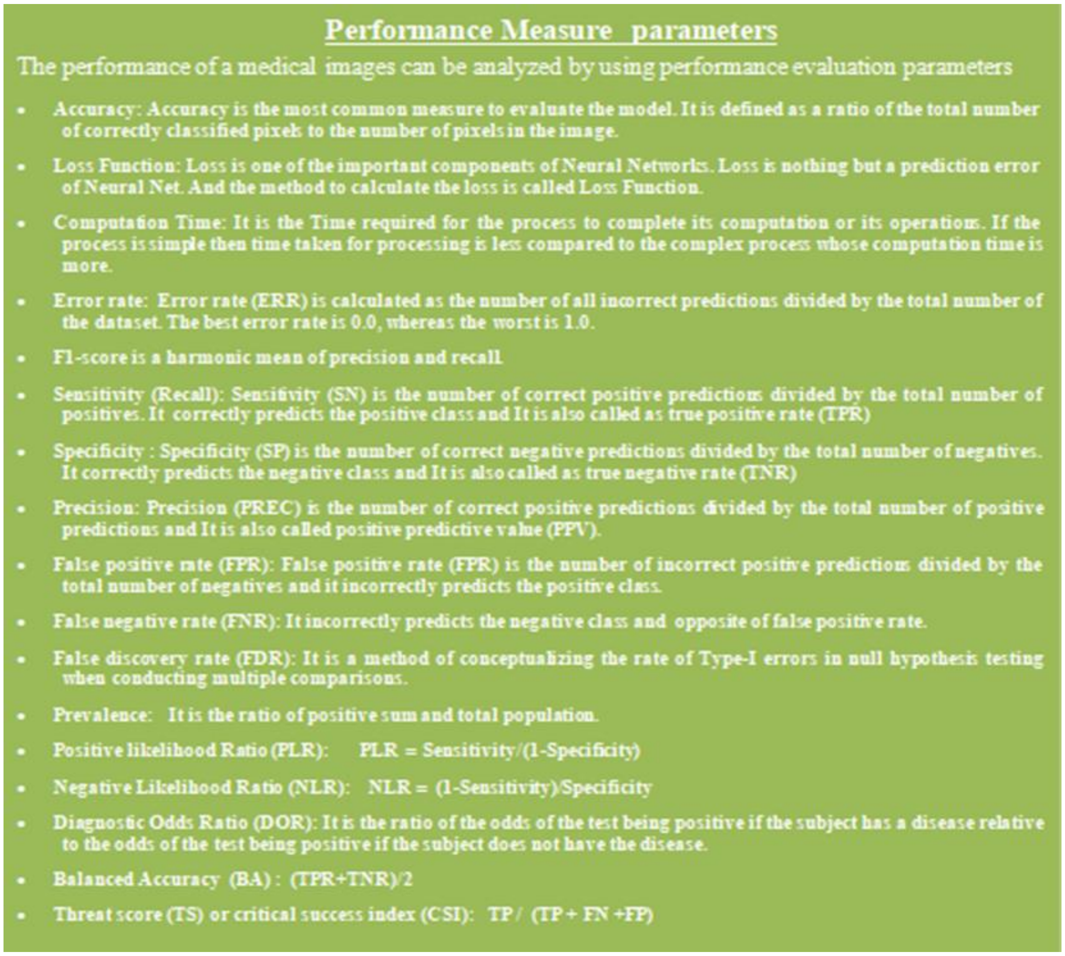
In both AlexNet Models, 80% of CT images were used for training purpose and 20% of the images were used for testing purpose, thereby classification accuracy was found which dictates the amount of accurately identifying the images into benign and malignant.

3.4. Confusion Matrix

Confusion Matrix: Confusion Matrix as shown in figure 6, dictates about the level of prediction of classification model as it correlates between label and the model's classification It is a two by two table formed by four outcomes of a binary classifier denoted as TP, FP, TN, and FN. Where TP is true positive, FP is false positive, TN is true negatives and FN is false negatives.

Actual/Predicted	Tumor (Predicted)	Non-Tumor (Predicted)
Tumor (Actual)	TP	FN
Non-Tumor (Actual)	FP	TN

Figure 6 Confusion Matrix



Performance Measure parameters

The performance of a medical images can be analyzed by using performance evaluation parameters

- Accuracy: Accuracy is the most common measure to evaluate the model. It is defined as a ratio of the total number of correctly classified pixels to the number of pixels in the image.
- Loss Function: Loss is one of the important components of Neural Networks. Loss is nothing but a prediction error of Neural Net. And the method to calculate the loss is called Loss Function.
- Computation Time: It is the Time required for the process to complete its computation or its operations. If the process is simple then time taken for processing is less compared to the complex process whose computation time is more.
- Error rate: Error rate (ERR) is calculated as the number of all incorrect predictions divided by the total number of the dataset. The best error rate is 0.0, whereas the worst is 1.0.
- F1-score is a harmonic mean of precision and recall.
- Sensitivity (Recall): Sensitivity (SN) is the number of correct positive predictions divided by the total number of positives. It correctly predicts the positive class and It is also called as true positive rate (TPR)
- Specificity : Specificity (SP) is the number of correct negative predictions divided by the total number of negatives. It correctly predicts the negative class and It is also called as true negative rate (TNR)
- Precision: Precision (PREC) is the number of correct positive predictions divided by the total number of positive predictions and It is also called positive predictive value (PPV).
- False positive rate (FPR): False positive rate (FPR) is the number of incorrect positive predictions divided by the total number of negatives and it incorrectly predicts the positive class.
- False negative rate (FNR): It incorrectly predicts the negative class and opposite of false positive rate.
- False discovery rate (FDR): It is a method of conceptualizing the rate of Type-I errors in null hypothesis testing when conducting multiple comparisons.
- Prevalence: It is the ratio of positive sum and total population.
- Positive likelihood Ratio (PLR): PLR = Sensitivity/(1-Specificity)
- Negative Likelihood Ratio (NLR): NLR = (1-Sensitivity)/Specificity
- Diagnostic Odds Ratio (DOR): It is the ratio of the odds of the test being positive if the subject has a disease relative to the odds of the test being positive if the subject does not have the disease.
- Balanced Accuracy (BA) : (TPR+TNR)/2
- Threat score (TS) or critical success index (CSI): TP / (TP + FN +FP)

Figure 7 Performance Measure Parameters

4. RESULTS AND DISCUSSIONS

The LIDC dataset collection is an international image resource for evaluating and identifying lung cancer. It consists of CT images in DICOM format of 1018 cases. The size of the original images are 512 x 512 but it is difficult to train large size images in AlexNet network model so preprocessed images by reducing the dimension suitable for the network were utilized. Hence training and testing images are categorized for evaluating the network for efficient classification of images into cancerous and non-cancerous images and helps for diagnosing the patient in the early stages [4][5].

4.1. AlexNet Results

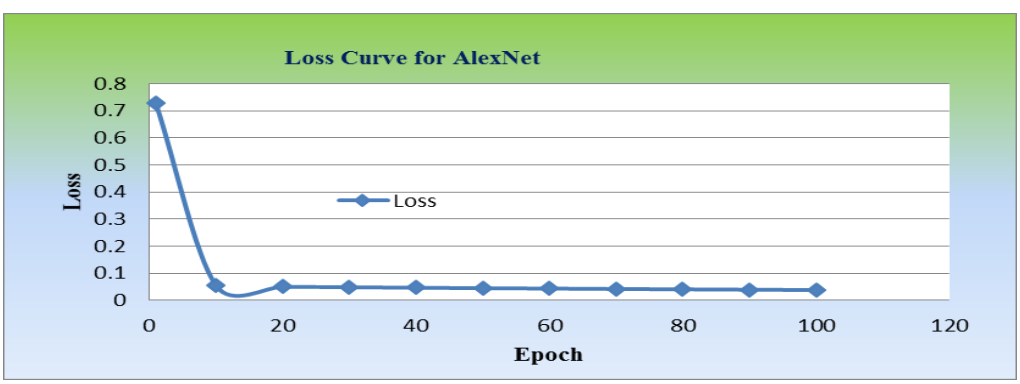


Figure 8 Loss Curve for AlexNet

From the Figure 8, it is shows that as epochs increases towards higher end then loss curve decreases towards higher end and hence loss decreases.

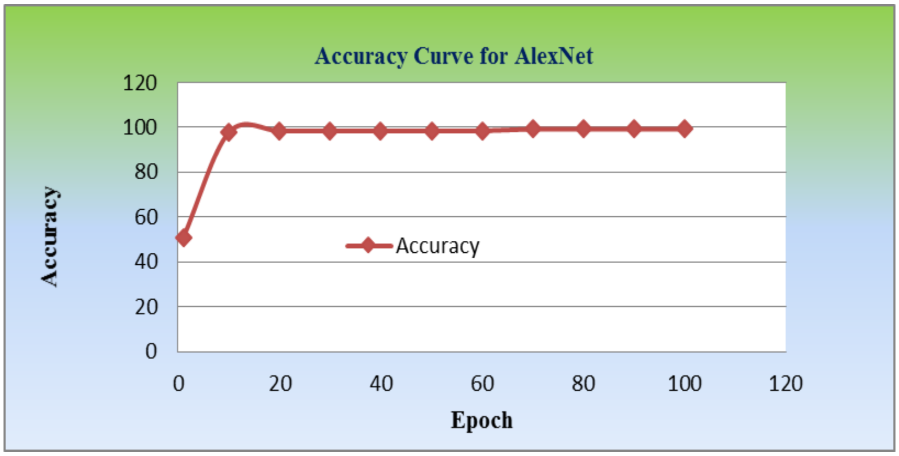


Figure 9 Accuracy Curve for AlexNet

From the Figure 9, it is shows that as epochs increases towards higher end then Accuracy curve increases towards higher end and hence accuracy increases.

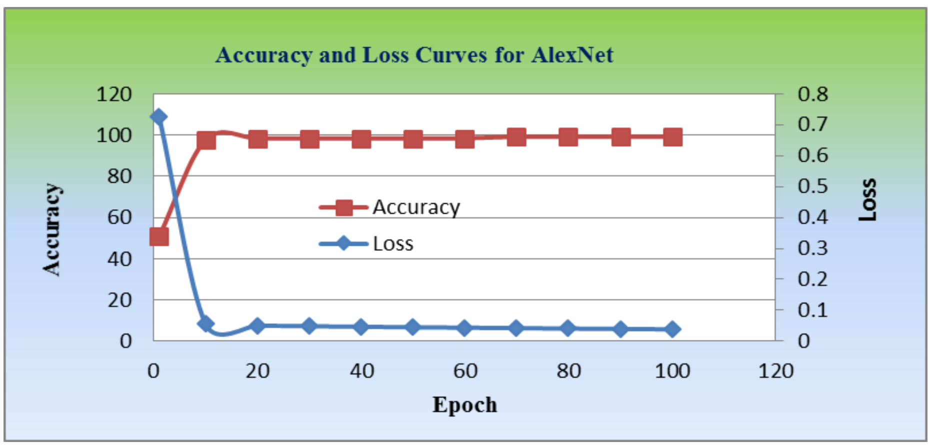


Figure 10 Accuracy and Loss Curves for AlexNet

Figure 10 shows both accuracy and loss curves and their relationship between them with reference to epoch.

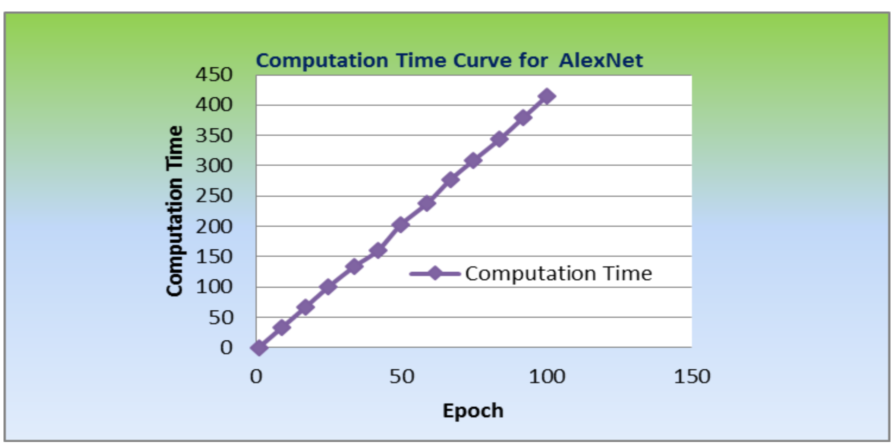


Figure 11 Computation Time curve for AlexNet

From the Figure 11, it shows that computation time increases as epoch approaches to higher end so higher computation needs more computation time and hence computation time increases.

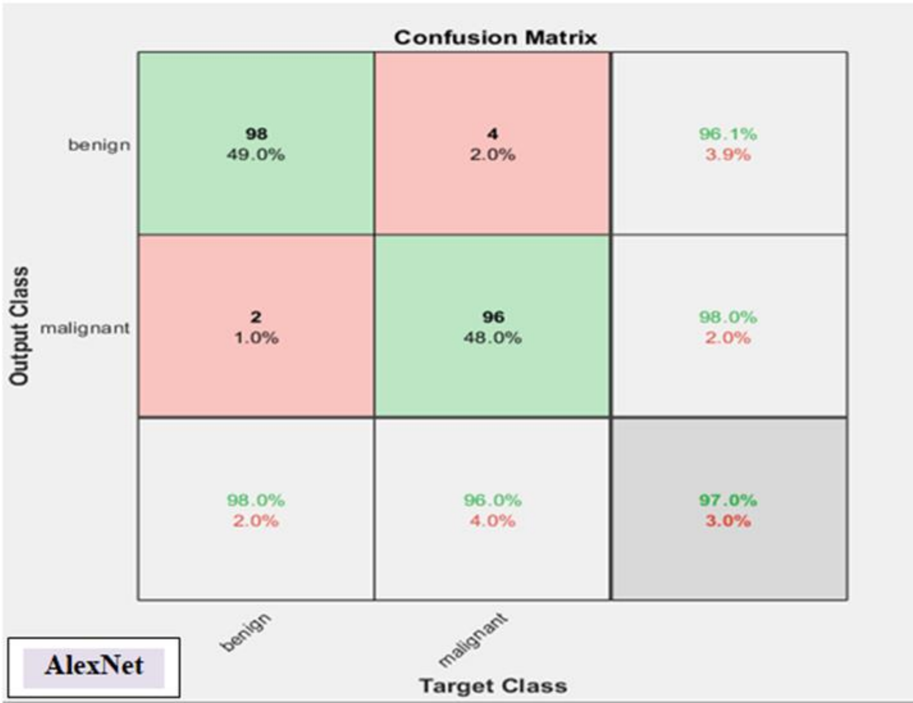


Figure 12 Confusion Matrix for AlexNet

Performance Measure Parameters for AlexNet (a)										
Accuracy	**Loss**	**Computation Time (sec)**	**F1 Score**	**Error Rate**	**TPR**	**FPR**	**TNR**	**FNR**	**BA**	**PPV**
0.9700	**0.0383**	**410**	**0.9610**	**0.0300**	**0.9608**	**0.0392**	**0.9796**	**0.0204**	**0.9808**	**0.9608**

Table 3a Performance Measure Parameters for AlexNet

Performance Measure Parameters for AlexNet(b)							
FDR	**FOR**	**NPV**	**Prevalence**	**PLR**	**NLR**	**DOR**	**TS**
0.0392	**0.0204**	**0.9796**	**0.5000**	**24.5000**	**0.0208**	**1.1760e+03**	**7**

Table 3b Performance Measure Parameters for AlexNet

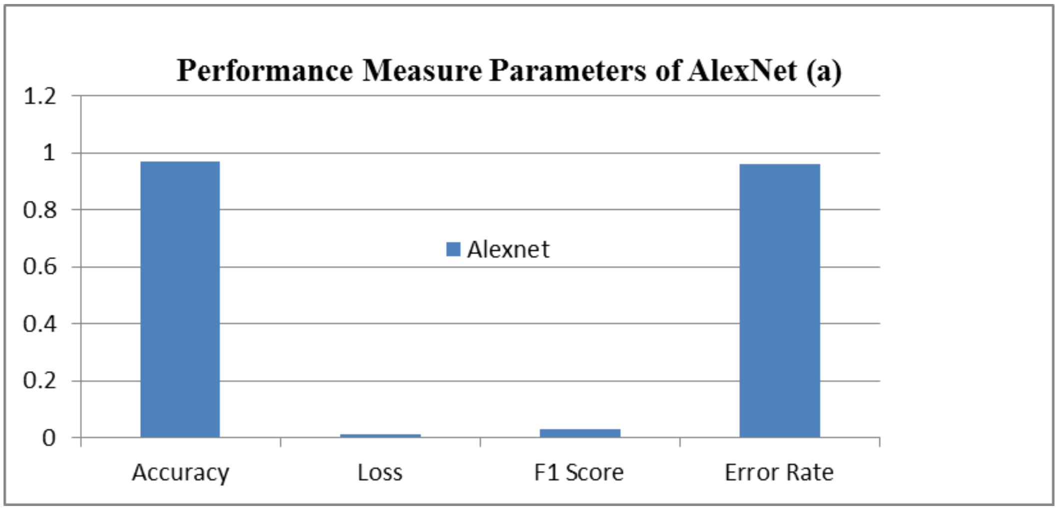


Figure 13a Performance Measure Parameters of AlexNet

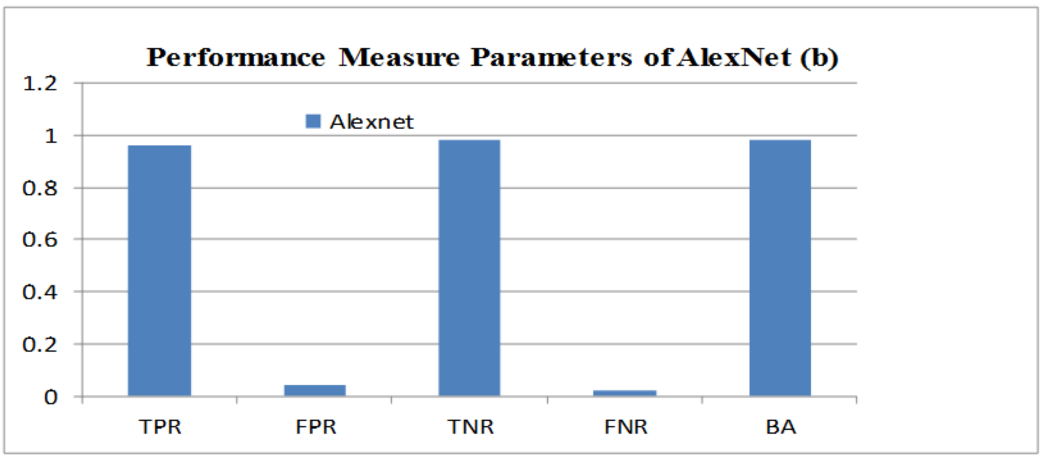


Figure 13b Performance Measure Parameters of AlexNet

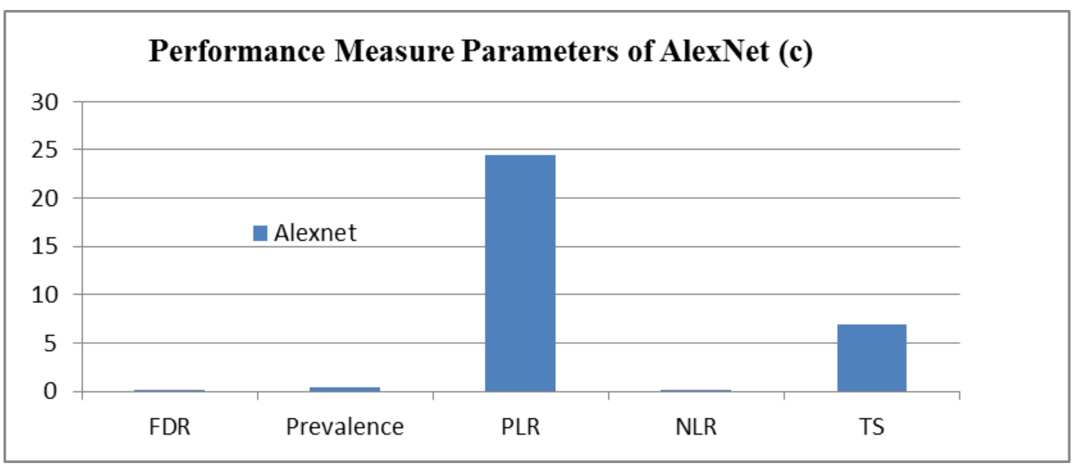


Figure 13c Performance Measure Parameters of AlexNet

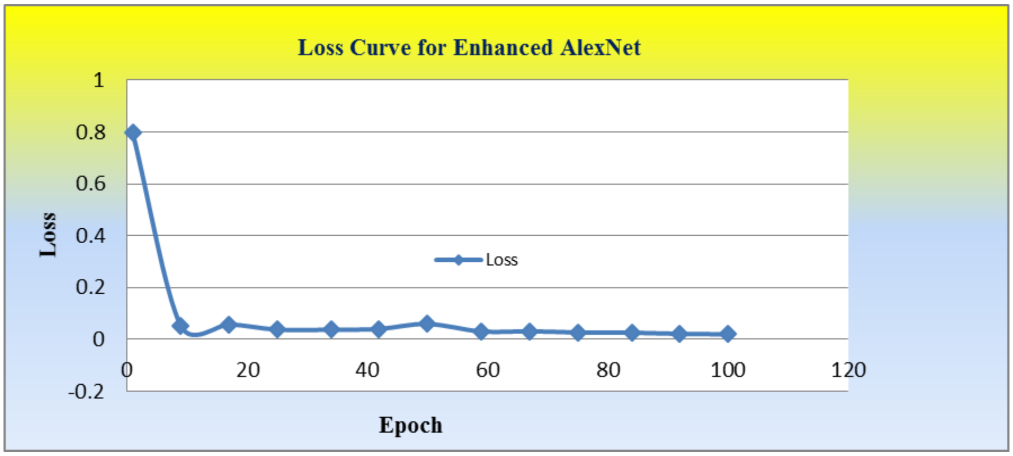


Figure 14 Loss Curve for Enhanced AlexNet

From the Figure 14, it is shows that as epochs increases towards higher end then loss curve decreases towards higher end and hence loss decreases.

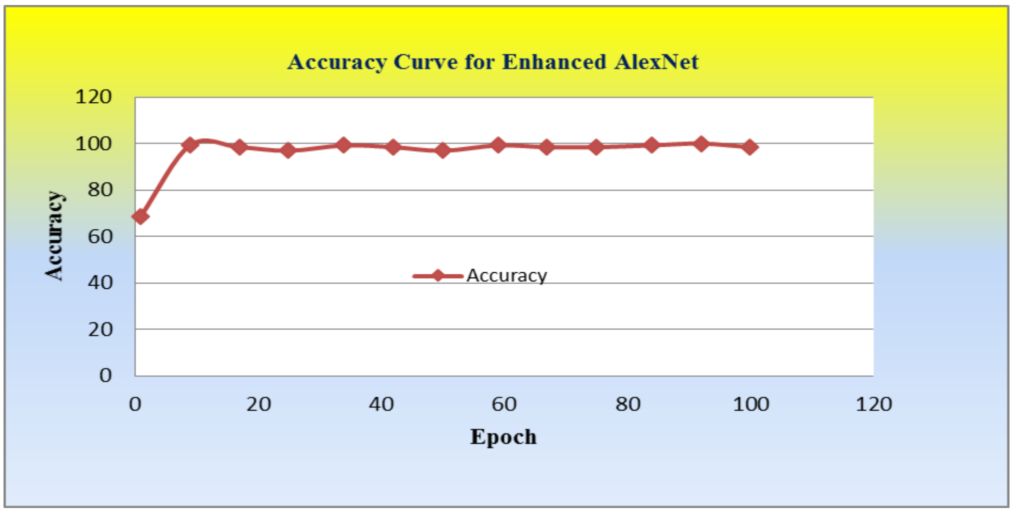


Figure 15 Accuracy Curve for Enhanced AlexNet

From the Figure 15, it is shows that as epochs increases towards higher end then Accuracy curve increases towards higher end and hence accuracy increases.

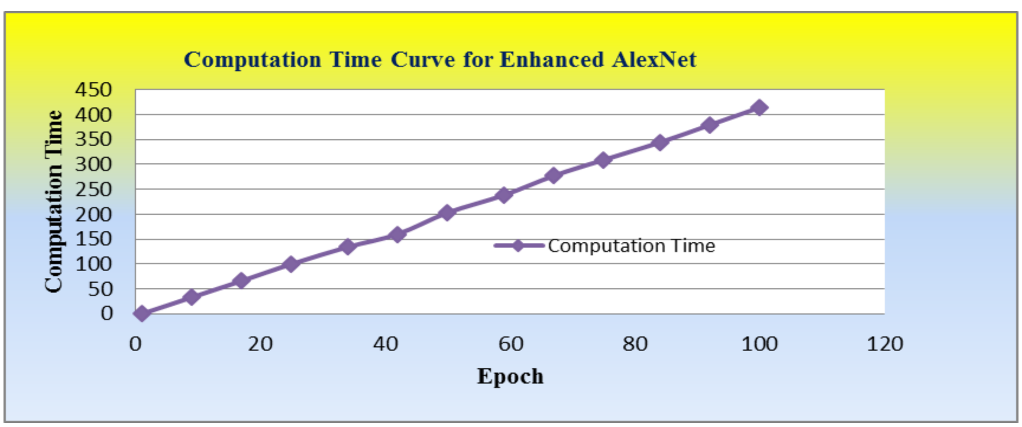


Figure 16 Computation Time Curve for Enhanced AlexNet

From the Figure 16, it shows that computation time increases as epoch approaches to higher end so higher computation needs more computation time and hence computation time increases.

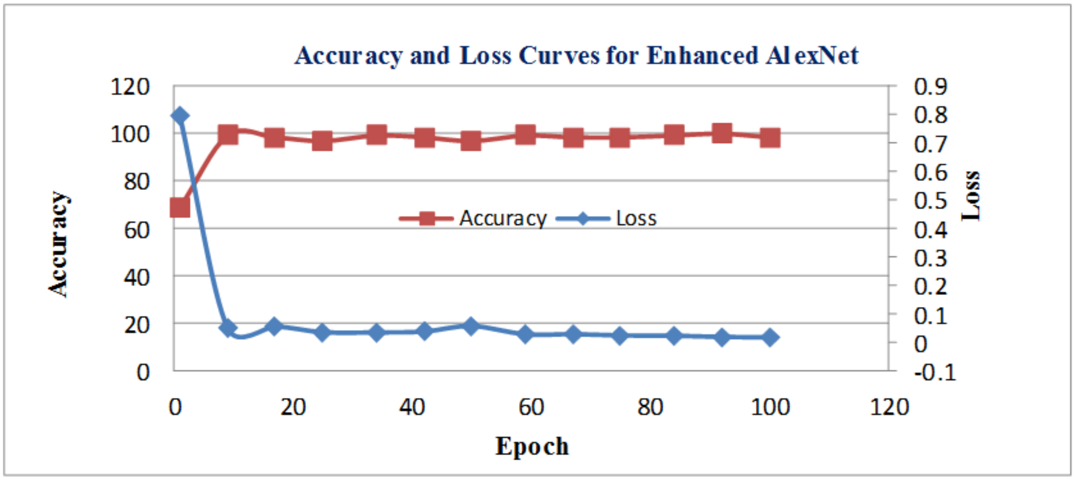


Figure 17 Accuracy and Loss Curves for Enhanced AlexNet

Figure 18 Confusion Matrix for Enhanced AlexNet

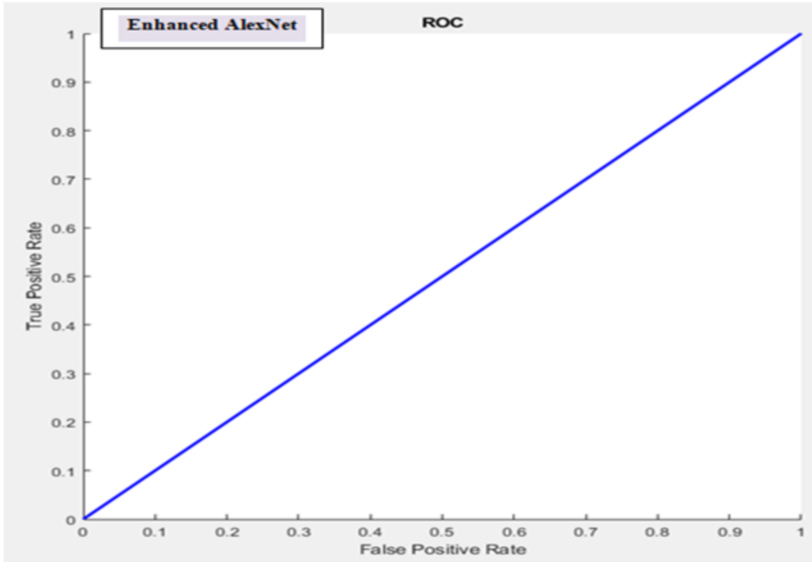


Figure 19 ROC Curve for Enhanced AlexNet

Performance Comparison between AlexNet and Enhanced AlexNet (a)										
Parameters	Accuracy	Loss	Computation Time (sec)	F1 Score	Error Rate	TPR	FPR	TNR	FNR	BA
Alexnet	0.9700	0.0383	410	0.9610	0.0300	0.9608	0.0392	0.9796	0.0204	0.9808
Enhanced Alexnet	0.9900	0.0192	415	1.0002	0.01	0.9804	0.0196	1	0.0002	1.0000

Table 4a Performance Comparison

Performance Comparison between AlexNet and Enhanced AlexNet(b)						
Parameters	FDR	Prevalence	PLR	NLR	DOR	TS
AlexNet	0.0392	0.5000	24.5000	0.0208	24.60	7
Enhanced AlexNet	0.0196	0.5000	50.0000	0.0002	30	3

Table 4b Performance Comparison

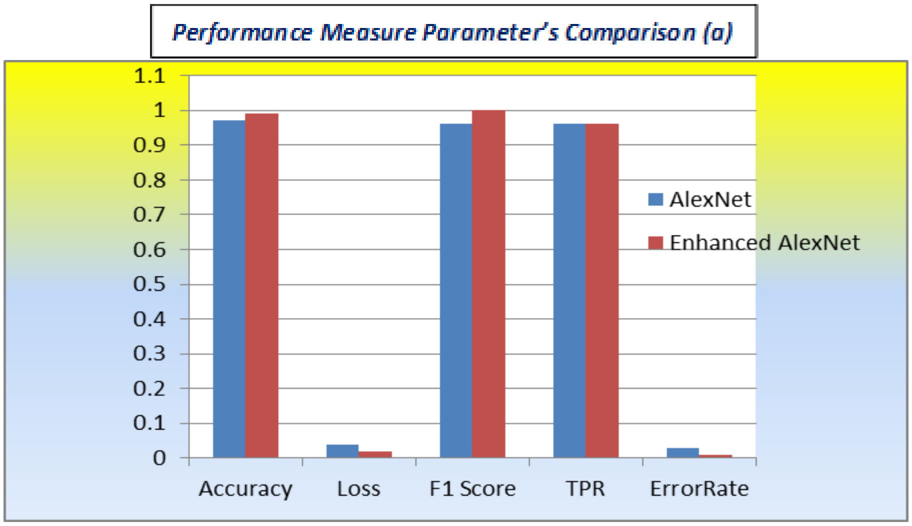


Figure 20a Performance Measure Comparison

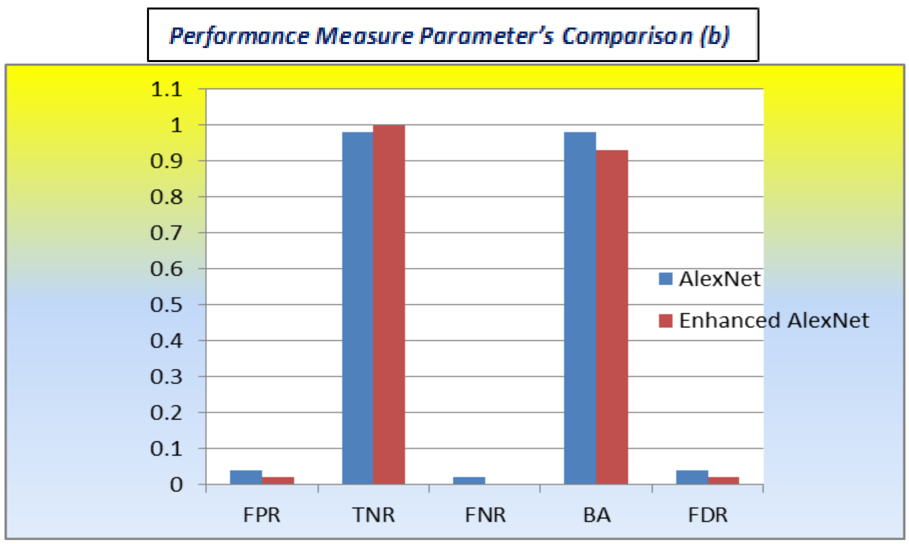


Figure 20b Performance Measure Comparison

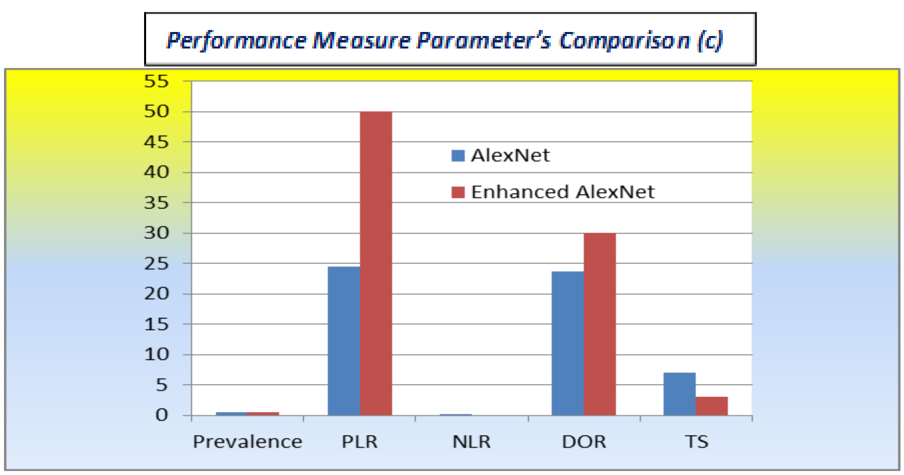


Figure 20c Performance Measure Comparison

The proposed lung cancer classification and identification models were developed in MATLAB 2018b and from the results it is seen that accuracy of classification increases as training progresses and loss percentage reduces however for the complete process AlexNet model provides an accuracy of 97% and precision of 96.08% in 410 seconds whereas Enhanced AlexNet model gives an accuracy of 99% and precision of 98.04% in 415 seconds. In this research work, the dataset used for training and testing purposes were taken from LIDC-IDRI were used to feed the network model which is able to detect and identify the malignancy that is cancerous (Malignant Images) and Non-Cancerous (Benign Images). As it is observed from the results that as training proceeds further classification accuracy will be increases with increase in the computation time, thereby decreases the percentage of loss as shown in above output graphs. The complete process of Enhanced AlexNet model gives 99% of accuracy with computation time of 415 seconds in GPU workstation, which is the best level of accuracy obtained compare to the work done in research papers [2][9][21].

5. CONCLUSION

In this paper, an improved version of AlexNet that is Enhanced AlexNet Convolutional neural networks were developed for classifying the CT images of lung tumor into malignant and benign. Thus preprocessing has been done before applying input CT images to network model to make equal sizes and format of the images. The dataset used in this research work belongs to LIDC dataset. Hence an accuracy of 99% is achieved which is an improved results comparable to the AlexNet accuracy of 97% as mentioned. Thus Enhanced AlexNet gains better accuracy then AlexNet which shows that image identification and classification performed more accurately in Enhanced AlexNet compare to AlexNet meodel.

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