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Improved VGG-16 Convolutional Neural Network Based Lung Cancer Classification and Identification on Computed Tomography

Amjad Khan
Department of Electronics and Communication Engineering, P.A College of Engineering (Affiliated to Visvesvaraya Technological University), Mangaluru, Karnataka, India.
amjad2meet@gmail.com

Zahid Ansari
University Polytechnic, Aligarh Muslim University, Aligarh, India.
zansari4@gmail.com

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ABSTRACT

Lung cancer is the dangerous disease where more number of death occurs in both men and women hence identifying such a disease is a challenging task. The identification of lung cancer tumor in the early stage will save the life of more number of patients by proper prognosis and treatment hence to decrease the death rate and increase the survival rate its identification and classification is necessary. Machine learning technique, opens the door 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 a clear and accurate classification VGG-16 model and its advanced model where more number of hidden layers was utilized which is an Improved VGG-16 model. The system developed were trained using LIDC-IDRI CT image dataset and it is evident from the experiments that the classification accuracy of Improved VGG-16 model is 97% and VGG-16 model is 86% with a very less false positive rates of 0.0567 and 0.12.

Index Terms – Lung Cancer, Computed Tomography, VGG-16, Classification.

1. INTRODUCTION

Lung cancer is one of the causes to increase death rate, since every year it is seen 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. If it is detected and identified in primary stage then survival rate of many number of patients can be improved. Later after disease identification, by providing proper diagnosis can reduce the death rate of patients. So in order to avail a suitable and instantaneous outcome the importantly, applying recent techniques of machine leaning in the medical image processing field by enhancing the amount of duplication for the methods use can increase the accuracy of the classification [3]. Therefore proper timely detection and identification in the prior stage will definitely improve the level of survival and can decrease the death rate. Medical imaging has improved 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 [8]. 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 [7].

Improved VGG-16 convolutional neural networks uses deep learning algorithm from the given input images which makes significance object in the images. Precise training using large dataset will increase classification accuracy of the network. 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 VGG-16, 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 I summarizes Related Work, Section II describes the Proposed architecture used, section III describes about results and discussions and section IV summarizes about conclusion.

2. RELATED WORK

The Convolutional neural network were used for classification by using 1006 images of LIDC dataset, 94% of accuracy results found with 90% training and 10% of testing images [1]. Identification of lung nodules by applying computed tomography images is proposed by the author [2] where it produces the sensitivity results of 90%, thereby patient survival rate becomes higher. The region of interest are retrieved by using methods such as wiener filter, image slicing. The nodule size of 3mm is obtained to recognize lung cancer in the primary stage. The author [3] proposed a method to classify the lung nodule by computed tomography images where the lung segmentation take place by applying thresholding and region growing technique, thereby the image features are extracted. The extracted features were used to apply as input to the KNN which then classifies the images. The author proposes Convolutional neural network classifier for identifying lung nodules [4] which gives an accuracy of about 84.6%. Also sensitivity of 82.5% and specificity of 86.7% were achieved. It is noted that the degree of treating the diseases will be higher as the dataset quantity increases. The author proposes a model [5] which is used to identify cancerous part of the lung by applying the methods of deep learning of neural network; the model gives an accuracy of classification of about 90% and also the model unable to find the nature and category of cancer disease.

The author [6] presented a model which gives an accuracy of 83.11% which classifies benign and malignant images using support vector machine form computed tomography images. A model which Recognizes lung cancer nodules from CT images were presented [7] which uses SVM classifier thereby improves the efficiency and reduces the error rate. The author [8] presented a system which classifies the lung cancer nodules depends on the size of nodules between 3mm-10mm from LIDC dataset. The system uses the methods of machine learning such as K-Nearest Neighbor, Random Forest; the system gives an accuracy of classification of 82%. Deep Convolutional neural network is trained from CT images of LIDC dataset to classify the malignant and benign images. The network provides a sensitivity of 78.9% using back propagation methods by extracting the image features. The author [9] presented a classification model based on principal component analysis using CT images which achieves an accuracy of about 90% by applying principal component analysis method. The model uses lung organ segmentation as a first step, lung nodule segmentation and classification of benign and malignant images in the last step. The system identifies the malignancy of disease in the primary stage [10] by undergoing different steps of the disease. The detecting phase first step consists of preprocessing and segmentation which improves the accuracy of classification by adopting support vector machine and fuzzy logic classifiers. The classifier identifies and classifies the images based on the degree intensities of images as benign and malignant tumor.

Convolutional neural network by employing deep learning techniques does lung segmentation in CT images [11] were used. The challenging task for the radiologist is to identify malignancy of lung diseases hence deep learning model assist much in this task as lung cancer images have different degree of opacities in region of interest. This is texture based problem which employs 42 CT images with high degree of cancerous and low degrees of cancerous images are collected. The machine learning methods are utilizes to classify the lung images [12]. The classification accuracy can be enhanced by deep learning techniques, thereby cancerous and non-cancerous image classification can be performed. In the work [13], the different classifiers were employs which includes decision trees, support vector machine as these provides higher accuracy of classification. The model achieves an accuracy of 94% by using Convolutional neural network classifier and also SVM classifier gives an accuracy of 86%. Compare to these results of classification, CNN provides the more accuracy then SVM classifier. The hybrid segmentation network based CNN is designed [14] which use hybrid 2D and 3D features to train CNN model. This model provides a good performance of accuracy of 88%, average sensitivity of 87.2% and average precision of 90.9%. The author proposes Convolutional neural network [15] that minimizes the rate of false positives, enhances the accuracy of classification of 91.23% for identifying diseases. The proposed method gives an improved accuracy of 97% using deep neural network [16] and hence reduces the complexity of time with greater accuracy.

From the literature review it is seen that many authors had used many techniques for classification of lung nodules to classify 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 VGG-16 with deep learning features. When a VGG-16 adopted the deep learning features of classification can be called as the Improved VGG-16 and it does more number of computations by utilizing hidden layers, Convolutional layers, softmax layer and fully connected layer. Hence an Improved VGG-16 does the classification task efficiently with precise computation time.

3. PORPOSED ARCHITECTURE

The VGG model stands for the Visual Geometry Group from Oxford, very simple and had a greater depth than AlexNet. All the network layers were using 3 by 3 filters with stride and a pad of size 1 and a max pooling size of 2 with stride 2. Though the size is decreasing because of max pooling, the number of filters is increasing with layers. The architecture used for image classification model is VGG-16 as shown in Figs. 2 and 3 however it is seen that the architecture were having 16 layers as depicted in Table_1. Architecture in the given table depicts about each layer depth, kernel size of pooling filters, strides, Rectified Linear Unit (ReLu) is most widely used activation function in image classification and a softmax activation loss function was used at the final end classification task. Figure 1 given below gives a basic CNN architecture consists of hidden layers and dense layers for feature extraction and classification.

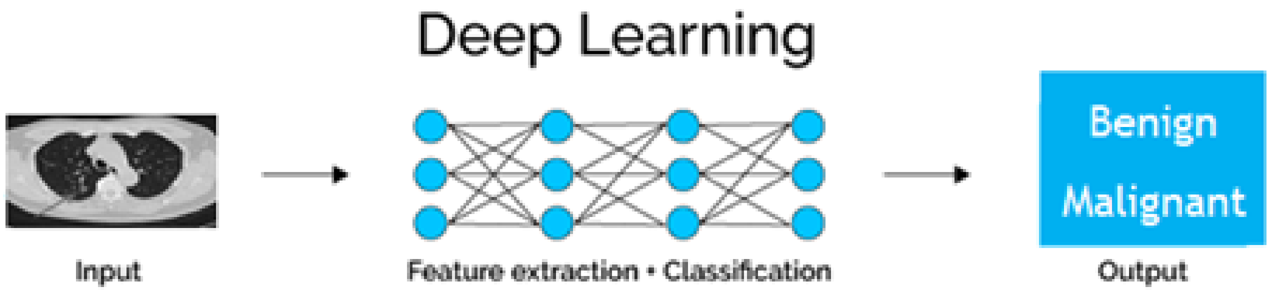

Figure 1 Basic CNN Architecture

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. VGG-16 Network Model

The VGG model stands for the Visual Geometry Group from Oxford is very simple and had a greater depth than AlexNet. All the network layers were using 3X3 filters with both stride and a pad of size 1 with a max pooling size of 2. VGG-16 architectural block diagram shown in Figure 2 consists 16 layers of which thirteen convolution layers followed by ReLu layers, max- pooling layers of five and three fully-connected layers with softmax layer. Finally fully connected layer containing softmax layer decides the probability of containing the lung cancer or not.

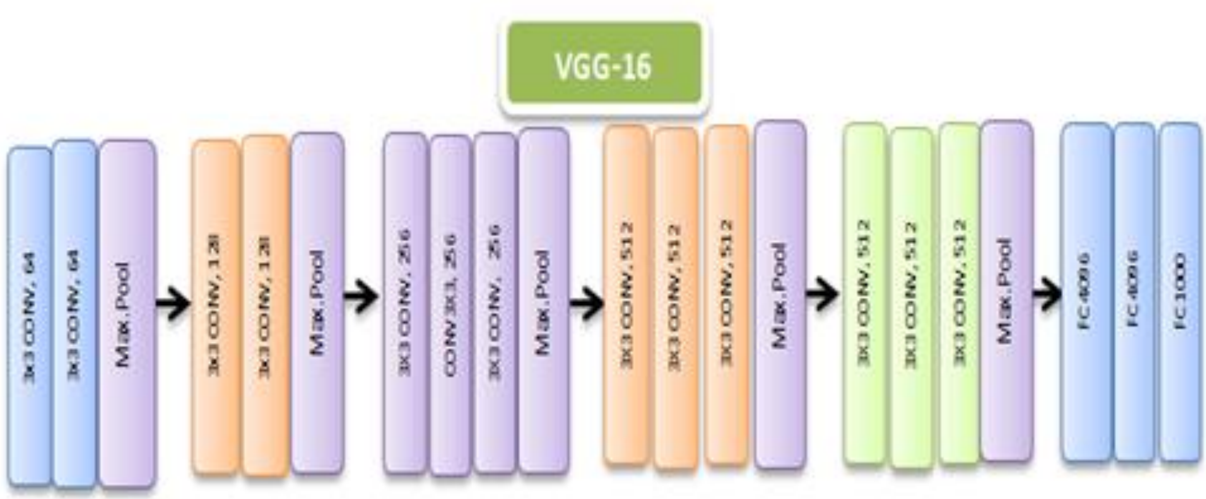

Figure 2 Architecture of VGG-16 Model

Layer	Depth	Filter/Pooling VGG-16	Stride
Input	3	-	-
Convolution1	64	3 X 3	1 X 1
Relu	-	-	-
Convolution2	64	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	64	3 X 3	2 X 2
Convolution3	128	3 X 3	1 X 1
Relu	-	-	-
Convolution4	128	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	128	3 X 3	2 X 2
Convolution5	256	3 X 3	1 X 1
Relu	-	-	-
Convolution6	256	3 X 3	1 X 1
Relu	-	-	-
Convolution6	256	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	256	3 X 3	2 X 2
Convolution7	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	512	3 X 3	2 X 2
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	512	3 X 3	2 X 2
Fully connected Layer	4096	-	-
Fully connected Layer	4096	-	-
Fully connected Layer	1000		-
Output	2	-	-

Table 1 Details of VGG-16 Architecture Used

3.2. Improved VGG-16 Model

The modified version of VGG-16 is Improved VGG-16 developed 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 Improved VGG-16 network model shown in Figure 3 which identifies malignant or benign at the output.

Figure 3 Improved VGG-16 Model Architecture

Algorithm of Improved VGG-16 Model
Acquire the images of Lung Cancer containing both diseased and non-diseased using existing LIDC dataset and augmentation technique. Preprocess all the images to resize 224X224X3 based on VGG-16 algorithm used. Assign the class labels to the images that are benign and malignant. Categorize the images among training and testing dataset selecting from all the class labels. Train the Improved VGG-16 Model with the help of 80% training images. Test the Improved VGG-16 Model with the help of 20% testing images. Calculate the various performance measure parameters. Validate the performance of the proposed Model.

Algorithm 1 Algorithm of Improved VGG-16 Model

An Improved VGG-16 architectural block diagram shown in Algorithm 1 consists of 18 layers in that fifteen convolution layers followed by fifteen Rectified Linear Unit layers, six max- pooling layers and three fully-connected layers with softmax layer. The input image of size 224x 224 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.

Layer	Depth	Filter/Pooling	Stride
		VGG-16	
Input	3	-	-
Convolution1	64	3 X 3	1 X 1
Relu	-	-	-
Convolution2	64	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	64	3 X 3	2 X 2
Convolution3	128	3 X 3	1 X 1
Relu	-	-	-

Convolution4	128	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	128	3 X 3	2 X 2
Convolution5	256	3 X 3	1 X 1
Relu	-	-	-
Convolution6	256	3 X 3	1 X 1
Relu	-	-	-
Convolution6	256	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	256	3 X 3	2 X 2
Convolution7	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	512	3 X 3	2 X 2
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Convolution8	512	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	512	3 X 3	2 X 2
Convolution9	512	3 X 3	1 X 1
Relu	-	-	-
Convolution10	512	3 X 3	1 X 1
Relu	-	-	-
Max-pooling	512	3 X 3	2 X 2
Fully connected Layer	4096	-	-
Fully connected Layer	4096	-	-
Fully connected Layer	1000		-
Output	2	-	-

Table 2 Details of Improved VGG-16 Architecture Used

3.3. Training of Improved VGG-16 Model

In both VGG-16 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

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

Figure 5 Confusion Matrix

Confusion Matrix: Confusion Matrix 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. Table 3 lists the performance measure parameters.

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)

Table 3 Performance Measure Parameters

4. RESULTS AND DISCUSSIONS

Deep learning has a good performance in image classification which has been implemented to models such as AlexNet and VGGNet. VGG-16 is deeper than AlexNet as it has a better feature learning ability than AlexNet [29-31]. 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 VGG16 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. VGG-16 Model Results

From the Figure 7, it is shows that as epochs increases towards higher end then Accuracy curve increases towards higher end and hence accuracy increases.

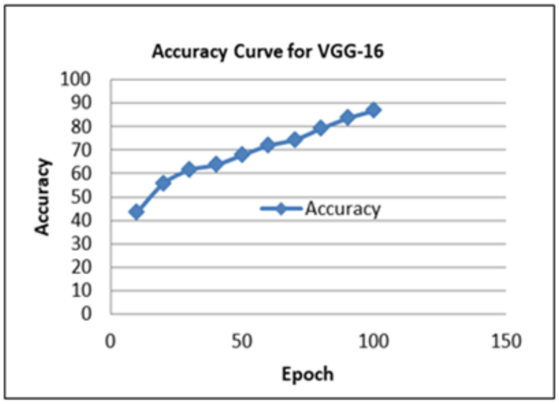

Figure 7 Accuracy Curve for VGG-16

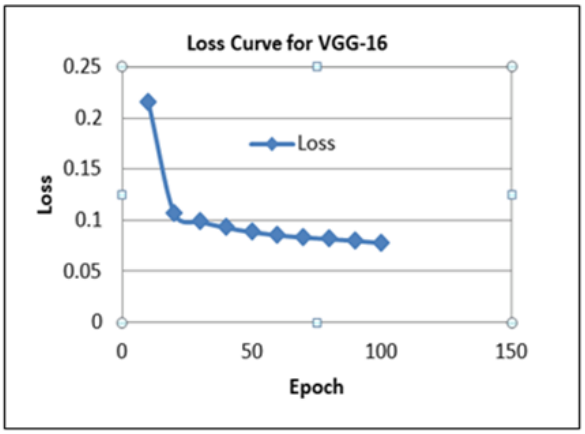

Figure 8 Loss Curve for VGG-16

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.

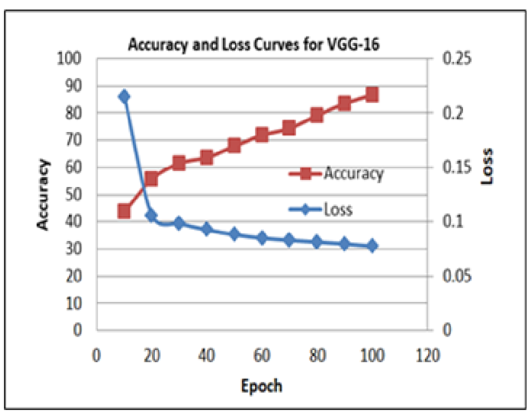

Figure 9 Accuracy and Loss Curves for VGG-16

Figure 9 shows both accuracy and loss curves and their relationship between them with reference to epoch.

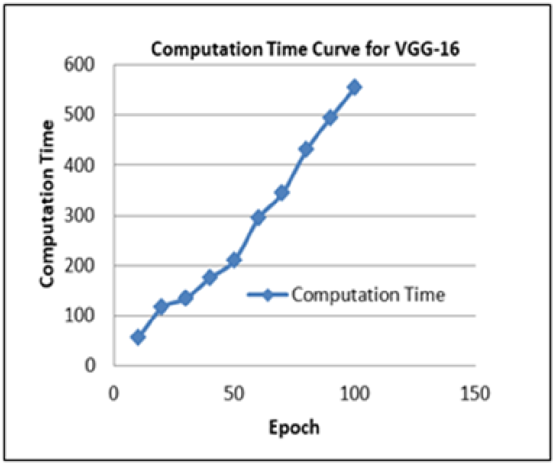

Figure 10 Computation Time Curve for VGG-16

From the Figure 10, it shows that computation time increases as epoch approaches to higher end so higher computation needs more computation time and hence computation time increases.

Performance Measure Parameters for VGG-16(a)										
Parameters	Loss	Computation Time (sec)	F1 Score	Error Rate	TPR	FPR	TNR	FNR	BA	PPV
VGG-16	0.0383	410	0.9610	0.0300	0.9608	0.0392	0.9796	0.0204	0.9808	0.9608

Table 4a Performance measure parameters for VGG-16

Performance Measure Parameters for VGG-16 (b)						
Parameters	FDR	Prevalence	PLR	NLR	DOR	TS
VGG-16	0.12	0.52	7.333	0.190	38.5963	0.7462

Table 4b Performance Measure Parameters for VGG-16

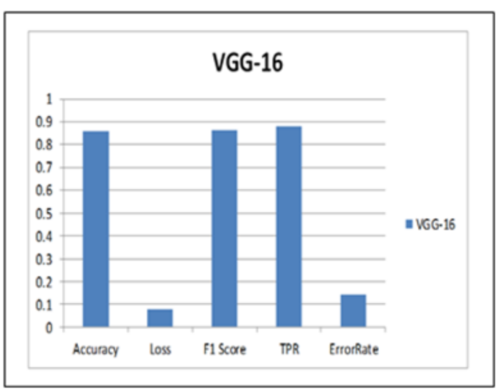

Figure 11a Performance Measure Parameters of VGG-16

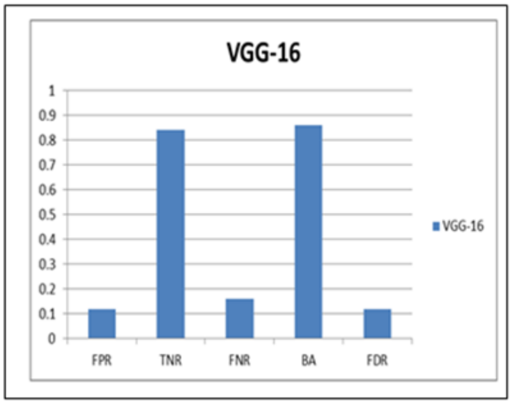

Figure 11b Performance Measure Parameters of VGG-16

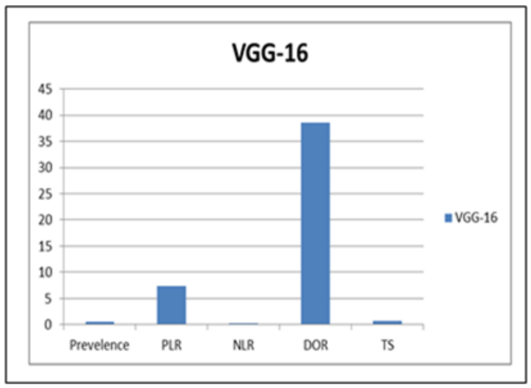

Figure 11c Performance Measure Parameters of VGG-16

4.2. Improved VGG-16 Model Results

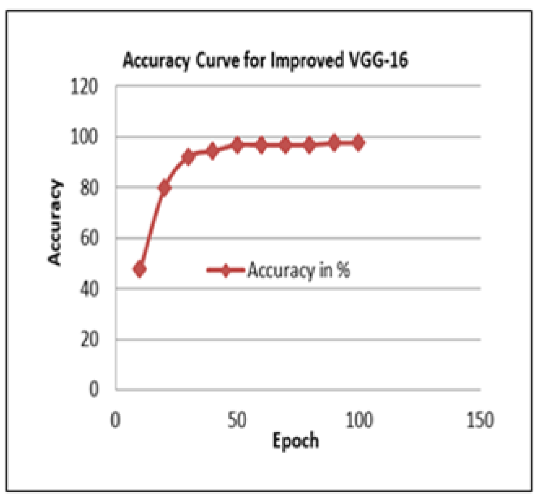

Figure 12 Accuracy Curve for Improved VGG-16

From the Figure 12, it is shows that as epochs increases towards higher end then Accuracy curve increases towards higher end and hence accuracy increases.

From the Figure 13, it is shows that as epochs increases towards higher end then loss curve decreases towards higher end and hence loss decreases.

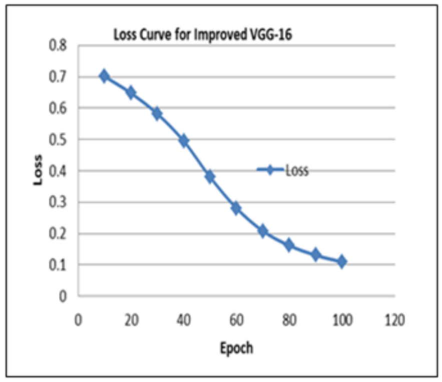

Figure 13 Loss Curve for Improved VGG-16

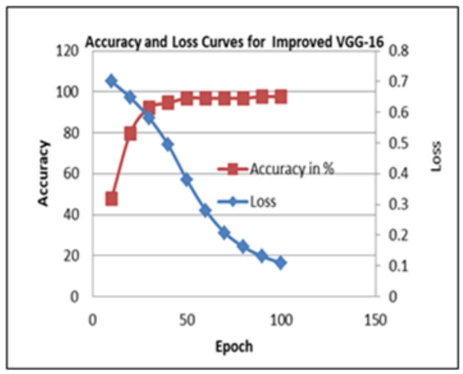

Figure 14 Accuracy and Loss Curves for Improved VGG-16

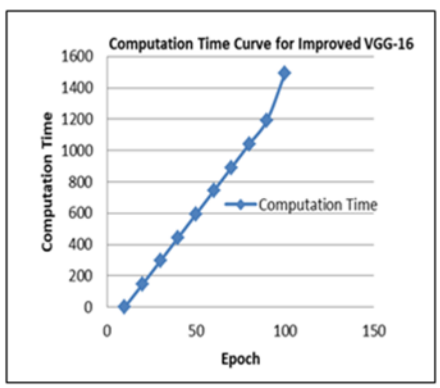

Figure 15 Computation Time Curve for Improved VGG-16

From the Figure 15, it shows that computation time increases as epoch approaches to higher end so higher computation needs more computation time and hence computation time increases.

Performance Measure Parameters for Improved VGG-16										
Parameters	Accuracy	Loss	Computation Time (sec)	F1 Score	Error Rate	TPR	FPR	TNR	FNR	BA
Improved VGG-16	0.9700	0.1092	1490	0.9708	0.0300	0.9433	0.0567	1	0.0002	0.9717

Table 5a Performance Measure Parameters for Improved VGG-16

Performance Measure Parameters for Improved VGG-16						
Parameters	FDR	Prevalence	PLR	NLR	DOR	TS
Improved VGG-16	0.0566	0.5000	16.636	0.0002	0	0.9433

Table 5b Performance Measure Parameters for Improved VGG-16

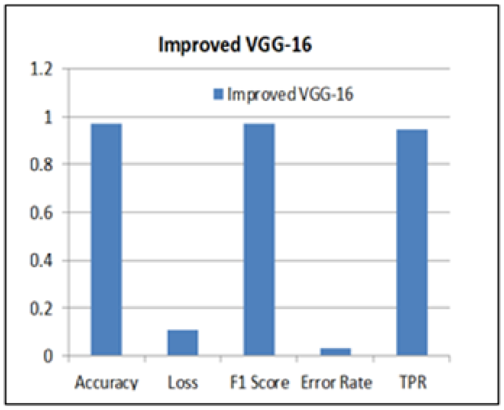

Figure 16a Performance Measure Parameters of Improved VGG-16

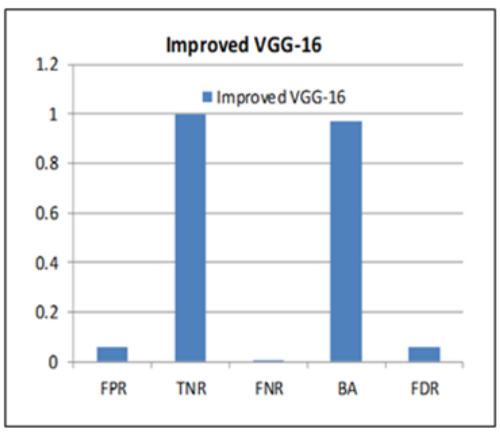

Figure 16b Performance Measure Parameters of Improved VGG-16

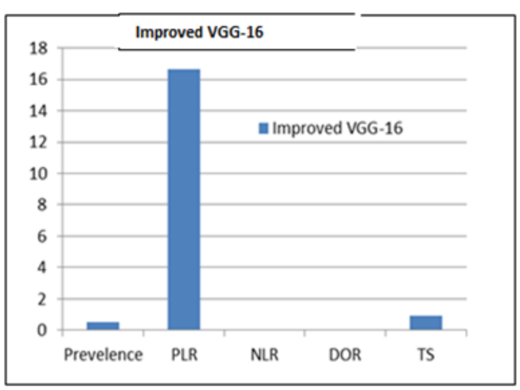

Figure 16c Performance Measure Parameters of Improved VGG-16

Performance Measure Parameters comparison in VGG-16 and Improved VGG-16										
Parameters	Accuracy	Loss	Computation Time (sec)	F1 Score	Error Rate	TPR	FPR	TNR	FNR	BA
VGG-16	0.86	0.0776	554	0.8627	0.14	0.88	0.12	0.84	0.16	0.86
Improved VGG-16	0.9700	0.1092	1490	0.9708	0.0300	0.9433	0.0567	1	0.0002	0.9717

Table 6a Performance Comparison

Performance Measure Parameters comparison in VGG-16 and Improved VGG-16						
Parameters	FDR	Prevalence	PLR	NLR	DOR	TS
VGG-16	0.12	0.52	7.333	0.190	38.5963	0.7462
Improved VGG-16	0.0566	0.5000	16.636	0.0002	0	0.9433

Table 6b Performance Comparison

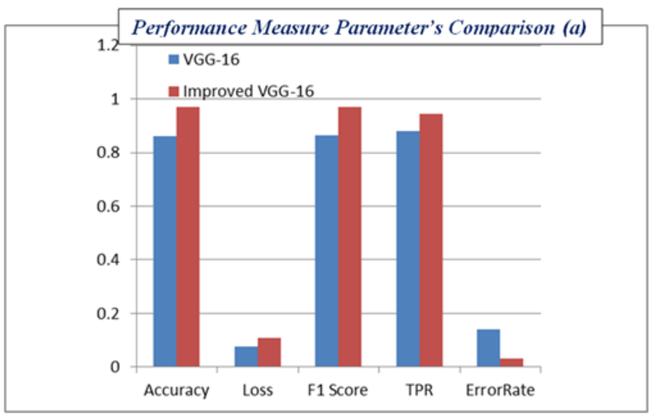

Figure 17a Performance Measure Comparison

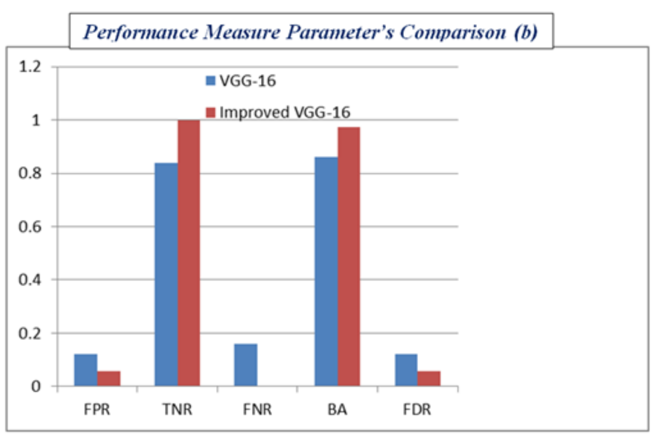

Figure 17b Performance Measure Comparison

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 VGG-16 model provides an accuracy of 86% and precision of 88% in 554 seconds whereas Improved VGG-16 model gives an accuracy of 97% and precision of 94.34% in 1490 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 increases with increase in the computation time, thereby decreases the percentage of loss as shown in above output graphs. The complete process of Improved VGG-16 model gives 97% of accuracy with computation time of 1490 seconds in GPU workstation, which is the best level of accuracy obtained compare to the work done in earlier research papers [17][21][37-38].

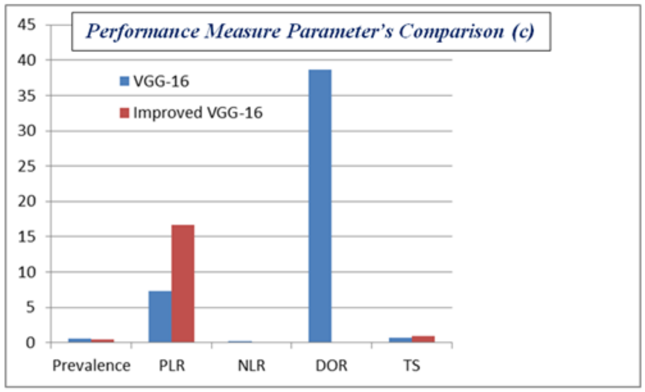

Figure 17c Performance Measure Comparison

5. CONCLUSION

In this paper, an advanced version of VGG-16 that is Improved VGG-16 Convolutional neural networks was developed for classifying the CT images of lung cancer tumor into benign and malignant. 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 and hence accuracy of an Improved VGG-16 model obtained is 97% which is the improved results comparable to the 86% accuracy of VGG-16. Thus VGG-16 gives an accuracy of 86% while an Improved VGG-16 achieved accuracy of 97%, which set the advantage of Improved VGG-16 compare to VGG-16 in lung tumor image identification and classification.

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Authors

Amjad khan received his B.E in Electronics & Communication Engineering and M.Tech in Digital Communication & Networking from Kuvempu University, Karnataka, India. He has teaching experience of 20 years at both UG and PG level in many reputed engineering colleges of Karnataka. He has published more than 20 research papers in National and International Journals. His field of interest are Image Mining, Deep Learning, Medical Image Processing, Softcomputing, Digital Communication, Computer Networks.

Dr.Zahid Ansari is working as Associate Professor in University Polytecnic, AMU, Aligarh, India. Earlier he was associated with Tata Consultancy Services R&D Center,Pune,GE-Harris Melbourne, Florida USA and San Antonio, Texas USA. He has obtained his B.E degree in Computer Science and Engineering from Govt.College of Engineering Aurangabad and M.E degree from BIT Pilani. He received his PhD degree from JNTU Kakinada He has published more than 85 Research papers in National and International Journals with impact factors. He is a reviewer of various International Journals. His field of interest are Data Mining, Soft computing, High Performance Computing and Model Driven Software Development.