JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AlexNet for Lung Cancer nodule Classification

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Abstract**—** Lung cancer is a hazardous disease which is the unrestricted growth of abnormal cells that can occur in one or both of the lungs. Identification of lung cancer is an efficient way to minimize the death rate of patients. It is a vital step to screen out the computed tomography (CT) images for pulmonary nodules for the diagnosis of lung cancer. The survival rate of lung cancer depends upon early identification of lung nodules which is a crucial process. However, due to the heterogeneity of the lung nodules and the complexity of the surrounding environment, robust nodule detection has been a challenging task. The use of machine learning to detect, predict, and classify disease has grown exponentially in the past few years, especially for complex tasks such as cancer detection and recognition. We propose a method for Lung nodule classification from Lung CT images by convolutional neural networks. This method eliminates the need of manual feature extraction which is a feedback of previous works. The network is fed with raw lung CT images from publicly available LIDC-IDRI dataset. Here, the lung images are classified into two classes such as benign and malignant. This classification is achieved with the help of Alexnet convolutional neural network. This method successfully classified the lung CT images into two classes and achieved 98% accuracy with comparatively less false positive rates.

Keywords— Lung cancer, computed tomography, Alexnet, classification

I. INTRODUCTION

Lung cancer is one of the important causes of the death among the world. As every year, it is seen that many deaths were occur due to lung cancer as compare to other types of cancer. Both men and women are being affected 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. Therefore proper timely detection and identification in the prior stage will definitely improve the level of survival and can decrease the death rate.

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 to detect and identify the various levels of lung cancer by using suitable techniques. 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. 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.

For lung cancer classification, the input image is classified as cancerous or non-cancerous after passing through Alexnet Convolutional neural networks. Alexnet is a deep learning algorithm that takes an input image, and then marks significance for each object in the image. The network further classifies each object in the image one from the other when it is trained precisely with more number of dataset. Deep learning methods needs minimum pre processing steps in comparable to the other image processing algorithms. The modified and improved version of Alexnet is enhanced Alexnet developed with the objective to achieve better accuracy. For achieving good accuracy of classification, depth of the networks, size of the Convolutional kernels and number of feature maps extracted are the three major parameters used for the design of Enhanced Alexnet network model. As the deeper the layer of network, it is able to detect high level of abstraction of features. But as the depth increases there exist a chance of increase in computation time because of large convolution operation. The preferred sizes of the convolutional kernels are either 5-by-5 or 3-by-3. The performance of the network may be reduce as the size of the Convolutional kernel increases. The organization of the paper is as follows: literature review is summarized in section II. Section III describes the details of methodology used. Section IV describes about results and discussions and section V summarizes about conclusion and future work.

II. LITERATURE REVIEW

Jiang et al. [1] proposed a Filter, Convolutional Neural Networks method they tested on 1006 samples of LIDC dataset with 90 % training and 10 % testing they got 94 % sensitivity. Disha Sharma & Gagandeep Jindal [2] has proposed an automated arrangement for identifying the lung tumor by using Computed Tomography (CT) images. The methods such as binary image slicing, Erosion, wiener filter were used to extract rigion of interest from CT image. It is shown that the system produces an sensitivity of 90% with a false positive of 0.05 per image. Besides the tumor size of diameter 3mm is determined to identify lung nodule in primary stage thereby patient's survival rate increases. Farzad Vasheghani Farahani *et al.* [3] introduced a system for the early identification of lung nodule using CT images. In this research first the lung is segmented using region growing and thresholding technique and then features were extracted CT scans such as circularity, eccentricity, compactness. In the classification phase features were used as a data for each classifier (KNN, SVM and MLP) and ensemble system, in which classifier makes its own decision and at the end majority voting is used for the combine decision of this system. Jin, Zhang and Jin [5] proposed a model which uses Convolutional neural network as classifier to identify the lung nodules. This model achieves an accuracy of 84.6%, sensitivity of 82.5% and specificity of 86.7%. Hence quality of diagnosis increases from the large dataset. Ryota Shimizu *et.al,* [6] 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. Po-Whei Huang *et.al,* [7] presented 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 collected from fractional Brownian motion model. Vaishali C.Patil [8] has presented a lung tumor recognition 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. Ailton Felix *et.al,* [9] proposed a 3D CAD System to extract texture features and 3D Margin Sharpness Features from LIDC dataset. This system classify small pulmonary nodules with diameters between 3-10mm. In this task they used three Machine Learning Algorithm: Random Forest, Multilayer Perceptron and K-Nearest Neighbor.

The classification model with MLP algorithm using the selected features achieved the highest accuracy of 82%. Rotem Golan *et.al,* [10] suggested a Deep Convolutional Neural Network which is trained using the back propagation algorithms, to extract volumetric features from dataset and identify lung nodule from CT images. This CAD system achieves a sensitivity of 78.9% with 20 false positive per scan. Sri Widodo *et.al,* [11] proposed a Principal Component Analysis for classification of pulmonary nodules and artery automatically on chest CT scan image. In this study they consider 3 steps. The first step is lung organ segmentation using Active Appearance Model, the second step is segmentation of nodule using the morphological method and the third step is to classify pulmonary nodules and artery using PCA technique. Experimental result shows that the accuracy of the classification system is 90%. Ravindranath K [12] gives early detection of lung malignancy which includes detection of an uncertain tumor. The nodule is then classify according to the different stages of the disease. The detecting stage includes image pre-processing and segmentation which increase the accuracy by using statistical classifiers, SVM and fuzzy logic classifier. Difference in the level of intensity detects the normal and abnormal tumor at the early stage. The detected tumor is then classified using neural network classifiers, which distinguish the normal and abnormal lung malignancy. Rui Xu *et.al,* [13] introduced a deep Convolutional neural based system for the lung segmentation in CT scans for both mild and severe diseases. It's not easy task for radiologist to detect lung diseases which have complex opacities in ROI. So Deep-CNN model is introduced for lung segmentation. In this complex opacities is considered as a texture based problem in which pixel is classified as one inside or outside in ROI. This problem is solved by using CNN based model. This system takes 42 computed tomography images with severe lung disease and 7 Computed Tomography images with a mild lung cancer which includes six kinds of opacities. The jacquard index of this model is more than the mostly used lung segmentation method. Anna Poreva [14] proposed the fundamental strategies of the machine learning to use them for the classification of lungs sound. Various signal parameters were used, which becomes the foundation of lungs sound data. In the lung sounds seven important factors were taken. Classification is done on two classes (healthy and sick), second class is subdivided into different subclass.

In this research various classifiers are used such as Naive Bayes classifier, decision trees, SVM, k-nearest neighbors, logistic regression. In the lung sound data decision tree classifier and SVM classifiers gives the great accuracy of decisions and results. It is assumed that with the increase in the input data, accuracy also increases. Pratiksha Hattikatti [15] proposed Convolutional Neural Network for finding the range of the lung texture pattern of diseases from computed tomography images. The term called interstitial lung disease includes various disease related to lung, characterization of lung tissue is an important element of CAD system for determining the interstitial lung diseases. The system is of five steps which include preprocessing, segmentation, feature extraction, training and followed by classification using CNN. Classification of data is done by SVM classifier and also by using CNN. The Convolutional neural network achieves accuracy of 94% with high sensitivity and same data is passed through SVM classifier which gives the accuracy of 86% only. It concludes that CNN gives more accurate results for interstitial lung diseases. Wei Chen *et al.* [16] designed a hybrid segmentation network (HSN) based CNN. They used a hybrid feature fusion module to fuse 2D and 3D features like size and volume and used those features jointly train the two CNN model. This system achieved high performance with a mean Dice core of 0.888, a mean sensitivity score of 0.0872 and a mean precision of 0.909. Pouria Moradi [17] proposed 3D Convolutional Neural Network, which can reduce the false positive rate and provide high sensitivity in detecting lung cancer. The main objective of this research is to improve classification accuracy. Researcher achieved 91.23% accuracy for 3.99 false positive per scan using the method for combining different classifiers. Sakif Rahman *et.al*, [18] proposed a lung cancer identification and prognosis method using deep neural network (DNN) which reduce the time complexity and increase accuracy. They introduced Mobile Net, VGG-8 and Inception-v3 deep neural network model for image classification. Mobile Net gives the best accuracy 97% in all the model.

From the literature review it is seen that many authors had used many techniques for classification of lung nodules to find malignant and benign images to predict and identify the lung cancer in the early stage. It is evident from the review that one of the most efficient tool to classify the cancerous images is AlexNet Convolutional neural networks and its learning features.

III. METHODOLOGY USED

A. Alexnet Network Model

An Alexnet network model is a type of feed forward neural network where the individual neurons are tiled in such a way that they respond to overlapping regions in its receptive field. It is inspired by models of the biological visual system, proposed by, and continues to be consistent with the modern understanding of the physiology of the visual system. The first computational models based on these local connectivities between neurons are found in Fukushima's Neocognitron. Fukushima found that when neurons with the same parameters are applied on overlapping regions of the previous layer, at different locations, a form of translational invariance is obtained. In addition, this limited connectivity of CNNs reduces the computational requirements necessary for their training compared to fully connected neural networks.

The architecture of a Convolutional neural network as shown in the figure.1 is a multi-layered feed-forward neural network, made by stacking many hidden layers on top of each other in sequence. It is this sequential design that allows Convolutional neural networks to learn hierarchical features. The hidden layers are typically convolutional layers followed by activation layers, some of them followed by pooling layers.

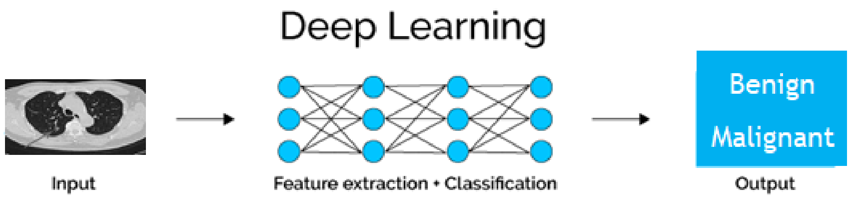


Figure 1 shows the basic CNN architecture, which consists of input, Convolutional, pooling and fully-connected layer.

1 Convolutional layer: This layer is where images are translated into feature-map data by Convolutional kernels or filters. In a 3D CNN, the kernels move through three dimensions of data (height, length, and depth) and produce 3D maps. A 3D CNN is necessary for analyzing data where temporal or volumetric context is important.

2 Pooling layer: Pooling, or down-sampling, is done on the Convolutional output. During pooling, a filter moves across the Convolutional output to take either the average or the weighted average or the maximum value. The goal of pooling layer is to progressively reduce the spatial size of the matrix to reduce the number of parameters and to control over fitting.

3 Fully-connected layer: The fundamental goal of a fully connected layer is to take the results of the convolution and pooling processes and use them to classify the image into a label. In this layer, a softmax function is used to get probabilities as it pushes the values between 0 and 1. Batch normalization is used to improve the training speed and to reduce over fitting.

A. ALEXNET

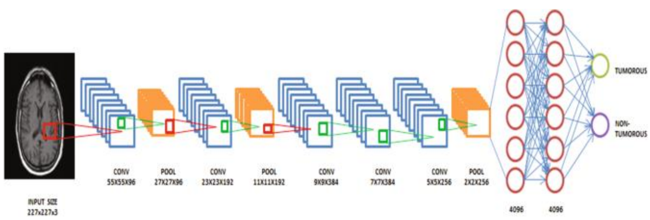


Figure 2: AlexNet for lung cancer nodule identification.

Algorithm

1. Acquire the images of lung cancer containing both diseased and non-diseased images and also, using existing dataset and augmentation technique.
2. Preprocess all the images for resize the images based on the algorithm /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 AlexNet with the help of training images
6. Test the AlexNet with the help of testing images
7. Calculate the various performance measure parameters
8. Validate the performance of the proposed model and compare the results with the other state-of-the-art approaches.

Fig.3. Algorithm for AlexNet

The proposed AlexNet architecture with block diagram shown in figure.2 mainly consists of the following layers: Five convolution layers which follows, three max- pooling layers and two fully-connected layers with softmax layer. As shown in Figure 2, the network begins with a convolution layer, in which the first convolution layer takes the image with input size of 256 × 256 pixels. The second convolution layer consists of 32 feature maps with the convolution kernel of 3 × 3. The kernel size for max pooling layers is 2 × 2 and the stride of 2 pixels, and the fully-connected layer generates an output of 1024 dimensions. These outputs are then passed to another fully connected layer containing softmax unit, which represent the probability that the image is containing the lung cancer or not. Sample experimented images of cancerous and non-cancerous are shown in Figure 4(a) and Figure 4(b).

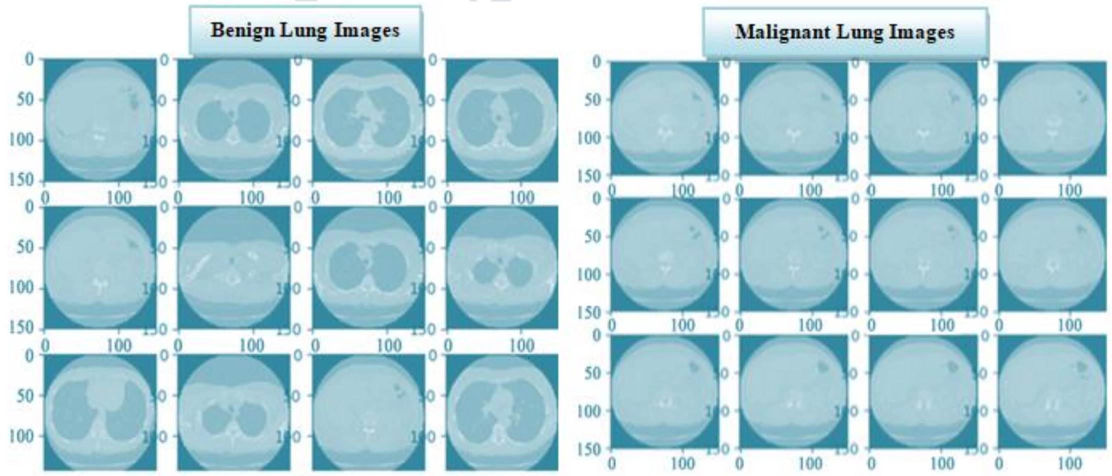


Figure.4 Experimental Images

B. Training AlexNet

Back-propagation algorithms are used to train the AlexNet using CT images of size 256x256x3. It consists of two phase, training phase and testing phase. In the first phase AlexNet are trained using CT images where 900 images are being used to train the network for the classification of lung as either cancerous or non-cancerous. In the testing phase an image unknown to the network is applied as input to classify as cancerous or noncancerous. For minimum loss of features images are trained and tested in the DICOM format itself by modifying the network parameters such that it can take DICOM images. The proposed designed network accuracy can be achieved by suitable evaluation.

C. Confusion Matrix

Confusion Matrix: A confusion matrix is formed from the four outcomes produced as a result of binary classification. A confusion matrix of binary classification is a two by two table formed by counting of the number of the four outcomes of a binary classifier. We usually denote them as TP, FP, TN, and FN instead of "the number of true positives", and so on.

	Tumor (Predicted)	Non-Tumor (Predicted)
Tumor (actual)	TP	FN
Non-Tumor (actual)	FP	TN

Confusion Matrix is the NxN table that summarizes how successful a classification Model's prediction was; that is the correlation between the label and the model's classification. One axis of a matrix is the label that the model predicted and the other axis is the actual label. Here N represents the number of classes. In a binary classification problem, N=2.

Four outcomes of classification: A binary classifier predicts all data instances of a test dataset as either positive or negative. This classification (or prediction) produces four outcomes – true positive, true negative, false positive and false negative.

D. Performance Measures 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. Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. It can also be calculated by 1 – ERR. ACC= (TP + TN) / (TP +TN +FP +FN)
- **Loss Function:** it 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:** 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. F1 = (2xPrecision.x Recall) /(Precision +Recall)
- **Sensitivity (Recall or True positive rate, TPR):** Sensitivity (SN) is calculated as the number of correct positive predictions divided by the total number of positives. Here the model correctly predicts the positive class. It is also called recall (REC) or true positive rate (TPR). The best sensitivity is 1.0, whereas the worst is 0.0. It is also called Positive Predictive Value (PPV). TPR=TP/(TP+FN)=1-FNR=Recall
- **Specificity (True negative rate (TNR)):**Specificity (SP) is calculated as the number of correct negative predictions divided by the total number of negatives. Here the model correctly predicts the negative class. It is also called true negative rate (TNR). The best specificity is 1.0, whereas the worst is 0.0.It is also called as Negative Predictive Value (NPV). TNR=TN/(TN+FP)=1-FPR=NPV
- **Precision (Positive predictive value):** Precision (PREC) is calculated as the number of correct positive predictions divided by the total number of positive predictions. It is also called positive predictive value (PPV). The best precision is 1.0, whereas the worst is 0.0. PPV=TP/(TP+FP)=1-FDR=Precision
- **False positive rate (FPR):** False positive rate (FPR) is calculated as the number of incorrect positive predictions divided by the total number of negatives. Here the model incorrectly predicts the positive class. The best false positive rate is 0.0 whereas the worst is 1.0. It can also be calculated as 1 – specificity. It is denoted by α and referred as Type I error.
- **False negative rate (FNR):** Here the classification model incorrectly predicts the negative class. This is opposite of false positive rate where the model incorrectly predicts the positive class. It is denoted as β and referred as Type II error.

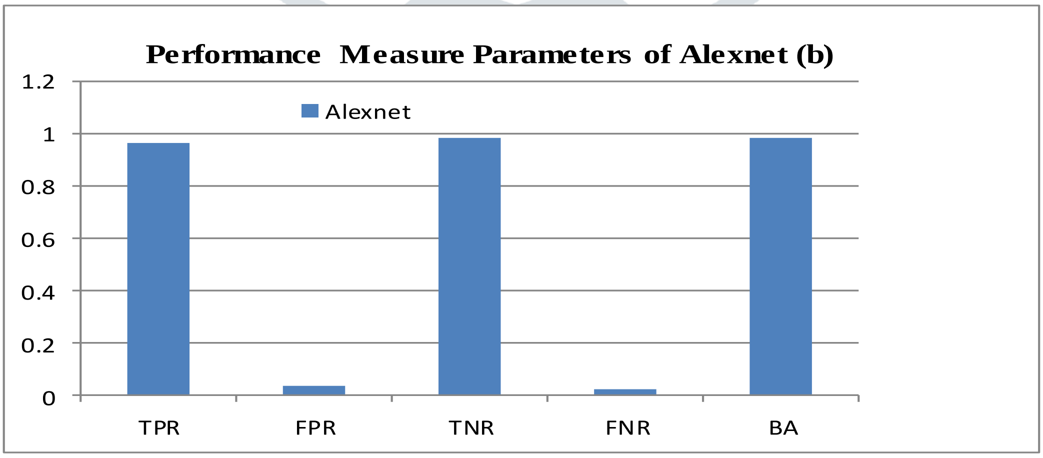
  FNR = 1- TPR = TN/(FN+TP)

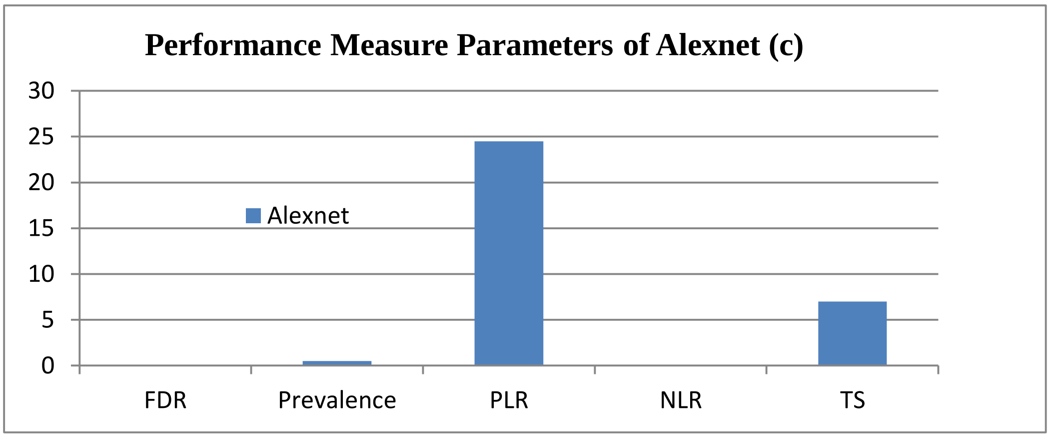
- **False discovery rate (FDR):** is a method of conceptualizing the rate of Type-I errors in null hypothesis testing when conducting multiple comparisons. It is the expected proportion of false discoveries that is incorrectly rejected null hypothesis among all discoveries. FDR=FP/FP+TP=1-PPV
- **Prevalence:** It is the ratio of positive sum and total population. Prevalence= (TP+FN) / (TP +TN +FP +FN)

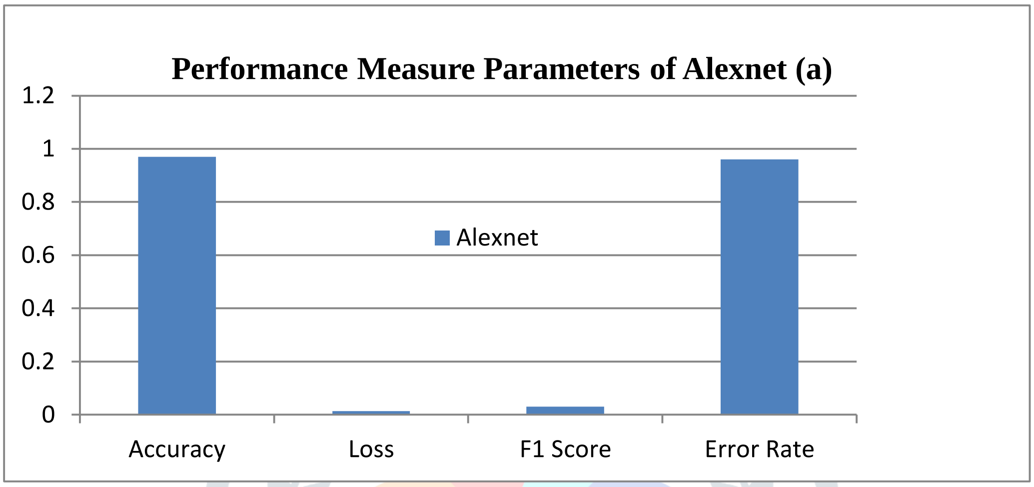
- **Positive likelihood Ratio (PLR):** PLR = Sensitivity/(1-Specificity)=TPR/(1-TNR)
- **Negative Likelihood Ratio (NLR):** NLR = (1-Sensitivity)/Specificity= (1-TPR)/TNR
- **Diagnostic Odds Ratio (DOR):** It is a measure of the effectiveness of a diagnostic test. It is the ratio of the odds of the test 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. DOR=PPV x NPV/(1-PPV)(1-NPV)
- **Balanced Accuracy (BA):** (TPR+TNR)/2
- **Threat score (TS) or critical success index (CSI):** TP / (TP + FN +FP)

VI. RESULTS AND DISCUSSIONS

The dataset used in the research work belongs to LIDC-IDRI which is the Lung Image Database Consortium image collection (LIDC-IDRI) consists of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with marked-up annotated lesions. It is a web-accessible international resource for development, training, and evaluation of computer-assisted diagnostic (CAD) methods for lung cancer detection and diagnosis [3]. This is initiated by the National Cancer Institute (NCI), further advanced by the Foundation for the National Institutes of Health (FNIH), and accompanied by the Food and Drug Administration (FDA) through active participation. Thus it will be used for training the classifier. Seven academic centers and eight medical imaging companies collaborated to create this data set which contains 1018 cases. Each subject includes images from a clinical thoracic CT scan and an associated XML file that records the results of a two-phase image annotation process performed by four experienced thoracic radiologists. In the initial blinded-read phase, each radiologist independently reviewed each CT scan and marked lesions belonging to one of three categories ("nodule > or =3 mm," "nodule <3 mm," and "non-nodule > or =3 mm"). The inputs are the image files that are in DICOM format, It is important to note that in order to preserve the original values of the DICOM images as much as possible, no scaling was applied to the CT images of the dataset. Actually, the images are of size (z × 512 × 512), where z is the number of slices in the CT scan and varies depending on the resolution of the scanner. Such large images cannot be fed directly into Convolutional neural network architecture because of the limit on the computation power. Hence it is preprocessed to reduce the size of the input data and thus segmenting the images into equal size and format. The dataset used for training and testing purposes are taken from LIDC-IDRI to get familiarize with lung cancer. Here the images samples are used to feed the network model which is able to detect and identify the presence of cancer that is cancerous images and Non Cancerous Images.







In this research work, Lung nodule classification has been implemented in MATLAB 2018b and the dataset used for training and testing purposes are taken from LIDC-IDRI to get familiarize with lung cancer. Here the images samples are used to feed the network model which is able to detect and identify the presence of cancer that is cancerous images (Malignant Images) and Non Cancerous Images (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 AlexNet gives 97% of accuracy with computation time of 410 seconds which is the best level of accuracy obtained compare to the work done in earlier research papers [19][20].

V. CONCLUSION AND FUTURE WORK

In r research work, Alexnet Convolutional neural networks for classifying the CT images of lung into cancerous (malignant) and non-cancerous (benign) were used. 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 our research work belongs to LIDC dataset. Hence an accuracy of 97% is achieved. The high false positive is particularly indicative of this issue even though the accuracy is good. AlexNet's strength lies in its ability to identify diverse and wide ranging objects in images but it stumbles when faced with less diversity and a more subtle classification problem.

REFERENCES

[1] Makde et al., Deep Neural Network Based Classification of Tumorous and Non-tumorous Medical Images, Information and Communication Technology for Intelligent Systems (ICTIS 2017) - Volume 2, Smart Innovation, Systems and Technologies 84, DOI 10.1007/978-3-319-63645-0 22.

[2] Hiroyuki Sugimori, Classification of Computed Tomography Images in Different Slice Positions Using Deep Learning, Hindawi Journal of Healthcare Engineering Volume 2018, Article ID 1753480, 9 pages https://doi.org/10.1155/2018/1753480,pages1-9.

[3] Joel Than Chia Ming1, Norliza Mohd Noor2, Omar Mohd Rijal3 , Rosminah M. Kassim4 , Ashari Yunus5., Lung Disease Classification using Different Deep Learning Architectures and Principal Component Analysis, 2018 2nd International Conference on BioSignal Analysis, Processing and Systems (ICBAPS), 978-1-5386-1278-1/18/187-190 ©2018 IEEE.

[4] J. T. C. Ming, O. M. Rijal, R. M. Kassim, A. Yunus, and N. M. Noor, "Texture-based classification for reticular pattern and ground glass opacity in high resolution computed tomography Thorax images," in Biomedical Engineering and Sciences (IECBES), 2016 IEEE EMBS Conference on, 2016, pp. 230–234.

[5] M. Awais, H. Muller, and F. Meriaudeau, "Classification of SDOCT images using Deep learning approach," in 2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA), 2017, pp. 3–6.

[6] R. Hooda, S. Sofat, S. Kaur, A. Mittal, and F. Meriaudeau, "Deep learning: A potential method for tuberculosis detection using chest radiography," in 2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA), 2017, pp. 497–502.

[7] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv Prepr. arXiv1409.1556, 2014.

[8] N. Tajbakhsh, J. Y. Shin, S. R. Gurudu et al., "Convolutional neural networks for medical image analysis: full training or fine tuning," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1299–1312, 2016.

[9] Yuechao Zhang, Jianxin Zhang, Lasheng Zhao1, Xiaopeng Wei1, Qiang Zhang, Classification of Benign and Malignant Pulmonary Nodules Based on Deep Learning, 2018 5th International Conference on Information Science and Control Engineering,978-1-5386-5500-9/18/156- 60, ©2018 IEEE, DOI 10.1109/ICISCE.2018.00042.

[10] S.G. Armato, G. McLennan, L. Bidaut, M.F. McNitt-Gray, C.R. Meyer, A.P. Reeves, et al., The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): a completed reference database of lung nodules on CT scans, Medical Physics 38 (2) (2011) 915–931, https://doi.org/10.1118/1.3528204.

[11] J.-P. Charbonnier, E.M. van Rikxoort, A.A.A. Setio, C.M. Schaefer-Prokop, B. van Ginneken, F. Ciompi, Improving airway segmentation in computed tomography using leak detection with convolutional networks, Medical Image Analysis 36 (2017) 52–60, https://doi.org/10.1016/j.media.2016.

[12] Ravindranath K , K Somashekar, "Early Detection of lung cancer by nodule extraction – A Survey", International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT), 2017.

[13] Rui Xu, Jiao Pan, Xinchen Ye, Yasushi Hirano, Shoji Kido, Satoshi Tanaka "A Pilot Study to Utilize a Deep Convolutional Network to Segment Lungs with Complex Opacities" Chinese Automation Congress (CAC), 2017

[14] Wei Chen, Haifeng Wei , Jiawei Sun ,Xu Qiao , Boqiang Liu, "Hybrid Segmentation Network for Small Cell Lung Cancer Segmentation" IEEE Access, vol. 7, pp. 75591 - 75603, June 2019.

[15] Moradi, P. & Jamzad, M., "Detecting Lung Cancer Lesions in CT Images using 3D Convolutional Neural Networks". 4th International Conference on Pattern Recognition and Image Analysis, 2019.

[16] Md. Sakif Rahman, Pintu Chandra Shill, Zarin Homayra, "A New Method for Lung Nodule Detection Using Deep Neural Networks for CT Images". International Conference on Electrical, Computer and Communication Engineering (ECCE), 2019.

[17] Pathan, A. and Saptalkar, B.K. (2012) Detection and Classification of Lung Cancer Using Artificial Neural Network. International Journal on Advanced Computer Engineering and Communication Technology , 1, 2278-5140.

[18] Dandil, E., Cakiroglu, M., Eksi, Z., Özkan, M., Kurt, Ö.K. and Canan, A. (2014) Artificial Neural Network-Based Classification System for Lung Nodules on Computed Tomography Scans. 6th International Conference of Soft Computing and Pattern Recognition, Tunis, 11-14 August 2014, 382-386.

https://doi.org/10.1109/SOCPAR.2014.7008037

[19] Qaisar Abbas, "Nodular-Deep: Classification of Pulmonary Nodules using Deep Neural Network," International Journal of Medical Research & Health Sciences", vol. 6, pp. 111-118, 2017.

[20] Worawate Ausawalaithong, Arjaree Thirach, Sanparith Marukatat, Theerawit Wilaiprasitporn, "Automatic Lung Cancer Prediction from Chest X-ray Images Using Deep Learning Approach," arXiv:1808.10858v1 [eessIV], August 2018.

[21] Brett A. Simon, Gary E. Christensen, […], and Joseph M. Reinhardt. "Computed Tomography Studies of Lung Mechanics", American Thoracic Society, 2005.

[22] S. M. Salaken, A. Khosravi, A. Khatami, S. Nahavandi, and M.A. Hosen, "Lung cancer classification using deep learned features on low population dataset," In Electrical and Computer Engineering (CCECE), IEEE 30th Canadian Conference, pp.1−5 , IEEE, 2017.

[23] Siddharth Bhatia, Yash Sinha and Lavika Goel, "Lung Cancer Detection: A Deep Learning Approach", Soft Computing for Problem Solving, Advances in Intelligent Systems, 2019.

[24] Yutong Xie ,Yong Xia , Jianpeng Zhang ,Yang Song , Dagan Feng , Michael Fulham , Weidong Cai, "Knowledge-based Collaborative Deep Learning for Benign-Malignant Lung Nodule Classification on Chest CT" IEEE Trans. Med. Imag., vol. 38, no. 4, pp. 991 - 1004, April. 2019.

[25] M. Gomathi , Dr. P. Thangaraj "Automated CAD for Lung NoduleDetection using CT Scans" 2010 International Conference on Data Storage and Data Engineering.

[26] Song QZ, Zhao L, Luo XK, Dou XC. Using deep learning for classification of lung nodules on computed tomography images. J Healthc Eng 2017;2017. http://dx.doi.org/10.1155/2017/8314740