Lung Cancer Detection using 3D CNN

Dr. S Ayyasamy

Ayyasamy.S@reva.edu.in

Koushik R

R18CS189@cit.reva.edu.in

Manjunath S

R18CS216@cit.reva.edu.in

Manoj S

R18CS217@cit.reva.edu.in

Kushal P

R18CS197@cit.reva.edu.in

Abstract:

Lung cancer detection is an effective technique to reduce mortality rates and increase patient survival rates. Screening computed tomography (CT) scans for pulmonary nodules is a pivotal step in the effective treatment of lung cancer. Due to the complexity of the surrounding environment and the variety of the lung nodules, robust nodule identification and detection is a key task. In the recent years, the utilization of machine learning to identify, forecast, and categorize illness has exploded, particularly for complicated tasks like detecting and identifying lung cancer. 3D Convolutional Neural Networks (3DCNNs) have risen in prominence as a method of revolutionizing research in machine learning. In this study, we use a 3D Convolutional Neural Network for classifying lung cancer utilizing CT scan images from the IQ-OTHNCCD lung cancer dataset for identifying malignant and noncancerous lung nodules and assessing classification accuracy.

Keywords: Computer Vision, Lung Cancer, DCNN, Computed Tomography

I. INTRODUCTION

One of the major causes of increased fatality rates throughout the world is lung cancer, with many more fatalities occurring each year owing to lung cancer than from other forms of cancer. This terrible illness affects both men and women equally. As a result, adequate procedures for early detection and identification of this disease should be adopted in order to help and save people's lives. The survival rate of a large number of patients can be enhanced if it is diagnosed and identified in the early stages. After a condition has been identified, offering correct diagnosis can help patients live longer. Thus, increasing the quantity of duplication for the methods utilized will increase classification accuracy by utilizing new machine learning approaches in the medical image processing domain in order to produce a suitable and quick result. Consequently, quick diagnosis and identification in the early stages of the disease will almost certainly enhance the degree of survival and lower the death rate.

Images from computed tomography (CT), magnetic resonance imaging (MRI), and mammography were employed in the bulk of the early studies. The expert doctors in this field analyses these photographs with proper instruments in order to detect and diagnose various degrees of lung cancer. Among the laboratory and clinical approaches employed are treating using chemicals to kill or suppress malignant cell duplications, chemotherapy, and radiation therapy. All of the methods for detecting and diagnosing cancer problems are tedious, pricey, and inconvenient for the patients. To solve all of these challenges, appropriate machine learning algorithms for analyzing medical images, including CT scan data, were used. When compared to other diagnostic imaging such as MRI and X-Ray, CT scan images are selected over other images because they have lesser noise.

In the process of lung cancer classification, the pictures applied at the input layer of Deep Convolutional neural networks are labelled as malignant or non-malignant at the output layer after processing in all the hidden layers of the network. DCNN is a deep learning system that accepts input in the form of an image and assigns importance to each item in the image. When the network has been trained with a large number of datasets, it may further classify each item in the image. In comparison to other image processing techniques, deep learning approaches need the fewest pre-processing steps. The goal of DCNN is to transform input pictures into processing-ready formats with the least amount of image feature loss possible to attain the highest degree of accuracy. To develop and increase classifying accuracy in the DCNN, the filter size, the number of invisible layers, and the obtained number of feature maps are all used. As the network layers get more complex, a higher detection level and a higher level of feature abstraction may be attained. Due to the increased number of Convolutional operations, the deeper the network, the longer it takes to compute. Convolutional filters of 3 x 3 or 5 × 5 dimensions are the most suited. The network's performance may degrade as Convolutional kernel’s size becomes greater. The following is an overview of the structure of the paper: Section II describes the literature review, Section III summarizes the methods employed in depth, Section IV discusses the findings and comments, while Section V sums up the conclusion and future work.

II. LITERATURE SURVEY

With 1006 photos from the LIDC dataset [1] the Convolutional neural network was utilized for classification, yielding 94 percent accuracy with 90% training and 10% testing images. The author [2] proposes using computed tomography scans to identify lung nodules, with a sensitivity of 90% and a greater patient survival rate. Employing techniques such as the wiener filter and picture slicing, the region of interest is extracted. The 3mm nodule size is used to detect cancerous nodules in the lung still in the early stages.

The author [3] suggested a process to categorize nodules of the lung using Computed Tomography scan images, in which the scanned lung is sub-divided using thresholding and region growth techniques, and image characteristics are retrieved as a result. The collected characteristics were fed into several classifiers, such as the support vector machine and the KNN, which subsequently determined and classified benign and malignant pictures. For recognizing lung nodules, the author suggests a Convolutional neural network classifier [5], which has an accuracy of roughly 84.6 percent 82.5 percent sensitivity and 86.7 percent specificity are also reached. It should be highlighted that as the dataset size grows, so will the degree of illness treatment. The author offers a model [6] that uses deep learning and neural network methods to detect malignant parts of the lung; the model has a classification accuracy of around 90%, but it fails to determine the kind and type of cancer sickness. The author [7] proposes a model that uses a support vector machine to detect benign cancerous and non-cancerous images from CT scans, with an accuracy of 83 percent. The fractal features acquired from the Brownian motion model are used to categorize the objects. In model [8] identification of cancerous nodules in lungs from computed tomography scans, employs a variety of classifiers to detect the malignancy, including support vector machine classifiers, which enhance efficiency and hence lower error rate.

The author [9] described a method that uses the LIDC dataset to classify cancerous nodules in lungs according to their size, which ranges from 3mm to 10mm. Methods such as Random Forest and K-Nearest Neighbor in Machine Learning are used in the system. to achieve an accuracy of 82 percent in categorization. To categorize cancerous and benign pictures, a Deep CNN was trained using computed tomography scans from the dataset

LIDC. Using back propagation methods to extract picture information, the network achieves a sensitivity of 78.9%. Using CT scans, the author [11] developed a categorization model based on principal component analysis that achieves an accuracy of roughly 90%. A lung organ is used in the model. As a first step, segmentation of lung nodule is performed, followed by categorization of malignant and non-cancerous nodules. In the final phase, we'll look at malignant photos. The technology detects the malignancy of illness in its early stages [12] by analyzing the data by enduring various stages of the illness. Preprocessing and detection are the first steps in the detecting phase. Support vector machine and fuzzy logic are used in segmentation to increase classification accuracy. The classifier recognizes and categorizes pictures as benign or harmful based on their degree intensities.

Lung segmentation in CT images was done employing a CNN [13] that utilized deep learning techniques. Because lung cancer scans show varying degrees of opacities in the region of interest, the radiologist faces a difficult problem in identifying malignancy. The deep CNN model can help with this task. This is a texture-based issue that uses 42 CT pictures with high and low levels of malignancy. [14] To categorize lung pictures, machine learning approaches are used. Deep learning approaches can help to improve classification accuracy, allowing for the categorization of malignant and non-cancerous images. Different classifiers, such as SVM's and decision trees, were used in the research [15]. Different classifiers were used in the study [15], including decision trees and support vector machines, because they give greater classification accuracy. Large data input photos at the network model's input can boost classification accuracy even further. The model has a 94 percent accuracy when using a Convolutional neural network classifier, and an 86 percent accuracy when using an SVM classifier. In comparison to these classification results, CNN outperforms the Support Vector Machine classifier.

The network-based hybrid segmentation CNN [16] is a tool for training CNN models with both 2D and 3D data. This model performs well, with an accuracy of 88 percent, sensitivity of 87.2 percent, and precision of 90.9 percent. The author suggests using a Convolutional Neural Network [17] to reduce false positives and improve sensitivity in detecting lung cancer illnesses from CT scans. It was possible to reach a classification accuracy of 91.23 percent. Using a deep neural network [18], the suggested technique improves accuracy by 97 percent and so minimizes time sophistication with increased accuracy by applying MobileNet. According to the literature study, numerous scientists employed a variety of strategies for classifying lung nodules in order to locate malignant and benign pictures that may be used to predict and diagnose lung cancer in its early stages. CNN and its deep learning features are clearly one of the most potent techniques for classifying malignant photos, as evidenced by the review. Deep

Convolutional Neural Networks are formed when a Convolutional neural network uses deep learning techniques to classify malignant pictures (DCNN). To do additional calculations, Deep CNN employs several hidden layers, Convolutional layers, SoftMax layers, and fully connected layers. Because it utilizes several hidden layers, Deep CNN performs the classification operation effectively and takes more time to compute. The main functionalities of DCNN are feature extraction and classification.

III. METHODOLOGY USED

A. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of feed forward neural network inspired by biological visual system models [15], in which individual neurons are lined in such a way that they respond to overlapping regions in its receptive field and continues to be reliable with modern perceptions of image system structure [21]. Translational invariance is achieved when neurons with the same parameters are applied to overlapping portions of the previous layer at various places.

This makes it possible for CNNs to detect objects in their receptive field regardless of their size, location, orientation, or other visual features. In addition, as compared to fully connected neural networks, CNNs have less constrained connectivity, which reduces the computational requirements of training [26]. The figure depicts the architecture of a convolutional neural network. 1 is a multi-layered feed-forward neural network that is created by stacking multiple hidden layers on top of one another in a sequential order. Convolutional neural networks may learn hierarchical features because to their sequential construction. Convolutional layers are usually followed by activation layers, with some of them being followed by pooling layers.

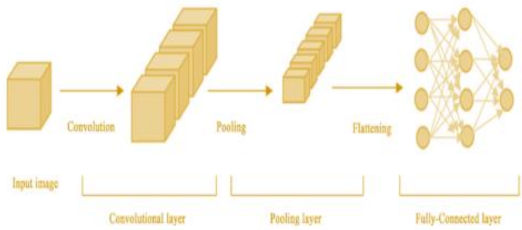

Figure 1: Architecture of CNN

The basic components of the CNN structure are shown in figure-1, which consist of 3 main layers: input, convolutional, pooling, and completely-linked.

The Convolutional layer- This layer combines input photos of a selected size, which can be appropriate for network training, with filters or convolutional kernels to produce function maps. These filters on this layer had been changed approximately in the dimensions.

Pooling layer- The reason behind this layer is to reduce the dimensions of the matrix and minimise the parameters, subsequently down sampling the characteristic maps of the Convolutional layer A sliding filter across the output of the Convolutional layer is used to calculate the most common or weighted average.

Layer that is completely linked - The motive of this deposit is to locate and label the pixel that arise from the preceding two layers. This accretion makes use of the SoftMax layer to become aware of the possibilities of values between 0 and 1 because it makes use of the SoftMax layer to determine the likelihood of values among 0 and 1. The Batch normalisation is likewise used to growth the schooling price and reduce overfitting.

Deep CNN can come across two kinds of lung most cancers: non-small cellular lung most cancers and small mobile lung most cancers. The primary class provides pre-processing sports important for DCNN to train and analyze photographs and extract functions. The second one category sorts via the CT scans and determines if the nodule is benign or malignant.

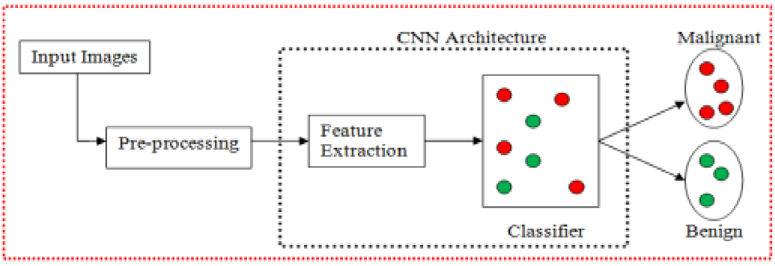

Fig.2. DCNN for lung cancer nodule identification.

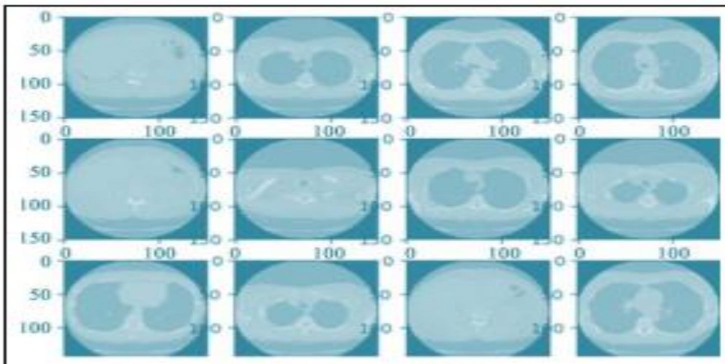

Figure 3(a) Benign Images

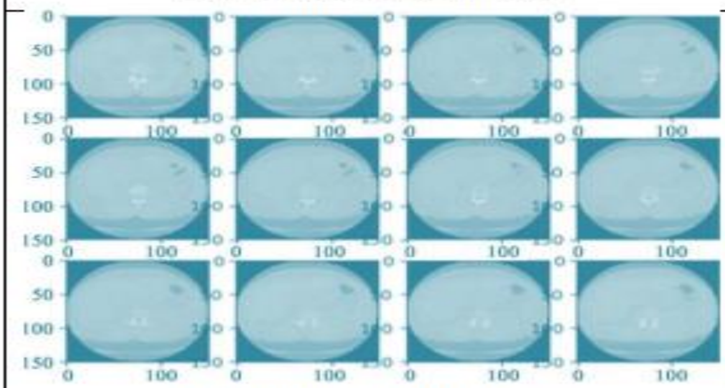

Figure3(b) Malignant Images

Figure.3 Experimental Images

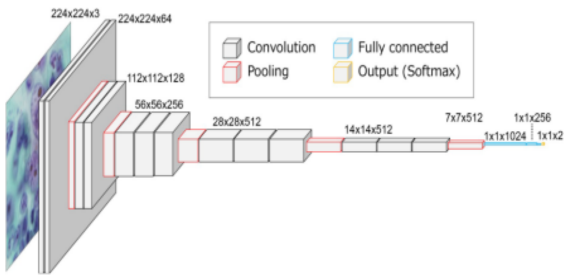

Fig.4. Architecture of Deep CNN

B. Training a deep convolutional neural network

The Deep CNN is skilled with 256x256x3 CT snap shots the use of returned-propagation methods. its miles divided into phases, education and trying out. DCNNs are educated the use of the CT scans in the first segment, with 900 photographs utilised Train the network for lung cancer classification.

During the checking out process, the community is given an unknown photo to assess as cancerous or non-cancerous.

by way of converting the community parameters so that it may take DICOM pics, images are educated and evaluated within the DICOM layout for minimal lack of features. The counseled planned community accuracy may be executed by using suitable evaluation.

C. Performance Measure parameters:

Accuracy, Loss, and Computation Time are performance evaluation metrics that may be used to assess a clinical photo's performance. When analyzing a model, accuracy is a crucial overall performance metric statistic to recollect. It reports the number of pixels from the given photograph that had been effectively categorized.

Loss Function: Loss, as determined by Loss, can predict the neural network's mistake. Another network performance measure parameter is this one.

Computation Time: How long it takes a method to finish its calculations or movements. It takes less time to technique a simple process than it does to manner a complicated technique, which takes longer to compute.

IV. Outputs and Discussions:

The Lung photograph Database Consortium's (LIDC-IDRI) photo series is a worldwide dataset.

a diagnostic and assessment tool for lung cancer it's made of 1018 DICOM-formatted CT scans.

The actual pictures are 512 512 pixels in length, but due to the fact schooling massive images in DCNN is tough, preprocessed photos have been utilized as a substitute.

To make the images extra community-pleasant, reduce their size. As a result, education and trying out photos are segregated.

comparing the community for correct photo type into malignant and non-cancerous pictures and helping in order to diagnose the patient early on [5][6].

The Deep CNN model is fed the input pix from the furnished dataset, that's skilled the usage of ninety% of the training images. Following education, the model is evaluated with

10% of the same dataset's testing photograph dataset. The photos are fed into a network model that classifies them as cancerous or non-cancerous.

TABLE.1 (a) DCNN Results

Resultant Curves of Deep CNN for 900 CT Images (A)		
Epoch	*Loss*	*Accuracy%*
1	0.8171	48.44
13	0.0336	100
25	0.0108	100
38	0.0091	100
50	0.0051	100
63	0.0033	100
75	0.0037	100
88	0.0024	100
100	0.0028	100
113	0.0019	100
125	0.0023	100
138	0.0015	100
150	0.0019	100
163	0.0013	100
175	0.0016	100
188	0.0011	100
200	0.0014	100
213	0.0014	100
225	0.0010	100
238	0.0013	100
250	0.0009	100

records on computing time, loss, and accuracy received from empirical work on a CT image dataset are shown within the table. b (c)

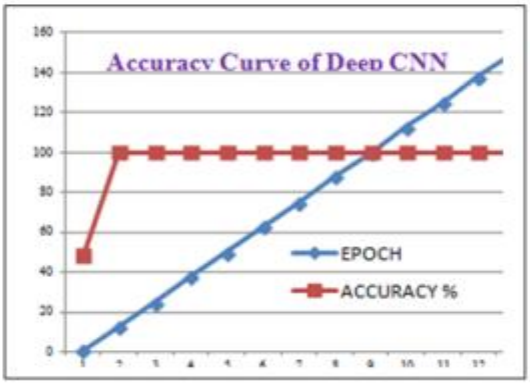

Figure.5 Epoch Verses Accuracy Curve

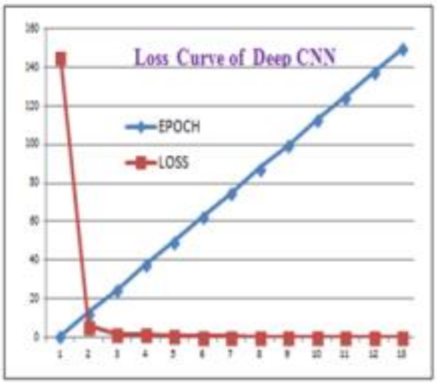

Figure.6 Epoch verses Loss Curve

To familiarize oneself with lung cancer, we used MATLAB 2018b to implement lung nodule class, and the dataset used for education and trying out became obtained from LIDC-IDRI. The pictures are fed into a network version that may locate and distinguish between malignant (Malignant snap shots) and non-cancerous (non-Cancerous pics) pics (Benign photographs). As may be seen from the results, type accuracy improves as computation time will increase, minimizing the proportion of loss as validated in the output graphs above.

With a computation time of 45,141 seconds, on a single CPU workstation, DCNN achieves 100 percent accuracy, which is higher than previous research articles [19][20]. For training and assessment, 900 CT images were used in this study, which is a bigger number than in previous studies [21][22].

Accuracy (%)	Year	Citation
78.9	2017	[10]
82	2016	[9]
83.11	2016	[7]
84.6	2016	[5]
90	2011	[2]
90	2016	[6]
90	2017	[11]
90	2019	[16]
91.23	2019	[17]
94	2017	[15]
94	2018	[1]
97	2016	[19]
97	2019	[18]
98	2014	[20]

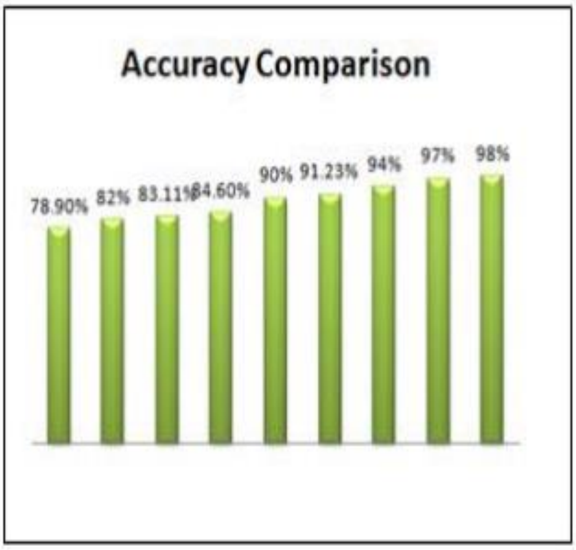

Figure.15 Comparison of Accuracy from Literature Review

Table. Three depicts the accuracy % stage from the numerous papers inside the literature assessment, with graphical illustration in figure.15, and figure.14 compares the accuracy of previous publications and the counseled method. This model changed into created the use of a computer with a 2.20 GHz Intel center i3-2330M CPU, four GB RAM, and a sixty-four-bit home windows 10 working system. As a result, categorization accuracy has increased, surpassing [19] [20].

CONCLUSION AND SCOPE FOR FUTURE WORK

In our study, deep Convolutional neural networks were used to classify CT images of lung nodules into carcinogenic (malignant) and non-carcinogenic (benign) categories. Preprocessing was done prior to inserting input CT scan images to the network model to verify that the images were of comparable size and format. The dataset that we used in our research is part of the IQ-OTHNCCD dataset. As a result, we attained a precision of 100 percent, which is superior to the results of earlier study articles. The tests could be repeated using Deep CNN architecture for various forms of cancer in the future.

1. REFERENCES

1. Jiang, H., Qian, W., Gao, M., Li, Y. “An automatic detection system of lung nodule based on multigroup patch-based deep learning network” IEEE Journal of Biomedical and Health Informatics,22(4):1227-1237.

2. Disha Sharma, Gagandeep Jindal, “Identifying Lung Cancer Using Image Processing Techniques”, International Conference on Computational Techniques and Artificial Intelligence, pp. 116-120, 2011.

3. Farzad Vasheghani Farahani “Lung Nodule diagnosis from CT images Based on Ensemble Learning.” IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology, 2015.

4. Atsushi Teramoto at el. “Automated classification of benign and malignant cells from lung cytological images using deep convolutional neural network” Informatics in medicine unlocked 16,2019,100205 elsvier.

5. Xin-Yu Jin, Yu-Chen Zhang, Qi-Liang Jin “Pulmonary Nodule Detection Based on CT Images Using Convolution Neural Network.” 9Th International Symposium on Computational Intelligence and Design. 2016.

6. Ryota Shimizu, Shusuke Yanagawa, Yasutaka Monde, Hiroki Yamagishi,Mototsugu Hamada, Toru Shimizu, and Tadahiro Kuroda “Deep Learning Application Trial to Lung Cancer Diagnosis for Medical Sensor Systems” International Symposium on Computers and Communications, 2016.

7. Po-Whei Huang, Phen-Lan Lin, Cheng-Hsiung Lee, C. H. Kuo, “A Classification System of Lung Nodules in CT Images Based on Fractional Brownian Motion Model”, IEEE International Conference on System Science and Engineering, July 2016.

8. Vaishali C. Patil, Shrinivas R. Dhotre, “Lung Cancer Detection from Images of Computer Tomography Scan”, International Journal of Advanced Research in Computer and Communication Engineering, Vol. 5, Issue 7, July 2016.

9. Ailton Felix, Marcelo Oliveira, Aydano Machado, Jose Raniery, “Using 3D Texture and Margin Sharpness Features on Classification of Small Pulmonary Nodules” ,29th SIBGRAPI Conference on Graphics, Patterns and Images, 2016.

10. Rotem Golan, Christian Jacob, Jorg Denzinger, “Lung nodule detection in CT images using deep convolutional neural networks” International Joint Conference on Neural Networks , 2017.

11. Sri Widodo, Ratnasari Nur Rohmah, Bana Handaga,

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 , 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 , 2017.

14. Anna Poreva, Yevgeniy Karplyuk, Valentyn Vaityshyn, “Machine Learning Techniques Application for Lung Diseases Diagnosis” , 5th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering , 2017.

15. Pratiksha Hattikatti, “Texture based Interstitial Lung Disease Detection using Convolutional Neural Network”, International Conference on Big Data, IoT and Data Science , 2017.

16. 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.

17. 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.

18. 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 , 2019.

19. Golan, R., Jacob, C. and Denzinger, J, “Lung Nodule Detection in CT Images Using Deep Convolutional Neural Networks”, International Joint Conference on Neural Networks, Vancouver, 24-29 July 2016, 243- 250. Identification of Lung Cancer Using Convolutional Neural Networks Based Classification 203

20. Kaur, J., Garg, N. and Kaur, D, “An Automatic CAD System for Early Detection of Lung Tumor Using Back Propagation Network”, International Conference on Medical Imaging, m-Health and Emerging Communication Systems , Greater Noida, 7-8 November 2014, 257-261.

21. Pathan, A. and Saptalkar, B.K, “Detection and Classification of Lung Cancer Using Artificial Neural Network”, International Journal on Advanced Computer Engineering and Communication Technology , 1, 2278-5140,2012.

22. Ahmed, S. T., Kumar, V. V., Singh, K. K., Singh, A., Muthukumaran, V., & Gupta, D. (2022). 6G enabled federated learning for secure IoMT resource recommendation and propagation analysis. *Computers and Electrical Engineering*, *102*, 108210.

23. Basha, S. M., Janet, J., Balakrishnan, S., Ram, S., Ramasubbareddy, S., Iyengar, S. N., & Ch, N. (2022). Impact of Early Termination of Lockdown and Maintaining Social Distancing: COVID-19. In *How COVID-19 is Accelerating the Digital Revolution* (pp. 1-15). Springer, Cham.