© March 2023| IJIRT | Volume 9 Issue 10 | ISSN: 2349-6002

Artificial Intelligence Based Lung Cancer Detection Using Deep Learning Techniques

Dr.S.Pathur Nisha [1], S.Srividhya[2], Dr V S Thangarasu[3]
[1]*Professor /CSE , Nehru Institute of Technology, Coimbatore*
[2] *PG Student (M.E- CSE), Nehru Institute of Technology, Coimbatore*
[3]*Professor/ Mechanical, Indra Ganesan College of Engineering, Tiruchirappalli*

Abstract-The majority of deaths in both men and women are caused by lung cancer, one of the deadliest cancers in the nation. 10% to 20% of lung cancer patients only have a five-year survival rate. The death rate can be reduced, though, if lung cancer is found early and treated right away. It is a highly challenging assignment for radiologists, but many nations have developed screening programmes to promote early identification of lung cancer from Computed Tomography (CT) pictures. It takes a lot of time to manually identify malignant lung nodules from these CT pictures. The clinical response to therapy may differ and can have a very favourable response when lung cancer is discovered early during the screening phase. A trustworthy, automated method may be very beneficial in both rural and early-stage lung cancer identification. A recent development in medical image analysis, particularly for lung cancer, is deep learning. The focus of the work that has been presented is on fusing clinical practises with deep learning algorithms to help radiologists diagnose pulmonary nodules and eliminate most false-negative images in lung cancer screening. The availability of a vast amount of data for training and testing is the primary factor contributing to the higher success rate of deep learning algorithms in medical imaging. A variety of datasets are available for the detection of lung cancer nodules, enabling deep learning to boost screening operations' efficiency and ultimately contributing to a decrease in lung cancer mortality and benefiting individuals in remote areas. Numerous studies have been done on identifying and classifying lung cancer, but the precision needed to apply such models for clinical applications and for radiologists to diagnose the carcinoma remains a significant barrier. The goal of transfer learning is to transfer information from one domain to another. It is a deep learning approach where characteristics from the source problem are applied to a different but related target problem. For achieving better accuracy, the research work presented functioning of pre-trained models MobileNet, Xception and VGG-16 for finding of lung cancer nodules from lung CT images. The dataset was collected from the LIDC-IDRI dataset. The achieved accurateness of the implemented pre-trained models is 98%, 97.97% and 96.95% respectively.

Index Terms: Convolution Deep Learning, Lung Cancer Detection, and Neural Network

1. INTRODUCTION

Cancer is still viewed as a serious illness with a high mortality rate. Comparing all cancers, lung cancer has the highest mortality rate or death rate [1, 2], and it is thought to be the deadliest carcinoma globally [3]. As a result, many researchers are concentrating on techniques for spotting lung cancer nodules in digital images, particularly Computed Tomography (CT). The use of X-rays in CT scans produces many pictures, making it difficult for radiologists to identify minute nodules from these images [4]. The fundamental task carried out by the radiologist for the diagnosis of lung cancer is the analysis and interpretation of nodules. To reduce time and money, several scientists and researchers are creating automated medical procedures [5–9]. In the majority of cases, the size and appearance of nodules—which can be classed as benign or malignant—provided the first sign of malignancy. When a lung nodule measures less than 3 cm in diameter, it is normally considered benign; when it measures more than 3 cm, it is considered cancerous or a lung mass. Figures 1 and 2 provide illustrations of benign and malignant lung cancer, respectively.

Cancer risk can be calculated based on nodule classification and other data. The primary level identification and categorization of distinct cancer kinds is where AI approaches play a significant role [10–14]. In recent years, deep learning (DL) models have been applied in a variety of industries, such as games, agriculture, and medical [15]. In all of these areas, DL models perform admirably, especially in particular types of applications like picture segmentation, object recognition, and image classification [16–17]. DL is a branch of artificial intelligence that uses networked nodes to carry out challenging tasks. DL algorithms are able to learn from training data rather than using pre-programmed instructions [13]. Deep learning has previously been used by many researchers to identify cancer.

Due to their exceptional performance, convolutional neural networks (CNNs) have lately grown in prominence in the machine learning sector. Neurons with programmable weights and biases make up CNNs. This method is based on the artificial neural network (ANN) structure, which was modelled after the biological neuron. The fact that CNNs learn filters on their own gives them an advantage over conventional neural networks. The learnable filters that make up the CNN layer parameters enable the system to adapt to new problems. These filters use a convolutional method to extract spatial information from the incoming data. Because of this, CNNs excel at a variety of tasks, including object detection, video analysis, speech recognition, natural language processing, and medical image analysis . However, CNNs frequently need a large amount of training data in order to prevent overfitting. CNN classifies the images using a series of convolutional and pooling layers. Regardless of the spatial information, or where the object is actually located in the image, the pooling layer in CNN minimises the dimension and classifies the object [12]. The benefit and the disadvantage of CNN's pooling feature are both present. Some crucial information that is crucial for object detection and image segmentation is lost during the pooling operation.

II. RELATED WORKS

Machine learning algorithms deliver exceptional outcomes in computer vision technologies and medical picture analysis. Massive training artificial neural networks (MTANNs) and revolutionary neural networks are two forms of artificial neural networks that can be trained end to end (CNNs). End-to-end learning makes it possible to directly map unprocessed data into required features, doing away with the requirement for manually created features. In order to compare these two classes of end-to-end learning for the detection of lung nodules and differentiation between benign and malignant tumours in low-dose CT scans, Nima Tajbakhsh et al. adopted a theoretical and practical technique. For the analysis, the authors used two CNN architectures and four MTANN designs, all of which have different depths. The authors of this study tested their theories in two distinct situations. In the initial phase, they trained MTANNs and CNNs using a small or constrained dataset, and then evaluated their performance. Their research suggests that MTANN performs better with a smaller dataset. In the second phase, they used a large dataset to train CNN, and the results point to a narrower performance gap between MTANN and CNN. They used both theoretical and practical methods to show that MTANN outperforms CNN. The authors [13] created an end-to-end trainable multiview deep Convolutional Neural Network for nodule characterisation (CNN). Beginning with a two-dimensional patch for each dimension, they used median intensity projection. The three images are then combined to create a tensor, with each image acting as one of the three separate channels in the input image. By resizing, rotating, and adding noise to the original image, they were able to increase the number of training instances through the technique of data augmentation. The trained network is used to extract features from the input image, followed by a Gaussian Process (GP) regression, to create the malignancy score. Additionally, they demonstrate the significance of specific high-level nodule characteristics, such as calcification and others, in identifying malignancy. These traits are found to be compatible with the deep multi-view CNN capabilities, leading to a considerable advancement above current methods. Changmiao Wang et al. employed non-medical training data and custom-made picture attributes to lower the false positive rate in nodule detection. With 1.19 false positives, deep feature fusion results in better results per image in terms of sensitivity and specificity (69.27 percent and 96.02 percent, respectively) [11]. Wei Shen and al. presented the method for classification of scepticism in lung nodules using thoracic CT scan pictures. For the lung nodule in this study, a suspiciousness classification modelling for raw nodular patches is carried out. multiple crops Lung nodule features are extracted using a convolutional network, which divides the nodule into various regions and repeatedly applies max pooling. According to their research, this technique successfully identifies the nodule's edge and diameter, which is helpful in figuring out whether or not the nodule is malignant [13].

To learn high-level properties of the Convolution layer at the first level for lung cancer binary classification, Mehdi Fatan Serj et al. developed a Deep Convolutional neural network. To compare their results from the Kaggle competition, the authors used high rank techniques [18]. Hwejin Jung and others A three-dimensional deep convolutional neural network (3D DCNN) with quick connections and a 3D DCNN with dense connections were both used to classify lung nodules. Shortcut connections and dense connections, which enable the gradient to pass quickly and directly, successfully address the gradient vanishing problem. Connections in deep structured networks can be used to gather both common and distinctive properties of lung nodules. Furthermore, in order to gather 3D features, we increased the DCNN dimension from two to three. Deep 3D CNNs are more effective at capturing the characteristics of spherical-shaped nodules than the shallow 3D CNNs used in earlier investigations. The authors also used a different ensemble method called the checkpoint ensemble method to enhance performance. [15]. Woniak et al[11] .'s new method of classifying lung carcinomas was mentioned. The locating and extraction of the lung nodule by calculation leads to the local variance for each pixel of the original image, which produces the outcome image (the "variance image") of the same image size. Unsupervised deep auto encoder for the categorization of lung cancer by Mao et al. [14]. The suggested framework includes the following two types of features to guarantee an appropriate diagnosis of lung nodules discovered. There are two types of appearance characteristics: I geomemetric features that describe the form geometry of the lung nodules, and (ii) appearance features modelled with a higher-order Markov Gibbs random field (MGRF) model [12]. Suren Makajua and colleagues reviewed the advantages and disadvantages of the cancer cell detection models that are currently in use. The authors were able to develop a model for lung cancer diagnosis based on detection precision after upgrading the real model. The researchers used image segmentation and the watershed approach on CT images to classify the lung lesion as benign or malignant using a support vector machine [13].

III. LUNG CANCER CLASSIFICATION USING CNN TECHNIQUES

According to previous study, CNN has the ability to diagnose lung cancer more accurately using CT scans than radiologists can manually. CNN has also been shown to outperform professional radiologists in the detection of lung nodules in several trials. To identify and categorize lung cancer, CNN used two methods. The first stage involves the extraction of functions by the CNN, followed by the artificial neural network categorization of lung images in the second stage. End-to-end learning is utilized in CNN, or transfer learning can be applied with pre-trained models. To avoid over-fitting difficulties and achieve improved accuracy, a big dataset is necessary. Figure 35 depicts the classification model used to determine if lung pictures are normal or malignant lung nodules.

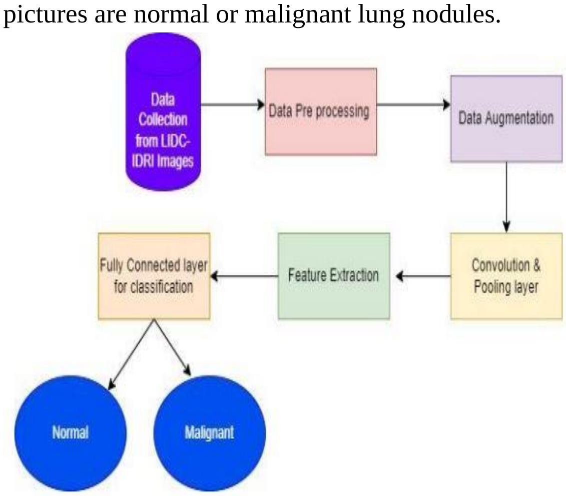


Figure 1 Overall Proposed System Architecture

A. DATA COLLECTION

Using the LIDC-IDRI dataset, the lungs' CT scans for this application were gathered. The 1018 low-dose CT imaging cases from 1010 individuals that makes up this LIDC-IDRI dataset were collected by a group of eight pharmaceutical companies and seven academic institutions. Each of the 1018 instances has XML files containing CT picture descriptions. Four radiologists collaborated to produce this dataset, which they used to annotate CT scans and divide them into three categories (nodule > 3 mm, nodule > 3 mm, and non-nodule >>, respectively). There are 244,527 512*512 photos in this collection, whose widths range from 65 to 764 pixels. With the use of this dataset, two level diagnoses might be made: one at the nodule level and one at the patient level. Nodules on a CT scan can be of four different types: Unknown levels, early or typical lung cancer, and metastatic lesions round out the list. Carcinoma Data Preprocessing & Augmentation, Section 4.5 Using the radiant Dicom viewer, the captured CT Dicom images are converted to jpg format during the processing stage. These photos have a range of pixels that don't provide any information to the images; as a result, these pixels are removed using a compression technique based on artificial intelligence.

B.DATA PREPROCESSING & AUGMENTATION

Using the radiant Dicom viewer, the acquired CT Dicom images are converted to jpg format during the processing stage. These photos have a range of pixels that don't provide any information to the images; as a result, these pixels are removed using a compression technique based on artificial intelligence. There are two types of LIDC-IDRI images: benign and malignant images. Although a deep learning model performs well when given a lot of data, gathering a lot of data requires time and effort. As a result, the fictitious dataset was produced using the data augmentation method, which involved brightness, rotation, cutting, padding, and flipping adjustments.

C. CONVOLUTION & POOLING LAYER FOR FEATURE EXTRACTION

Extraction of attributes is essential for CT image categorization. In comparison to manual learning, automatic learning of CNN functions will be extremely different. The malignant nodule has lesions larger than 3 millimetres, according to the graphic description of lungs CT scans. In order to process images that have been classified as either normal or cancerous, the CNN model is used. In the training phase, CNN will use the automated weight updation to extract the image's features. Two layers of the CNN model are included in our suggested method. Convolutional layer I I. Pooling layer (ii) After convolution, more filters will be added to improve the depth of the input, and a pooling layer will be used to maintain the same depth while reducing the size of the filters. Classification The fully connected layer, which generates the performance metric for displaying loss and accuracy, receives a flattened weighted layer feature map from the final pooling layer as input. The internal node values are then automatically updated to improve the result based on the weights of the metric values. These layers are combined when the pre-processing has been completed. As is customary, the output of the final layer is used as the final output.

D. POOLING LAYER

To lessen the output of the convolution layer's spatial scale and to streamline the network's processing, the pooling layer, sometimes referred to as the down sampling layer, is used. The pooling layer also regulates over fitting. The pooling layer is often composed of two convolution layers or two convolution layers that are fully coupled. Maximum pooling and average pooling are the most used pooling techniques. While average pooling takes the average of the data in a certain window, max pooling selects the biggest value within that window. For pooling operations, the window size and stride value are two essential hyper-parameters. The window size determines how wide of a region will be focused on. The size of the steps in a sliding window is determined by the stride. If the input tensor size is 8@32x32 and the stride is 2, the output tensor will be 8@16x16.

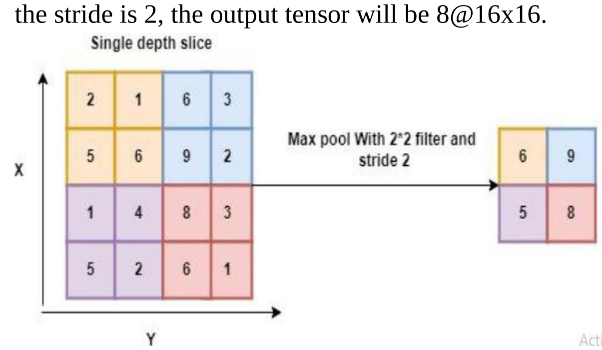


Figure 2 Max Pooling Operation

Layer Completely Connected Rectangular shapes are produced by the convolution and pooling layers. So that the weight matrix can multiply them, these outputs are converted to vector representation. In the completely linked layer, these volumes are turned into a 4800x1 vector (5x5x3x64 = 4800) if there are 64 features map layers, each with 5x5x3 pixels. The layer that comes before the completely linked layer represents high-level properties. With the help of a completely linked layer, these high-level attributes can be multiplied by the weights of the buried layers. Similar to MLP, the rest of the system runs well.

IV. RESULT & DISCUSSION

After our model for lung nodule classification using convolution and pooling layer is successfully developed, sample images from the training dataset are taken, and each layer's output visualisation is finished and presented in figures 4.1 and 4.2.

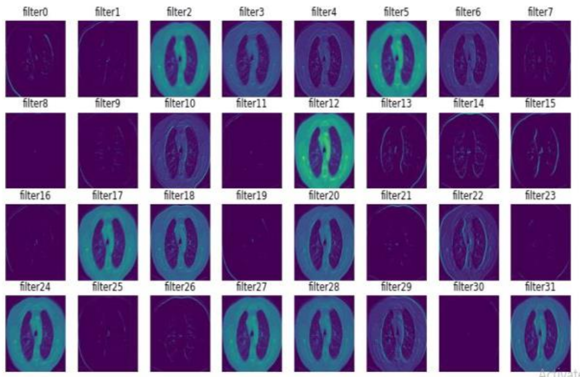


Figure 4.1 Visualization of layers (conv2d_1)

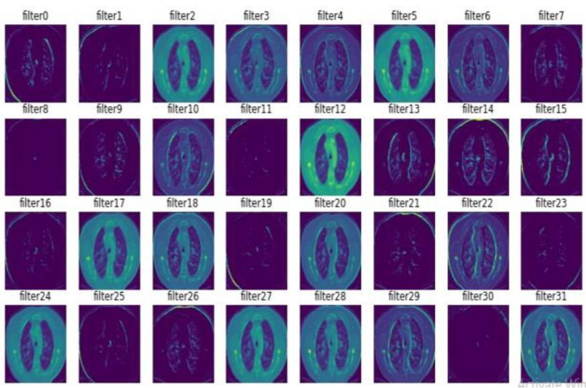


Figure 4.2 Visualization of layers (max_pooling2d_1)

V CNN MODEL PERFORMANCES

This section categorises the CNN model's accuracy, loss, and other performance metrics for lung cancer diagnosis. The accuracy and loss for training and validation are displayed in graphs 5.3 and 5.4.

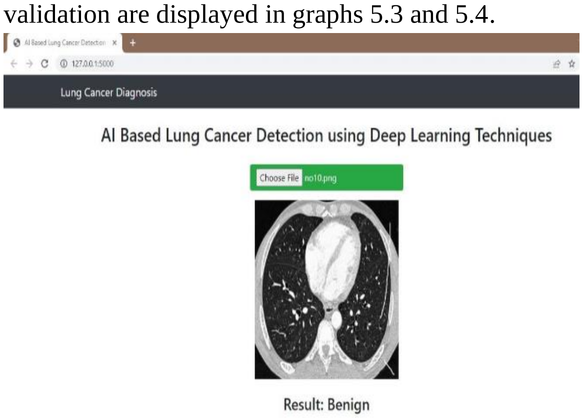


Figure 5.1 Model Output for Healthy Prediction

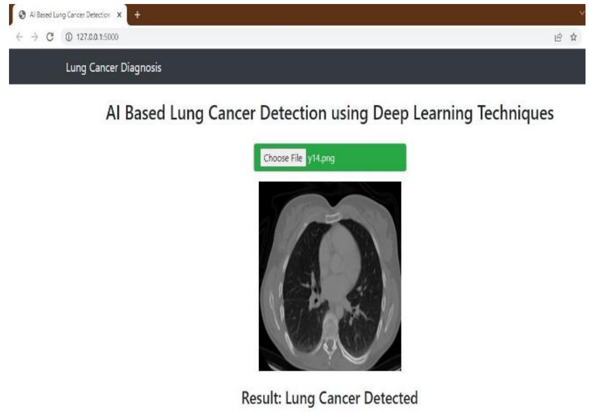


Figure 5.2 Model Output for Cancer Prediction

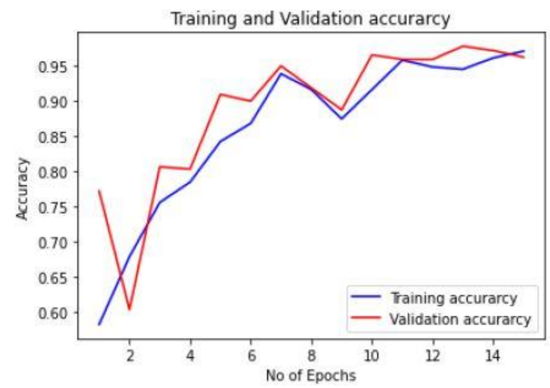
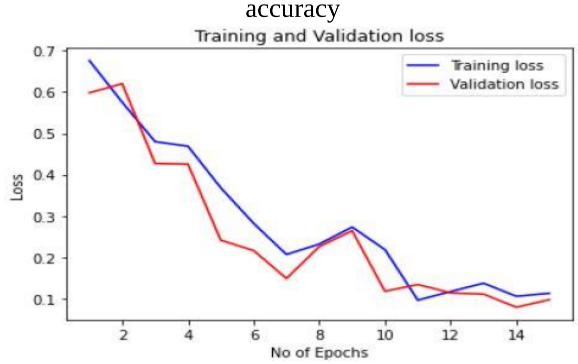


Figure 5.3 : Deep CNN Training & validation accuracy



Graph 5.4 : Deep CNN Training & validation loss

Table 1. Performance Comparison Different Feature Extraction

Detection (%)	Sensitivity	Specificity	Accuracy
Discrete Wavelet Transform (DWT)	72.50%	70.30%	70.10%
Fast Fourier Wavelet Transform (FFWT)	75.70%	76.10%	74%

HAAR Wavelet Transform	75.80%	77%	76.50%
Two Level HAAR wavelet transform	78.40%	79.30%	78.60%

VI.CONCULSION

Lung cancer is regarded as a serious condition with a high mortality rate. When compared to other cancers, lung cancer has the highest fatality rate, and it is widely acknowledged as the deadliest carcinoma worldwide. As a result, many researchers are concentrating on techniques for spotting lung cancer nodules in digital pictures, particularly Computed Tomography (CT). It can be difficult for radiologists to identify small nodules from the images produced by CT scans, which use X-ray to generate multiple images. The fundamental task carried out by the radiologist for the diagnosis of lung cancer is the analysis and interpretation of nodules. Many scientists and researchers are developing automated medical procedures that will save time and money for doctors. With the help of the CT scans gathered from the LIDC-IDRI dataset, we were able to implement the CNN model for the detection of lung nodules. The model was successfully implemented in Python using Keras, and the accuracy was 96.50%. F-score, sensitivity, AUC, and specificity values are 96%, 97%, 96.2%, and 96.40%, respectively.

REFERENCE

[1]. National Lung Screening Trial Research Team. (2011). Reduced lung-cancer mortality with low-dose computed tomographic screening. New England Journal of Medicine, 365(5), 395-409.

[2]. Chartrand, G., Cheng, P. M., Vorontsov, E., Drozdzal, M., Turcotte, S., Pal, C. J., & Tang, A. (2017). Deep learning: a primer for radiologists. Radiographics, 37(7), 2113-2131.

[3]. Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R. L., Torre, L. A., & Jemal, A. (2018). Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 68(6), 394-424.

[4]. Singh, D., Kumar, V., Yadav, V., & Kaur, M. (2021). Deep neural network-based screening model for COVID-19-infected patients using chest X-ray images. International Journal of Pattern Recognition and Artificial Intelligence, 35(03), 2151004.

[5]. Agrawal, manoj, and shwetaagrawal. "rice plant diseases detection and classification using deep learning models: a systematic review."Journal of critical reviews JCR. 2020; vol. 7 issue: 11: 4376-4390

[6]. He, K., Zhang, X., Ren, S., & Sun, J. (2015). Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In Proceedings of the IEEE international conference on computer vision (pp. 1026-1034).

[7]. Do, S., Song, K. D., & Chung, J. W. (2020). Basics of deep learning: a radiologist's guide to understanding published radiology articles on deep learning. Korean journal of radiology, 21(1), 33-41.

[8]. Agrawal, S., & Jain, S. K. (2020). Medical text and image processing: applications, issues and challenges. In Machine Learning with Health Care Perspective (pp. 237-262). Springer, Cham.

[9]. RituTandon, M., & Goyal, P. (2020). Sequential Convolutional Neural Network for Automatic Breast cancer image classification using Histopathological Images. methods, 7, 10.

[10]. Sathyakumar, K., Munoz, M., Singh, J., Hussain, N., & Babu, B. A. (2020). Automated Lung Cancer Detection Using Artificial Intelligence (AI) Deep Convolutional Neural Networks: A Narrative Literature Review. Cureus, 12(8).

[11]. Mathew, C. J., David, A. M., & Mathew, C. M. J. (2020). Artificial Intelligence and its future potential in lung cancer screening. EXCLI journal, 19, 1552.

[12]. Choudhury, Avishek, and Sunanda Perumalla. "Detecting breast cancer using artificial intelligence: CNN." Technology and Health Care 29.1 (2021): 33-43.

[13]. Watanabe, A. T., Lim, V., Vu, H. X., Chim, R., Weise, E., Liu, J.,& Comstock, C. E. (2019). Improved cancer detection using artificial intelligence: a retrospective evaluation of missed cancers on mammography. Journal of digital imaging, 32(4), 625-637.

[14]. Cruz, Joseph A., and David S. Wishart. "Applications of machine learning in cancer prediction and prognosis." Cancer informatics 2 (2006): 117693510600200030.

[15]. Montagnon, E., Cerny, M., Cadrin-Chênevert, A., Hamilton, V., Derennes, T., Ilinca, A.& Tang, A.

(2020). Deep learning workflow in radiology: a primer. Insights into imaging, 11(1), 1-15.
[16]. Dargan, S., Kumar, M., Ayyagari, M. R., & Kumar, G. (2020). A survey of deep learning and its applications: a new paradigm to machine learning. Archives of Computational Methods in Engineering, 27(4), 1071-1092.
[17]. Gianchandani, N., Jaiswal, A., Singh, D., Kumar, V., & Kaur, M. (2020). Rapid COVID19 diagnosis using ensemble deep transfer learning models from chest radiographic images. Journal of ambient intelligence and humanized computing, 1-13.
[18]. Tekade, Ruchita, and K. Rajeswari. "Lung cancer detection and classification using deep learning." 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). IEEE, 2018.
[19]. Asuntha, A., and Andy Srinivasan. "Deep learning for lung Cancer detection and classification." Multimedia Tools and Applications 79.11 (2020): 7731-7762.
[20]. Kalaivani, N., Manimaran, N., Sophia, S., & Devi, D. D. (2020, December). Deep Learning Based Lung Cancer Detection and Classification. In IOP Conference Series: Materials Science and Engineering (Vol. 994, No. 1, p. 012026). IOP Publishing