International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Recognition of Lung Cancer Using CNN Model

Ms. Sukhwani Divya Maheshkumar[1] , Prof.Ramesh P. Daund[2]

[1]PG Student, S.N.D.COE and RC,Yeola

[2] Asst. Professor, S.N.D.COE and RC,Yeola

ABSTRACT

Lung cancer is one of the most lethal cancer types; thousands of peoples are infected with this type of cancer, and if they do not discover it in the early stages of the disease, then the chance of surviving of the patient will be very poor. For the suggested reasons above and to help in overcoming this terrible, early diagnosis with the assistance of artificial intelligence procedures most needed. Also, it is one of the most common and contributing to deaths among all the cancers. Cases of lung cancer are increasing rapidly. There are about 70,000 cases per year in India. Over the past decade, Cancer detection using deep learning models has been a hot topic, especially in medical image classification. It is worth remarking that CNN models are more advanced at addressing diagnose diseases such as lung cancers because of the higher performance and ability of the CNN. This system presents an approach which utilizes a Convolutional Neural Network (CNN) to classify the tumours found in lung as malignant or benign. The accuracy obtained by means of CNN is 99%, which is more efficient when compared to accuracy obtained by the traditional existing systems. This done by applying convolutional neural network technique to a data set of lung cancer CT scans.

Keywords: Lung, Computed Tomography, Convolutional Neural Network, Detection, Classification

1. INTRODUCTION

This application aims to early detection of lung cancer to give patients the best chance at recovery and survival using CNN Model. Using a data set of thousands of high-resolution lung scans, this model will accurately determine when lesions in the lungs are cancerous. This will dramatically reduce the false positive rate that plagues the current detection technology, get patients earlier access to life-saving interventions, and give radiologists more time to spend with their patients.

Medical imaging and related fields have taken centre stage in the digitally connected world. Medical information is used in several disciples from biometrics to insurance. These increases the need of this information to be trustworthy and reliable across platforms [1], [2]. Effective systems need to be developed for this information, which is usually in the form of medical images, to be used in the automatic diagnosis of diseases.

One of the major causes of human death is cancer. The most common malignant tumor is lung cancer and its worldwide incidence is increasing by 2% per year. Lung cancer is linked to the use of tobacco products in 90% of the cases. An asymptomatic person (smoker) goes through the computerized (CT) examination which is one of the best ways to diagnose lung cancer [3]. Detection of CT-like nodules is not a simple task because they include, in an area of complex anatomy contrasts similar to other structures, low density and a low size, etc. [4]. A number of computer-aided tumor detection and characterization techniques were suggested in the literature. Two key categories for the development of these techniques are computer-aided (CAD) identification and CADxdiagnosis. The installation of a CADx device will minimize the amount of unnecessary biopsies, reducing mental trauma in patients with benign tumours. CADx, therefore, acts as a second approach and assists cancer diagnostics experts at the earlier stages of disease [5]. This diagnosis is accurate and efficient.

In recent years, profound learning techniques have demonstrated the possibility to uncover features from training images automatically and to manipulate contact, even hierarchy, between the characteristics of a deep neural structure. The new learning system can also solve feature computing, selection and integration problems without using complicated processing and pattern recognition steps [6]. Using CNN as an extractor and classifier, this paper suggests a technique for classifying lung nodules in either benign or malignant, which may provide a second opinion to the specialist.

2.REVIEW OFLITERATURE

Convolutional neural network (ConvNet/CNN), Deep Learning or other machine learning algorithms have been used various researchers to perform experiments on different types of lung cancer detection. Shrinivas Arukonda used technique convolutional deep neural networks. In this the system capable to detecting lung cancer in its earlier stages because of its survival rate [1].

The dataset is used from the Data Science Bowl 2017 Kaggle competition, LUNA16. first step, they detected the annotated nodules. Cube of size 32 X 32 X 32 is around the nodules, with the nodule in the center. Region of Interest mask is applied for lungs. Then cubes are made around the predicted nodules and the prediction is done using a second 3D CNN. The precision achieved in the model is found to be 94.30% [2].

Different research studies have already been proposed with CADx systems to improve the accuracy of lung cancer detection. Hua et al. [6] proposed a deep-learning technique for lung cancer detection. The authors achieved a sensitivity of 73.40% and specificity of 82.20% with deep belief network(DBN) architecture. The authors also used CNN architecture and obtained a sensitivity of 73.30% and a specificity of 78.70%. Kumar et al. [7] proposed a deep learning system with 75.01% accuracy using stacked autoencoder (SAE).

1)In 2012, Mokhled S. Al Tarawneh published a comparison paper between different Image Processing techniques and the algorithms they use for a CAD system for lung cancer detection. The main aim of the paper is to detect features for accurate comparisons between images with different processing techniques. Three steps are Image enhancement, segmentation and feature extraction. The aim of image enhancement is to improve quality of image to provide better input for classification. Gabor filter, auto enhancement and fastfourier transform improve enhancement rate. Thresholding and Watershed methods are used for segmentation, of which, watershed provides a better quality of segmentation. Feature extraction uses binarization and masking approach. Binarization and Masking, on combined implementation, gives an optimal result.

2)In December 2017, Suren Makaju, P.W.C Prasad, AbeerAlsadoon and A.K. Singh worked on CAD system of lung cancer with CT Scan Images as primary focus. They believe the that CT Scan Images are the best input data for this research [2]. The proposed model uses noise removal algorithms before image processing. It uses the same segmentation as the current system, i.e., watershed algorithm and promotes a well-defined feature extraction before classification using SVM. The author has used images from LIDC dataset and the system gives a 92% accuracy and 50% specificity.

3) In May 2015, Md. BadrulAlam Miah and Mohammad Abu Yousuf proposed a Neural Network based CAD system for early detection and diagnosis. ANN and fuzzy clustering, IP, Curvelet transform, multinomial Bayesian algorithm, back propagation, gray-coefficient mass estimation and SVM are the basis of these observations. The goal is to create a fast and robust, more accurate system having a rotation, scaling and translation variant feature extraction [3]. A dataset of 300 images acquired from hospitals is used. Steps in proposed system are Image acquisition, processing, binarization, segmentation using thresholding, feature extraction and neural network classification. Steps in Image processing are grayscale conversion, normalization, noise reduction, binarization and removing unwanted portion of image. Feature extraction uses features like center of image, ratio of height to width, average distance between black pixels and the center, etc. Neural networks is used for classification with two outputs. The system gives an accuracy of 96.67%, higher than all existing systems.

4)In March 2014, Prof. Sanjeev N. Jain and Bhagyashri G. Patil proposed few methods to detect cancerous cells from CT scans of Lungs. The purpose of this paper is to find the cancerous cells and give more accurate result by using various segmentation techniques such as thresholding and watershed segmentation. In thresholding, a threshold value is set to differentiate object of interest from the background. If the pixel value is greater than the threshold value then it belongs to the object else it is in the background. Thus, the region of interest can be extracted by using thresholding approach. In watershed segmentation, the background and the object are separated using different markers: internal markers associated with object of interest and external markers associated with background. It is simple, intuitive and fast method [4]. According to the research, watershed segmentation approach has more accuracy (85.27%) than thresholding approach (81.24%).

5)In 2017, authors Pooja R. Katre and Anuradha Thakare described the various image processing techniques for detecting lung cancer. In their proposed approach for noise removal and enhancement, methodMedian Filter is used. The best part about median filter is it removes noise without blurring the image. It preserves the edges of the regions [5]. It is used to remove salt and pepper noise from the image. In enhancement stage gabor filter is used as it gives better result compared to fast fourier and auto enhancement. The purpose of this paper is to detect the tumour at an early stage. CT scan images are taken as input. After Image Processing is the feature extraction stage in which the area, perimeter, Eccentricity of the image is calculated. Support Vector Machine algorithm is used to classify the data. The features mentioned above help to identify the size of the tumour and from that, the stage of the cancer is detected.

6)In 2017, from China, Lei Fan and his group of researchers made use of deep learning algorithm for CAD lung cancer detection. In this paper, image processing is not applied on CT scans of lungs. The images are directly fed as an input to convolutional neural network which consist of two convolutional layers, two max pooling layers, one fully connected layer and one output layer [6]. Rectified linear unit (ReLU) are applied between convolutional and max pooling layers. The system gives an overall accuracy of 67.7%. It concludes that Support vector machines has lower classification accuracy than 3D convolutional neural network in the same number of input samples.

3.SYSTEM ARCHITECTURE

This architecture presents lung cancer detection based on chest CT images using CNN. In the first stage, lung regions are extracted from CT image and in that region each slices are segmented to get tumors. The segmented tumor regions are used to train CNN architecture. Then, CNN is used to test the patient images. The main objective of this study is to detect whether the tumor present in a patient’s lung is malignant or benign. Figure1 shows the block diagram of the proposed system. As shown in the figure, the trained system will able to detect the cancerous presence in lung CT image.

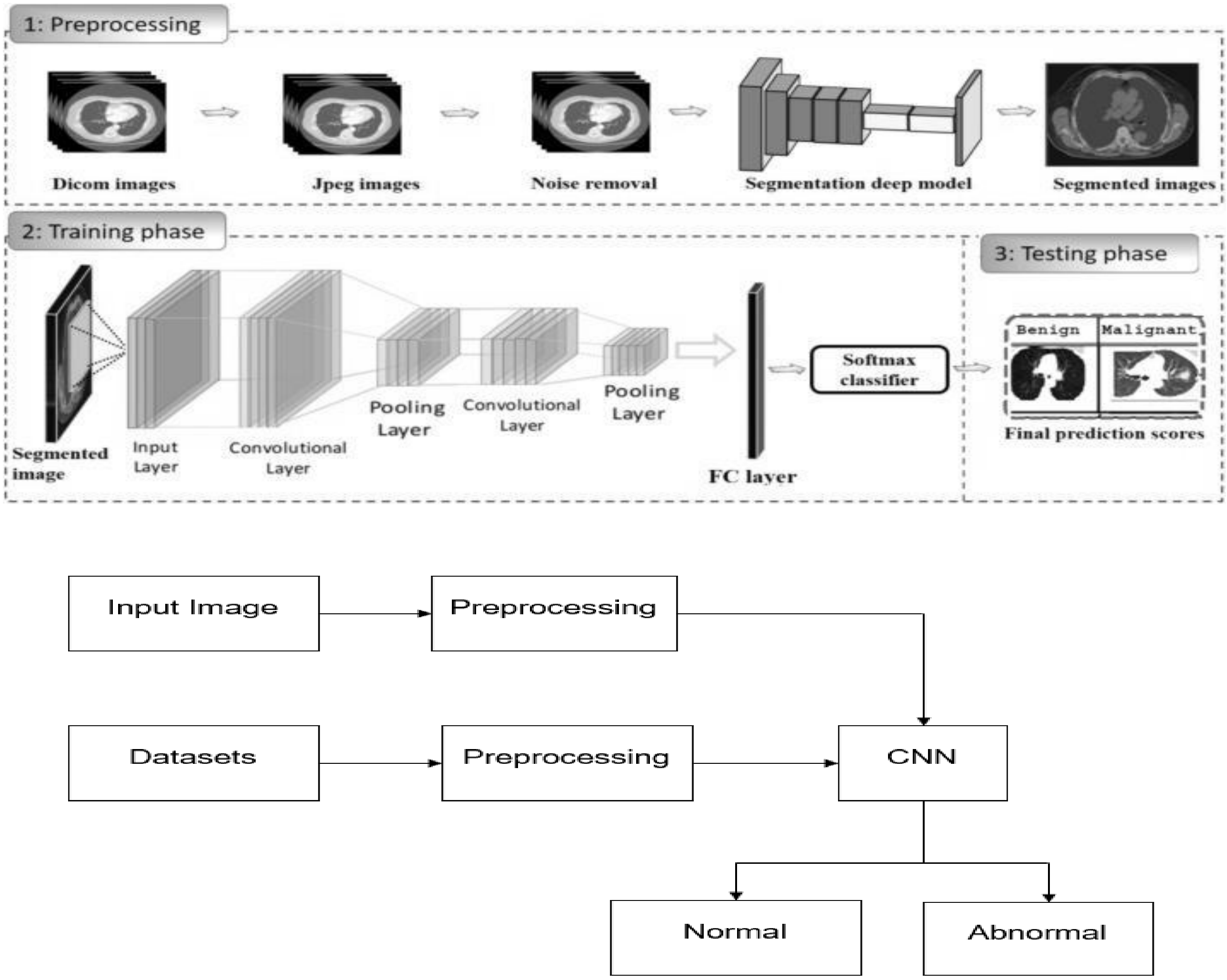

Figure 1: System Overview

Data Set:-

The database used is obtained from Lung Image Database LUNA16,Data Science Bowl 2017 This is a lung nodule classification database containing the scans of a total of 1018 patients. Each patients' CT scan in turn is comprising of around 150 to 550 dicom format images. The database provides four classifications namely-(i)Unknown, (ii)Benign, (iii)Malignant, and (iv)Metastatic

Preprocessing

In preprocessing stage, the median filter is used to restore the image under test by minimizing the effects of the degradations during acquisition. Various preprocessing and segmentation techniques of lung nodules are discussed in. The median filter simply replaces each pixel value with the median value of its neighbors including itself. Hence, the pixel values which are very different from their neighbors will be eliminated.

Convolutional Neural Network

The convolution layer of a produces a feature map by convolving different sub regions of the image with a learned kernel. Further, non-linear activation functions such as a sigmoid, tanh or rectified linear (ReLu) can also be applied. Another method for reducing computations is the pooling layer, where a region of the image/feature map is chosen and the maximum among them is chosen as the representative pixel. Hence, a 2x2 or 3x3 grid can be reduced to a single scalar value. traditional fully connected layer can also be used in conjunction with the convolutional layers, and are usually used towards the output stage.

Convolution Layer 1:

The data in 3-D hdf5 format forms the input to the first convolution layer. This layer of kernel size 50x50 with a stride of 6. The output of this layer produces 78 features. The weight filler is set to a 0.01 Gaussian distribution change and the bias is set at constant zero. This output is then fed to the Rectified Linear (ReLu) layer to bring all the negative activations to zero. The primary application of this layer is to detect the lowest level features, e.g., whether there is classification in some area of the image.

Convolution Layer 2:

The first Convolution layer output is fed into the second having a kernel size of 3x3 and a stride of 1. This layer pads the data with one enclosure of zeros. The weight filler is the same as convolution layer 1 and the bias is set to a constant value of 1. Also, this layer is followed by a ReLu layer. This layer is intended to make use of the information predicted from the previous layer and detect the pattern of classification - e.g., popcorn, diffuse etc. From the training phase, it will hence learn as to which among the patterns are benign, and which are malignant. In this way the CNN achieves two objectives - it learns features hierarchically, and it eliminates the need for specific feature engineering.

Max-pooling Layer:

After the convolution layer 2 comes the max-pooling layer where the most responsive node of the given kernel is extracted. The kernel size used in the proposed network is 13x13 with stride shift of 13. This is primarily intended to reduce the computational effort. Since each CT scan composes of 500 images, if we have a batch size of 50, the number of required computations can be significantly large, leading to frequent memory overload. The max-pooling layer is used particularly to ease memory and data bottlenecks by reducing the image dimensions.

Dropout layer:

The dropout layer is used in the network to prevent over-fitting. This is done by switching off random neurons in the network. Our proposed network uses a dropout layer with a drop ratio of 0.5. The intent of this layer is to improve the classification quality on test data that has not been seen by the network earlier.

Fully connected layer:

A fully connected layer which provides two outputs is used. It uses Gaussian weight filler of 0.5 and a constant bias filler of 0. The two output neurons from this layer gives the classification of benign or malignancy.

This layer is mainly intended to combine all the features into one top level image and will ultimately form the basis for the classification step.

4.METHODOLOGY & ALGORITHM

Modules Module 1:

Import the given picture from dataset We need to import our informational index utilizing keraspreprocessing ImageDataGenerator function additionally we make size, rescale, range, zoom range, flat flip. At that point we import our picture dataset from organizer through the information generator work. Here we set train, test, and approval likewise we set objective size, bunch size and class-mode from this capacity we need to prepare.

Module 2:

To prepare the module by given picture dataset To prepare our dataset utilizing classifier and fit generator work likewise we make preparing steps per age's at that point absolute number of ages, approval information and approval steps utilizing this information we can prepare our dataset

Module 3:

Working interaction of Layers in CNN model An algorithm in the field of Deep Learning which can take image as an input, assign biases and weights to multiple characteristics of a picture and classify one picture from the other is called a Convolutional Neural Network. Other classification algorithms require humongous pre-processing unlike ConvNet, which does not require much of processing. ConvNets do not require filters that are hand-engineered, the algorithm can learn on itself if it’s trained properly unlike the traditional methods. The Visual cortex present in the human brain is the organization which is synonymous and highly inspired for the working and architecture of ConvNet. Receptive Field is the area which consists of neurons which respond only in contained regions. Their association involves four layers with 1,024 data units, 256 units in the chief concealed layer, eight units in the subsequent mystery layer, and two yield units.

Input Layer:

Image knowledge is contained in this layer of convolutional neural network. Picture information is addressed by three dimensional frameworks. The input layer is responsible to reshape the image dimension into a singular column. Assume there is an image of measurement “28x28=784”, this dimension needs to be converted into a singular column before it is fed into the input.

Convolution Layer:

Convolution layer is also known as the “feature extractor layer” since highlights of the pictures removed inside this layer. As a matter of first importance, a piece of image is associated with Convo layer to execute complexity activity as witnessed before. It computes the speck item between open fields and the channel. Consequence is an individual whole number of the yield quantity. At that point, channel throughout following responsive field of a similar information picture by a Stride and do a similar activity once more. It will rehash a similar interaction and again until it goes through the entire image.

Pooling Layer:

The reduction of spatial volume of the image after convolution is done by the pooling layer. Pooling layer is used halfway through two convolution layers. Without applying pooling layer while fully connected layer is applied after convolution layer, it could require heavy computation power. Hence, the spatial volume of an input image can only be curtailed by the use of max pooling. With a stride of two, in a single depth slice max pooling has been applied. We can observe that a 4 x 4 input is

curtailed to a 2 x 2.

Fully Connected Layer (FC):

Completely associated layer includes loads and inclinations. Fully connected layer associates neurons in an individual layer to subsequent layers. By training, it is used to classify images among different classes.

Output Layer:

A one-hot encoded principle is followed which contains the name in the output layer.

Module 4:

Deploying the model in Django Framework and anticipating yield In this module the prepared deep learning model is changed over into various leveled information design document (.h5 record) which is then conveyed in our django system for giving better UI and foreseeing the yield whether the given Benign cases,Malignant cases, Normal cases.

5.IMPLEMENTATION

Algorithm The model will adopt CNN (convolution neural networks) which has proven to yield better, efficient, accurate, and enviable results correlated to other machine learning algorithms like Naive Bayes, Support Vector Machine (SVM), Random Forest, and other such algorithms. The feature extraction is automatically done by the CNN algorithm based on the information provided to the model which in our case is a set of CT-Scan images and an output tag. For training, the convolutional layers define the features and parameters.

Image Data Augmentation

Data augmentation is a technique which is used to increase the number of sample images in a dataset in order to reduce class imbalance. This technique is used to increase the number of samples of each image in the dataset to prevent the model from being undertrained. The diversity of the training set can be increased by applying several different transformation techniques to our image dataset such as flipping, rotating, stretching the image.

Convolution Neural Network (Manual CNN)

The Convolution Neural Network (CNN) bands characterize the specifications for training. The veracity of Convolution Neural Network (CNN) based operations can be upgraded by enhancing the nature of input data and by being contingent upon exceptional training. The Convolution Neural Network exemplified also plays a dominant aspect in enhancing results. Additional bands suggest exceptional training. Few important parts of a Convolutional Neural Network are as follows:

1. Input Layer-

The data which is pushed into the networks is called the input layer which is a box like array of pixels

2. Convolutional Layer-

The main responsibility the convolutional layer has is, extract the highlight from the image which is pushed into the layer from the input layer. It is one of the most supreme parts of CNN. The convolutional layer comprises kernels arranged in series which have to execute convolution. The initial layers extract lessened features from the input and as the profundity increases, higher and intricate-level characteristics are extracted

3. Activation Layer-

Intermittence in the system is introduced by the activation layer which supports the learning of complex data. The basic function for this model is ReLu which endows the pace of how the CNNs are being trained by gradient supervision which is constant at all network layers.

4. Max-Pooling Layer-

In this layer degradation of the dimensionality is done. It allows assumptions for the area where maxpooling has to be done. MPL is applied on the initial sector by applying a max filter on the non- intersecting region. Attribute extraction is implemented by coupling various steps which are alike, comprising of cascading layers specifically Convolutional, Activation, and Max-pooling. The proposed CNN model will predict whether the input image is a malignant (cancerous), benign (non-cancerous) or normal.

AlexNet Deep Learning Model

AlexNet is a complex and a successfully pre-trained model which is trained over ImageNet dataset containing 15 million labelled images categorized under 21,000 classes. AlexNet contains 5 convolutional layers and 3 fully connected layers which totals to 8 total layers. It originally performs on 2 GPUs. However, researchers nowadays tend to use only one GPU for the implementation of AlexNet. Relu-Nonlinearity: AlexNet makes use of the ReLu function instead of the tanh function. ReLu function makes the model more time efficient. Numerous GPUs: AlexNet allows to put one half of the neurons in one GPU and other half in another GPU owing to the large dataset. This allows to train larger models and cut down on processing time. A rigorous comparison will be established between the two models: Manual CNN and AlexNet. The model with the highest accuracy and negligible loss will be chosen for the further classification of the input image into malignant, benign or normal Equations.

Preparing from Scratch:

To prepare a profound organization without any preparation, you assemble a huge marked informational index and plan an organization design that will become familiar with the highlights and model. This is useful for new applications, or applications that will have an enormous number of yield classes. This is a more uncommon methodology on the grounds that with the huge measure of information and pace of learning, these organizations regularly require days or weeks to prepare.

Transfer Learning:

Exchange learning approach is used by many deep learning applications. A cycle that includes adjusting a pretrained model. You start with a current organization, like AlexNet or GoogLeNet, and feed in new information containing beforehand un-labelled classes. Subsequent to making a few changes to the organization, you would now be able to play out another undertaking, for example, sorting just canines or felines rather than 1000 unique items. This likewise enjoys the benefit of requiring considerably less knowledge (preparing a great many pictures, instead of millions), so processing time drops to less than few hours or even minutes.

Feature Extraction:

A somewhat more uncommon, deep learning can be dealt more particularly by making use of the organization as a component extractor. As specific features are extracted from each one of the layer, at the time of preparation cycle, we can get these features out of the organization. The features can thus be used to contribute to an AI model like support vector machine.

INCORPORATED PACKAGES

- Pandas – This library helps to load the data frame in a 2D array format and has multiple functions to perform analysis tasks in one go.

- NumPy – NumPy arrays are very fast and can perform large computations in a very short time.
- Matplotlib – This library is used to draw visualizations.
- Sklearn – This module contains multiple libraries having pre-implemented functions to perform tasks from data pre-processing to model development and evaluation.
- OpenCV – This is an open-source library mainly focused on image processing and handling.
- TensorFlow – This is an open-source library that is used for Machine Learning and Artificial intelligence and provides a range of functions to achieve complex functionalities with single lines of code.

6. CONCLUSION & FUTURE SCOPE

A convolutional neural network-based system was implemented to detect the malignancy tissues present in the input lung CT image. Lung image with different shape, size of the cancerous tissues has been fed at the input for training the system. The proposed system is able to detect the presence and absence of cancerous cells with accuracy of about 96%.

In addition to deep convolutional network, the same dataset was classified by multilayer perceptron network Backpropagation algorithm with using GLCM features. The results show only 93% accuracy.

In this proposed work, the specificity obtained is 100% which shows that that there is no false positive detection. Also, the accuracy, sensitivity and specificity of the proposed system is high when compared to previously available conventional neural network-based systems.

In the near future, the system will be trained with large datasets to diagnose the type of cancer with its size and shape. The overall accuracy of the system can be improved using 3D Convolutional Neural Network and also by improving the hidden neurons with deep network.

REFERENCES

1. http://globocan.iarc.fr/Pages/fact_sheets_ cancer.aspx.

2.https://www.livemint.com/Politics/3eXX60XBig4bWZ25Kr1iQO/India-recordedabout39-million-cancercases-in-2016data.html

3. Using Deep Learning for Classification of Lung Tumors on Computed Tomography Images.

4. M.S. Al-Tarawneh, “Lung cancer detection using image processing techniques,” Leonardo Electronic Journal of Practices and Technologies, vol. 20, pp. 147– 58, May 2012.

5. LUNA16, “Lung tumor analysis 2016.” https:// luna16.grand-challenge.org/.

6. A Manikandarajan, S Sasikala, Detection and Segmentation of Lymph Nodes for Lung Cancer Diagnosis. National Conference on System Design and Information Processing – 2013.

7. M.S. Al-Tarawneh, “Lung cancer detection using image processing techniques,” Leonardo Electronic Journal of Practices and Technologies, vol. 20, pp. 147– 58, May 2012

8. Albert Chon, Peter Lu, NiranjanBalachandar “Deep Convolutional Neural Networks for Lung Cancer Detection”.

9. Wavelet Recurrent Neural Network for Lung Cancer Classification”:3rd ICSTcomputer,2017.

10. A.Kavitha, Anusiyasaral and P.Senthil,” Design Model of Retiming Multiplier For FIR Filter &its Verification”, International Journal of Pure and Applied Mathematics, Vol116 No12, 2017, pp. 239-247

11. S Sasikala, M Ezhilarasi, Combination of Mammographic Texture Feature Descriptors for Improved Breast Cancer Diagnosis. Asian Journal of Information Technology, 2016.

12. K.Malarvizhi, R.Kiruba, “A Novel Method Of Supervision And Control Of First Order Level Process Using Internet Of Things “,Journal Of Advanced Research In Dynamical And Control Systems, Vol 9 No.6 2017, Pp.1876-1894.