

LUNGS TUMOR CLASSIFICATION WITH CT SCAN IMAGES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

Lungs cancer is one of important lung disease characterized by the unregulated separation of living organisms into cells. It expands to develop tumors and raises conflict with lung functioning by preventing the lungs from doing their tasks. Hence, the most effective means to minimize lung cancer mortality are early detection and accurate therapy of lung tumors for patient survival. Computed Tomography (CT) for lung cancer screening with images has thus begun to be commonly adopted across the world. Analysis of those CT SCAN images, though, is a massive burden for the oncologist. So, Intelligence computer-aided-diagnostic (CAD) systems are also built to detect the cancer at an earliest stage that assist radiologists and a pulmonary medical expert in making decisions regarding the detection and treatment of their patients. In this study, a new automated approach has been proposed that uses a 2-dimensional convolutional neural network (CNN) model to detect the tumor by Lung CT SCAN images and also classifies them into two types of labels i.e., normal lungs and tumor infected lungs. Various pre-processing techniques are used in proposed system to enhance the quality of the CT SCAN images and a CNN model is created for classification. Dataset of 4,337 Lung CT SCAN images have been collected from the Nishtar Hospital and Nishtar University Multan, Pakistan with 1,028 images of healthy lungs and 3,345 images of tumor infected i.e., Malignant or Benign and the dataset is used in training and validation. Our proposed design network randomly selects both normal and tumor class images from the dataset to give the best result for training. This study used 8:2 ratio of data, i.e., 80% of the data for the training set and 20% of the data for validation or testing. In our study, we differentiate these two classes (Normal, Tumor (Benign, Malignant)) through a softmax linear classifier. The final classification layer predicts the final validation accuracy of the trained network. In the end, the prediction of the labels is computed and based on predicated and true labels of the images, final accuracy is calculated. We benefit ourselves with 31 layers of CNN design with 5 number epochs for each iteration, which is the cycle operating in the neural network system and the learning rate set to 0.01. To validate the results of our model, we used the Alex Net network by altering its two layers. The Classification Accuracy that our research acquired is 98.74%.

1. INTRODUCTION

The evolving nature of the human echo system is affected by an alarming level of diseases that has originated from environmental pollution in the wake of industrial revolution. Lung cancer is the major cause of death from cancer among males and females. The total number of lung cancer-related deaths are greater as a combination of breast, colon, and prostate cancer. Many patients suffering with lungs cancer are diagnosed in later stages with a 5-year survival rate estimation that is 17.7% reduced than many other leading cancers, including metastatic Breast Cancer (about 89%), Prostate Cancer (98%), and Colon Cancer (65%) [1]. American Cancer Society (ACS) has reported total 609,640 expected deaths from cancer in 2018, out of which 154050 (25%) are related to lung cancer that turn out to be 428 deaths per day [2]. The ACS further states that the estimated number of new cancer cases were 1,735,350 in 2018, 42% (729,000) among them were potentially avoidable if detected at earlier stage [2]. Lung cancer is second most-diagnosed type of cancer and by far the leading cause of death due to cancer among males and females, making up almost 27% of all cancer deaths. The survival rate for five years is just 18%.

Most of the patients are diagnosed with lung cancer at late stage, at this stage, it is very difficult to detect the growth of the dime-sized lung lesion [3]. These lung lesions cannot be detected through X-Ray, rather it requires CT scans, a considerable amount of effort, expertise, and many follow-ups. Recently, the adoption of CT scan imaging technology can be considered one of the most important techniques using for the favor of lung cancer supervision [4].

In the medical field, the primary reader and decision-maker is the radiologist. However, there exist three main challenges. The main challenge every radiologist may face every day is the large volume of daily cases. Another challenge is that the interpretation of each lesion by radiologists is a very complex process and sometimes the experts overestimate the lung lesions [4]. Furthermore, its inefficiency may cause patients to lead towards misdetection and wrong treatment. Due to the physician's specific physical aspects such as deficiency of Human Visual System (HVS), constant overstressed, and distraction, radiologists and nodule

clinicians do not provide the perfect usage of CT SCAN image data [5]. To resolve these issues, a robust screening and automatic diagnostic tool is required for early diagnosis of lungs disease. As, early diagnosis can enhance the efficacy of appropriate treatment, significantly reduce the cost of treatment, and boost the chances of survival beyond 5 years of the patients.

CAD tools assist radiologists to detect the cancerous lesions growth at early stage and improve their efficiency and accuracy in making life-saving decisions. Subsequently, the CADe systems take images as an input and extract certain features to identify the specific irregularities for the classification of cancer, its stages, severity, and transformation, etc. [6]. The huge budget is utilized to develop CAD tools. According to the estimation, around 6.6 billion dollars will be consumed on health sciences, out of which 2.2 billion dollars are reserved for the global CAD market and 23% of these CAD systems are used for lung cancer detection [7].

A very important aspect of any CAD systems is that they are heavily dependent on the datasets that are obtained from different imaging modalities. The image obtained from these imaging techniques are not useful for CAD devices unless radiologists and specialists in this field properly mark them [8]. Typically, these images are labeled for nodule/non-nodule and their size growth follow-ups further define the nodule. A range of biomarkers is used as measuring metrics that are observable measures of certain biological states or conditions to form the clinical features [9]. Such metrics are used to label the image and become what is known as the metadata of the image, associate with each patient from modalities such as Positron Emission Tomography (PET/CT). CAD systems use these datasets with their related metadata to detect and classify cancerous pulmonary nodules.

Recent surveys have demonstrated that neural networks renamed as "deep learning methods" are commonly used in several computer vision fields and have shown significant improvements in the evaluation of computerized tomography scan image detection and classification accuracies, moreover, datasets applied to train the methods are remain inadequate [10]. Recently, the convolutional neural networks (CNNs) is the deep architecture most

generally utilized for classification and segmentation of images.

Tumor detection and its classification has become a major subject of interest for researchers and they have used several techniques. Its accurate detection and classification with high accuracy are intended difficulty in clinical and research areas as its symptoms differ from patient to patient. Numerous types of methods are proposed previously for detecting and classifying the tumor but most of the methods involved noisy data which decreases evaluation performance and human competence. Therefore, it can impact effectiveness by increasing error levels. A reliable, automatic and efficient method is required to isolate and classify lung tumors with great accuracy to make the right decisions about treatment. So that less time is consumed and patient is provided by good health care without any delay. In this purposed methodology, we plan to build a 2-dimensional convolutional neural network for lung tumor detection. The dataset consisted of Lungs CT SCAN images is collected from the Nishtar Hospital and Nishtar University Multan, Pakistan. That lungs CT SCAN volume has a variety of tomographic 'slices' and manually marks to denote instance of classes i.e., Tumor or Normal. In our framework, first, using the image processing techniques such as Image Acquisition, Image Registration, and Image Resizing. Lung CT SCAN images are preprocessed and then to measure the resize feature, the input image is loaded. Following those preprocessing stages, the input CT SCAN image are ready to pass through the design CNN architecture to get better classification results. The study works with 31 layers of CNN with softmax function for improved classification accuracy rate. We use the softmax linear classifier for a deep and optimize features classification, to best depict the separation among healthy and unhealthy (tumor) pictures. Moreover, it also discussed how the outcomes are influenced by different filter size and how the layers of classifier affect the overall precision.

Previous and current approaches have limitations, less accuracy and performance is degraded when noisy data is included. The goal of this research is to provide an automated approach by using Convolutional Neural Network (CNN) will decrease the burden for doctors and radiologists from manual

inspection of high-risk CT SCAN images and increase the efficiency and effectiveness. This proposed method can be used for the analysis of the classification structure of lung tumors more accurately, helps doctors to reduce lung tumor problems and excessive weight of Colossal screening status.

Related Work

The Computer-Aided Detection (CADE) systems are design to detect and classify lung nodules from Lung CT SCAN images using sophisticated deep learning algorithms. A lung cancer detection is a difficult process and can be uncounted in various ways, so this section provides a summary of the state-of-the-art of the processed employed.

In (Xie, 2019) [11] suggested an automatic pulmonary nodule detection scheme focused on a more rapid Regional- based 2-dimensional Convolutional Neural Network (CNN). In the analysis, an improved 2-D convolutional neural network-based system was developed to reduce FPs and also to gain the corresponding fused classification results. Experiments were organized on a total of 1,50414 candidates (labeled as group 0 for 150075 nonnodule images, class 1 for 339 nodule images) from LUNA 16 training datasets. The system displayed the maximum accuracy of the candidate nodules was 86.42 percent. (Zhao, 2018) [12] suggested an Agile convolutional neural networks framework for the classification of pulmonary nodules in that current research. The hybrid convolutional neural network method was developed using Le Net and Alex Net, by integrating Le Net layer settings and Alex Net parameter settings. A system had been trained and validated on a dataset by LIDC/IDRI dataset with 743 computed tomographic image nodule samples (368 Benign and 375 Malignant nodules). The best output was obtained by setting the kernel size 7 by 7 with just two layers of convolution, the learning rate to be 0.005, the batch size to be thirty-two, and using dropout and gaussian initialization. It achieved an estimation accuracy of 82.2% and area under the curve of 0.87%, respectively.

(Kuruvilla, 2014) [13] developed an architecture for classification of the pulmonary nodules in computed tomographic images founded on texture approach

through an artificial neural network (ANN), the structure first applied the grey threshold level to transform that slices into binary images then applied the morphological operation to extract from segment independent images consisting two lungs. Six statistical features including standard derivation, kurtosis, mean, 5th and 6th central moments and skewness used as besides the features referred to [14] for classification. The outcomes showed in which the system gains with a 93.3% classification accuracy rate, 91.4% sensitivity, 100% and mean square error rates of 0.998%. In reference [15] using the combination of texture, size and shape attributes tends to become a positive path in Computer-Aided diagnostic and classification of pulmonary nodules in LDCT scan can help to enhanced classification accuracy. Using a five-nearest neighbor model and a dataset having characteristics such as texture only, an accuracy of 90.91% was obtained.

A work presented by (Kumar, 2015) [16] had revealed this great efficiency can be gained that utilized deep features derived from an autoencoder among (5-layered trained through LBFGS for de-noising autoencoder) to identify annotated lung cancer as either Benign and Malignant. The learned features along with an autoencoder unsupervised learning network layer four of 5-layers were select to construct 200d deep features for each instance. The system had an accuracy rate of 75.01 percent, 83.35 percent sensitivity, and 0.39 per patient False-positive rate across 10-fold cross validation on the diagnostic database. Several years later, an author enhanced their research framework with a custom radiomic sequencers as a three-layered deep CNN, and accuracy increased to 84.49% [17].

In this study (Setio, 2016) [18], presented a CADE method for candidate pulmonary nodules were classified through Multi-Scale convolutional neural networks (ConvNets). Through the MCNN classifier, the researchers extracted discriminative features to capture nodule. They trained the MCNN system on CT images of 1,186 candidates with LIDC/IDRI database by the LUNA 16 challenge. Better to those works using low-level handcrafted features, the network achieved 90.1 % and 85.4 percent sensitivity at 1.0 and 4.0 FPs per sample, respectively. M5LCAD was established by [7] (Lopez Torres, 2015) as a computer-aided detection

structure. The study aims, which was to check the degree of M5L, which was a combination of two independent different algorithms, based on the Lung Channeler Ant Model (LungCAM) and the Voxel-based Neural Approach (VBNA) subsystems. To classify candidates, the architecture of the FFNN comprised of 13 input nodes, 1 hidden layer with 25 nodes, and 1 node in the output layer for a binary classifier. Candidates were evaluated and executed on 1,018 computed tomography images through the LIDC-IDRI dataset. This study used twelve texture and morphological algorithms derived across all nodule candidates. The system acquired sensitivity of up to 89.1 percent by the test results and their score was 0.608.

The work by (Song, 2017) provides a method of cancer classification by analyzing 3-kinds of Deep Neural Networks (e.g., Convolutional Neural Network's (CNN's), Deep Neural Networks (DNNs) and Stacked Auto Encoder (SAEs)) specifically designed a lung carcinoma classification approach. 9,106 nodule image was collected on LIDC-IDRI. The size of the input image was fixed consistently to 28 at 28-pixel. There were 2,265 benign lung nodules cases and others on 2,311 images were malignant pulmonary nodules (a total of 4,581 images for training section). The experiment results suggest in which convolutional neural network architecture has recorded the highest precision, with 0.8415 accuracy, 0.8396 sensitivity, and 0.8432 specificities respectively [19]. Three deep learning methods such as Convolutional Neural Networks (CNN's), Deep Belief Networks (DBN's) and Stacked Autoencoder (SDAE's) for the diagnosis of 1,74412 cases of the LIDC lung nodule dataset that were tested and implemented in reference [20]. The convolutional neural networks featured three CONV layers and three pooling layers. The deep belief networks were designed in a greed fashion on four layers of RBM. The SDAE contained three layers. After downsampling and data augmentation, the methods acquired 1,74412 samples resized to 52 by 52 pixels each. CNN's, DBN's, and SDA classification accuracies rate were 0.7976, 0.8119, and 0.7929.

(Dey, 2018) [21] four 2-pathway networks were proposed like (basic 3-D CNNs, new 3D multi-output networks, 3-D DensNet, and 3D DensNet (MoDensNet) with multi-outputs. Also, for

experiment 686 pulmonary nodules (46 percent non-cancerous and 54 percent cancerous, estimated a mean malignancy rate) were evaluated from LIDC/IDRI, and 147 tomographic images (37 percent Benign and 63 percent Malignant) were applied for assessment after their additional database. The experiment outcomes indicated that a 3D MoDensNet performs best and can be obtained maximum classification with an accuracy of 90.40% and AUC of 95.48%.

In [22] proposed a new deep learning approach used a 15-layer 2-dimensional DCNN design for the automated extraction to respond to the issue of classification of lung candidates as nodules or non-nodule. The LUNA 16 challenge gained 1,186 positive candidates and 549,879 derived by the LIDC-IDRI dataset. Data augmentation and focal loss used to counter the imbalance dataset. The focal loss is then added to the training operation to increase the model's accuracy in the classification of candidate nodules. There are 15 layers in proposed network, nine of that were Conv layers, each consisting of three convolution blocks and one pooling layer using the max operator. Use 5*5 filters for the first batch and 3*3 filter for the later. The Rectified Linear Unit (ReLU) function allows each convolutional layer. Experiment results demonstrated that our focal loss deep learning system was indeed a great quality genetic algorithm with 97.2% precision, 96% sensitivity, and 97.3% specificity.

In reference [23] suggested the CNN architecture and discover the interest points using U-Net prepared on LUNA 16 challenge with labeled candidates to passing throughout the network. The size of the revised U-Net was set as input 256 by 256 2-dimensional computed tomography slices, and labels were given (whereby nodule pixels were either pre-labeled as 1, or rest 0). The network was contained the 1st convolutional layer, 7 kernels with size 5*5*5 were applied, a 2nd Convo operation employed 17 kernels with 5*5*3, and 256 neurons were used by both fully connected layers. The proposed 3D CNNs model performed an accuracy rate of 86.6 percent. Convolutional neural networks threshold for FP and FN was 1.

In [24] the pulmonary nodules were categorized between nonnodule and nodule classes through

creating a 2-dimensional deep residuals system. Likewise, Deep CNNs were training and testing on 62,492 ROI input patches derived upon 1,010 tomographic slices of the Lung Image Database Consortium dataset. As a result, 40,772 out of a total of 62,292 ROI image patches were pulmonary nodules and 21,720 out of a total of 62,492 patches are nonnodule. A system can achieve 86.4% accuracy, 89.0% sensitivity classification of the lung nodule through experiments.

Convolutional neural networks model have performed significantly better than Deep Belief Networks (DBN's) under their own in current literature of benchmark computer vision datasets. The CNNs have drawn significant interest in traditional machine learning algorithms such as SVM, RF or shallow neural networks, etc. because they have a good ability to represent useful learning features from input data in recent years. Besides that, to the best of knowledge, there has been no work that use deep CNN model to classify lung tumors.

In our study, a new method of separating highlights from clinical sweeps has been proposed and used for arrangement. The present study focuses on accurate detection of lung tumor by CT SCAN images and then classifying it based on its types between healthy and tumor infected instance labels. Numerous types of methods were proposed previously for detecting and classifying the tumor but most of the methods involved the semiautomatic approaches that include the expert radiologists for examining and analyzing the images for further treatment. Our framework provides the reliable results and can effectively present itself in therapeutic divisions for forced fixation. In our study, we differentiate these two classes (Normal, Tumor (Benign, Malignant)) through a softmax linear classifier. The classification layer predicts the final validation accuracy of the trained network. To validate the results of our framework, we used the AlexNet network by alternating its two layers. This framework saves the state of the art result that validates the results obtained from our main proposed framework.

2. Methods

2.1 Hardware and Software Configuration

From the database images, we used 80% of the image data for training the model and 20% of the data for

validation or testing. We have implemented the proposed CNN model results by using the MATLAB R2018a with deep learning toolbox by running on an individual system with an Intel (R) Core i7 CPU @ 2.20GHz and 16GB of RAM. The MATLAB R2018a release has several new features, including an in-deep learning toolbox supporting the development of machine learning applications. We re-sized all the CT SCAN images of this dataset to 227*227 pixels in size before our training phase, because of memory space constraint on GPU training our CNN model.

2.2 Preparation of Dataset

The objective of this study is to facilitate the physicians by releasing the big load of manual study of Lung CT SCAN images and detection of the lung cancer. In this study, the dataset consists of total 4,373 number of CT lung images. Among them, 1028 images are labeled as normal class and the 3345 images are labeled as tumor class.

The CT SCAN image dataset was collected from the Nishtar Hospital and Nishtar University Multan, Pakistan. The Nishtar Hospital Department of Radiology helped in the collection of image data with its cooperative staff. The CT SCAN images were collected by Dr. Abdul Sattar, Head of the Department of Radiology of Nishtar Hospital Multan. The staff of the Department of Radiology

cooperated in labeling the images manually by using their medical skills.

The high-risk lung CT SCAN images saved in the layout of Digital Imaging and Communications in Medicine (DICOM) were taken from the CT Scanner machine. For each patient scan's, the CT SCAN data contains 2-D axial slices. All the CT SCAN images of this dataset are in size of 512 * 512 pixels. The DICOM Service Object Pair (SOP) instance tags have a header file containing relevant details about Patient ID, Patient Name, Patient Age, and scan parameters such as slice number. Type of collected CT SCAN images and sizes were different and random, ranges from 128 to 220 mm. The CT SCAN images of normal or lung tumor infected participants contain different age groups of patients lies between 25 to 80 years.

CT SCAN images were labeled manually by the experts. Figure 1 shows the dimension and the location of the abnormal growth of cells and tissues, and the presence of white spots in the lungs. So, this dataset includes CT SCAN of lung tumor patients and also healthy patients Scan which sub-divided into two major classes.

1. Normal or healthy Lung CT SCAN images
2. Lung CT SCAN Tumor images (containing both Malignant and Benign)



Figure 1. A typical example of Tumor Infected and normal Lungs CT SCAN Image

On the basis of above both classes, the complete dataset is analysed and labeled by the experts.

2.3 Basic Design: Convolutional Neural Networks

Recently, Deep convolutional neural network (ConvNet) is built on the design of a feed-forward neural network, that is encouraged through the

brain's axon. One edge of convolutional neural networks across typical artificial neural networks is this the kernels are learned their values automatically by the machine themselves during the training. A CNN is approximately composed of several connected nerves with learnable weights and biases. In CNN, such filters extracted the volumetric contextual data that is taken into the input image as

a convolution operation. Deep CNNs, in particular, are made up of many different types of layers, such as, convolutional layers, pooling layer succeeded by one or even more than fully connected layers and lastly the output layer. They are learned together, in an end to end way, to solve a specific problem.

A.1. Convolutional layers:

A convolutional layer contains neurons that link the input tensor or outputs of the preceding layers to the subsets. The Conv layer consists of a series of convolutional filters in which every neuron serves as a filter or kernel. As a results convolutional kerneals in neuron networks works by dividing the image into small perception, generally known as local respective fields and eventually squeezing a layer of few quadrangle perceptions in feature maps of size $m_2 * m_3$ that is traileed through the convo layer. To process the pre-nonlinearity input to a bit of unit x_{ij}^l in the current layer, then have to totality up the commitments (weighted through kernel parts) from the past layer unit. Convolutional layer operation can be given as follow:

$$x_{ij}^l = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} w_{ab} y_{(i+a)(j+b)}^{l-1} \quad (2.1)$$

The ij feature-map, represented output x_{ij}^l , w_{ab} is an element of input data image, that is element wise multiplied by $y_{(i+a)(j+b)}^{l-1}$ index of the keneral k_l of the l^{th} layer.

A.2. Activation Function:

The activation function applied to every part of a feature map can introduce Non-linearity in convolutional neural network. In this study, we used the Rectified Linear Unit (ReLU) as an activation function. The nonlinear activation works as follows,

$$f(a) = \max(0, a) \quad (2.2)$$

Here, nonlinear neurons $f(a)$ = Rectified linear unit
 a = the function input

$$f(a) = \begin{cases} 0 & \text{for } a < 0 \\ a, & \text{for } a \geq 0 \end{cases} \quad (2.3)$$

The above method contains 0 if the function input is negative, otherwise it returns the original figure.

This ReLU layer is used for its computational effectiveness.

A.3. Overlapping Pooling Layer

The pooling layer in a CNN is another essential operator. The pooling operator works on individuals feature channels, merging the surrounding feature values into one by applying the correct operator. Popular options include max pooling or average pooling. We tend to use max pooling, much like a few other researchers [25]. So max pooling is one of the ways of down sampling which is defined as

$$x_{ijk} = \max\{y_{i'j'k} : i \leq i' < i + p, j \leq j' < j + p\}, \quad (2.4)$$

Where p is the size of the pooling. $x = \text{MaxP}(y)$ is used to define it. There are two hyper parameters for Max pooling operation, the size of spatial window: f , the value of the stride: S .

A.4. Softmax Classifier

A softmax classifier may be used for a multi category classification, which is similar to a logistic classifier if only two kinds are included. In effect, the layer of the convolutional neural network is a softmax classifier whether it uses a cross-entropy cost function.

A.5. Response Normalization Layer:

Batch normalization is used to fix the challenges of internal covariate shift, i.e. the distribution of each layer of input changes throughout training by normalizing the layer inputs for each minibatch of training. The specifics of this approach are defined in [26].

3.1. Proposed Methodology

Design of the Main Framework of Proposed CNN Network:

As, we have discussed above, the structural design of the Convolutional Neural Network. So, for collection of the main framework for giving the best deep learning classification, we have selected an already developed structure for designing our network through manufacture modification in it. Following are some steps followed for developing the main structure:

- Loading and analyzing of data of images
- Specifying the architecture of the network

- Defining the options for training
- Network training using Training Image Data
- Estimating recent data labels and evaluation of the accuracy of classification

3.2 Proposed Methodology

The proposed methodology used an early tumor detection technique utilizing a factual methodology on CT SCAN images as the input. The detection results of tumor disorder for every CT SCAN image graphic showed either healthy or tumor patients (i.e., Benign or Malignant). At the first step, RGB images were preprocessed and then input image was loaded to measure the resize feature. Then, using the re-size factor, CT SCAN images were resized and the new input image size was (227*227*3) pixels. The database with normal or tumor labels were then attached to the images. Following those stages, the input CT SCAN images were ready to be feed into our designed CNN architecture for getting better classification result. The required features were extracted by using the CNN architecture. Besides, the important point of our technique was image improvement and the performance of the classification model.

3.2.1 CT SCAN lungs images

This study had selected CT SCAN images for performing the classification tasks. CT SCAN images provides detailed images of various types of structures of the human body, especially concerning the lungs as compared to other imaging techniques. CT SCAN images have several types i.e. T1 weighted, T2 weighted, and flair. These types have not the same sizes, dimensional and channels. Images were preprocessed methodically for achieving efficacy in results.

3.2.2 Preprocessing

The aim of preprocessing of dataset was to eliminate the unnessary things such as noises and unwanted detailed from our datasets. The input images were lung CT SCAN images and the slice images hold a lot of data such as patient id, patient name, patient age etc. that was not required for our CNN model.

A.1. Image Acquisition

While working with the images the first step is acquiring images. According to information that images are made up of numbers of pixels, each of the pixels saves the values of their channels. Channels maybe RGB images, grayscale, and binary image. We have used color and grayscale images as received CT SCAN images are in both types.

A.2. Image Registration

The process of alignment of the images is known as image registration. We take multiple images by using the different CT Scanner machine, in a different environment, at different times, and of different patients in different positions. To deliver a stable proportion of data needful for deep neural models, all the images need to bring in the same alignment and in one lane for further processing. This process helps us to put all images into the same lane.

A.3. Image Resizing

Uniform and proper sizes of all the images are required for efficient image analysis. So resizing an image is a way that helps to convert all images properly in the same size and fit for passing into the developed algorithm. We set a base size for all images and then convert all images according to base size. Suitable base size is required for true training of the network. Resizing of the images is done by adjusting the width and height of all the images for evading the ambiguity while the training the network put a bad effect on the results.

CT SCAN images which we collected for this research have different sizes. The slice size is 512 *512 pixels in our datasets. These samples had various sizes, and in this manner were scaled to have fixed resolution and channel. For visualization aim, the CT SCAN images are then re-sampled. Further, various voxel for different images could be troublesome for our 2-d CNN model.

It is an easy task for human experts for analyzing them manually through vision. The computer system is not having intelligence like a human expert and it's not analyzed images like us. It's just recognized patterns of the pixels and remembers them. More pixels need more processing power and if the sizes of the images are different then it is possible that the accepted results are not achieved able.

All the input images were converted into RGB three-channel image. The input layer contained the image data and transferred that image data to the next layer. The dimension (Width & Height) of the input image

size is set to 227*227 pixels. Figure 2 and 3 shows the original input image size and after resizing the input image size.

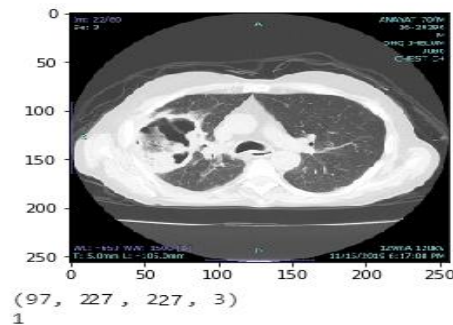
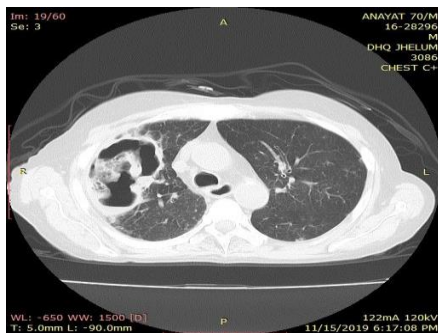


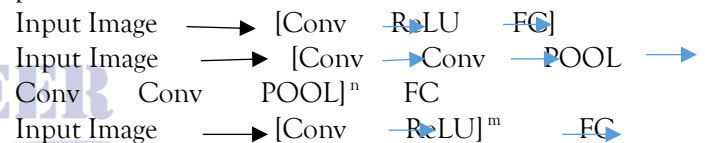
Figure 2: Original Input Image size 512*512 pixels Figure 3: After resizing the input image size 227*227 pixels

CNN Experiment

3.2.3 Proposed CNN Architecture for classification

Traditional machine learning approaches, particularly deep architectural learning networks have significantly performed the up-to-date findings in myriad domains like image processing and analysis, object recognition, audio recognition, and synthesis, and on health care bioinformatics, etc. In the last decade, CNN accomplished best execution contrast with physically tune classifying accuracies. In our study, we had used 31-layers of CNN including an input layer, a Convolutional Layer (Conv), Max Pooling Layer, Rectified Linear Unit (ReLU), Batch Normalization layer, Fully Connected Layer, Classification Layer, and Softmax Linear classifier.

Several Kernel sizes were used with CNN layers to improve the accuracy of the model. Some of the most frequently used convolutional neural network patterns can be described as follow:



While Conv is the Convolutional layer, ReLU is Rectified Linear Unit function, P is pooling layer, and FC is fully connected layer. N and M variables were the number of times the activity group used connectivity. We had followed the Figure 4 framework of CNN architecture by training it according to our network. The stride of fixed size 'three' is applied for the kernel size.

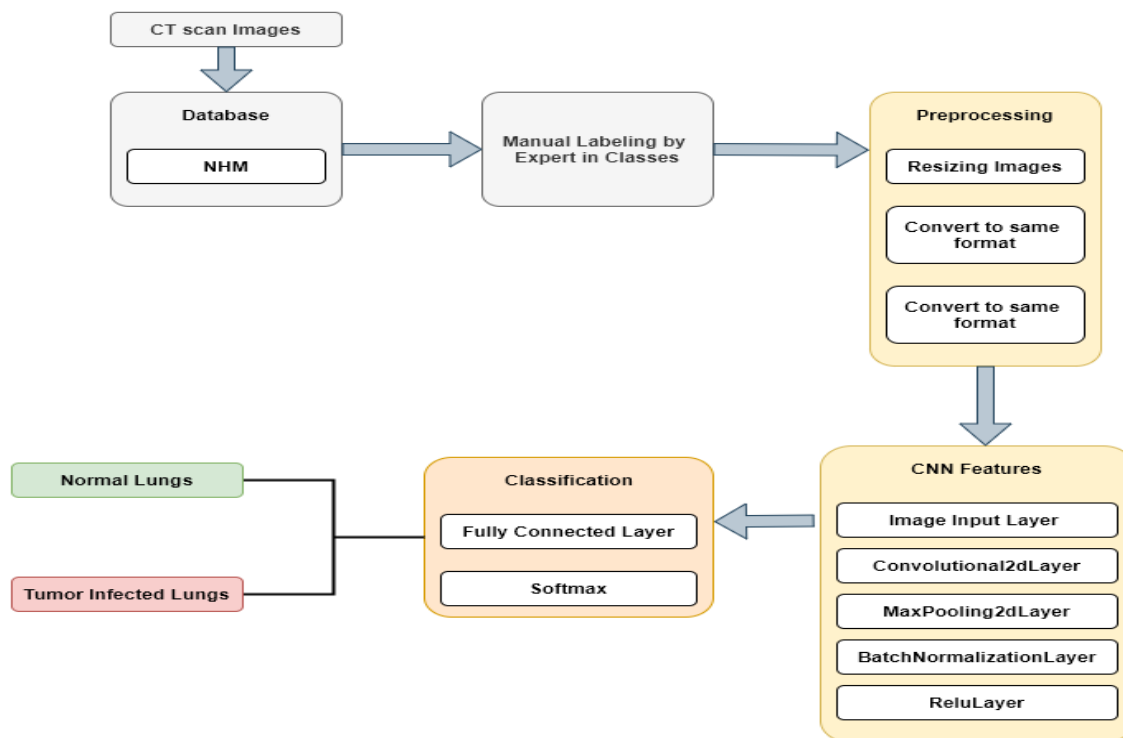


Figure 4. Modified Proposed CNN Architecture Flowchart

Loading and analyzing of data of images:

The first step of our pre-processing is to load a dataset. The entire image data was stored in the secondary memory folder. The folder includes images of the instances used for training and validation. Labeling and storing of the images are without human intervention done by the command of ImageDatastore. This ImageDatastore object allowed a reduction of the time to load a massive amount of data and during the training of the CNN model, it correctly read and labeled the set of the

Normal and Tumor infected images using the folder names and stored the image data as an image datastore object. Image's size was defined in the initial layer of the network which was the input layer. From the dataset of 4,373 images, we had set our arguments datastore to 40, so, it contained 40 random images from our datasets and we had specified the display images value in datastore to 20, it will display random twenty images. Some input images are displayed randomly in the Datastore, as shown in Figure 5.

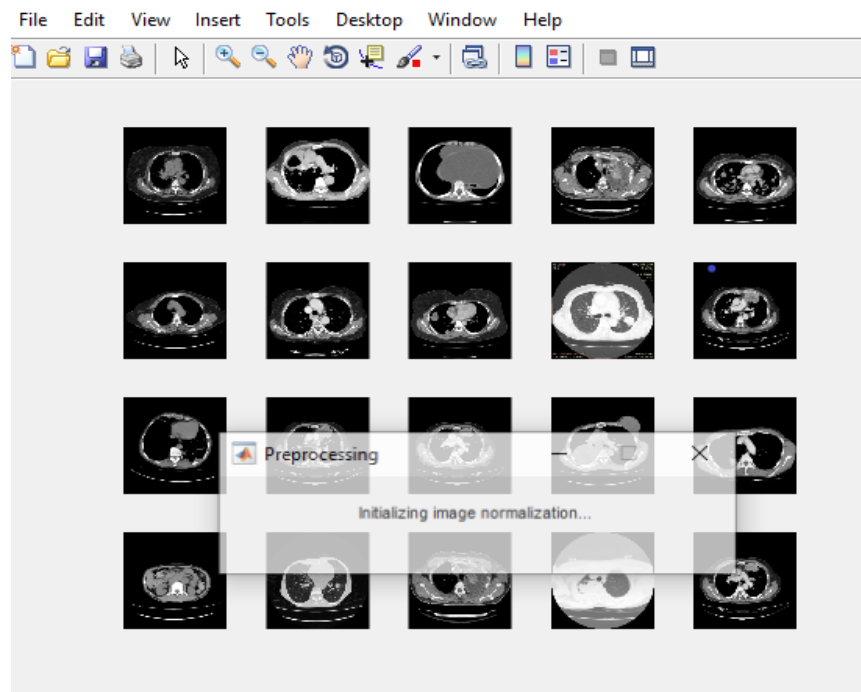


Figure 5: Randomly images are displayed in the Datastore

Then, measure the number of images for each class. LabelCount is a tabular form containing the Labels and the number of instances on each label. The data store includes total number of images 4,337 for each normal 1,028 and tumor 3,345 labels. Measure the size of the 1st image in the label Data file. Of image is 227-by-277-by-1 pixels in size. This dataset instance holds well-labeled data, which were necessary for the training and validation/testing set. After resizing and removing unnecessary things, Input Image Data file from both categories Normal and Tumor infected

lung images was shuffled and divided into training and test data. 80% of healthy and tumor classes were included in the training set and 20% of both classes are included validation/testing set. So, tumor class 20% (669) images were part of the validation dataset and the remaining 80% (2676) were part of the training dataset. Similarly, from Normal class, 20% (205) images were the part of the validation/testing dataset and the remaining 80% (823) were residents in the training dataset. Total Number of Images in the Training and Testing set are shown in Table 1.

Table 1: Total Number of Images in the Training and Testing set

Class	Images training set	Images in the testing set	Total Images of class
Normal	823	205	1028
Tumor	2676	669	3345
Total number of images in the data set			4373

3.2.4 Proposed CNN Architecture Layers

The Layer 1 for the proposed convolutional neural network was the Input Image layer of (227*227*3) that was specified by adjusting the width (W) of 227 pixel, height (H) of 227 pixel, and size of the channel was 3 RGB.

In 2nd convolutional layer, first of all, the filter size is specified through height (H) and width (W) according to the preference. It is done during the image's scanning by the function of training. Secondly for specifying the feature maps, several filters are applied. While in the input feature map

padding is added to analyze the image more accurately using the stride. At the stride of with padding, the 'same' is used for specifying that the input size and spatial output size both have the same width of the input image and height of the input image. The stride and learning rates of network and stride value can also be specified in this layer.

The convolution layer in CNN's recognized the filter size ($W * H * D$) as input. Each convolutional operation needs four hyper parameters including the number of kernels (K), Filter sizes, Spatial Dimension (F), the Stride (S), and the number of padding either zero as 'same' value (P).

The equation used to calculate the output volume size ($W*H*D$) of any given convolutional operation is:

$$O = \frac{W - K + 2P}{S} + 1 \quad (3.1)$$

Where O is the output volume size of height/weight, W is the weight of the input image, K is the filter size, S is the stride, and P is the number of padding.

There were seven convolutional layers of our proposed CNN architecture for feature extraction. In the first convolution layer, the filter size was (2, 2, and 3), the 'stride' was 2 and the 'padding' was the 1. The stride, learning rates of network and stride value can also be specified in this layer. The third layer is Batch Normalization Layer. This normalization layer was added in the structure to add swiftness up the network. The initialization of the weight was easily done through this layer. It was added between both convolutional and ReLU layer. A Batch-normalization was used to normalize the inputs x_j feature-map by first measuring the mean μ_B and variance σ_B^2 of a feature-map across a mini-batch size and over each input path, respectively. Therefore, the normalized activations for a transformed feature map N_l^k was determined as

$$N_l^k = (x_j - \mu_B) / (\sqrt{\sigma_B^2 + \epsilon}) \quad (3.2)$$

In equation 3.2, to prevent zero division, the Epsilon property ϵ was added to increase numerical stability. This also smoothest the motion of the gradient, on our modified proposed convolutional neural network of figure 4, the output filter size is shown in Table 2.

thereby helping to enhance the generalization of the channel. The ReLU layer-4 came after the batch normalization layer. As in the layer 1, the ReLU activation function was used. The nonlinear activation is described as below:

$$[f(a)] = \tan(a) \quad (3.3)$$

Where $f(a)$ is the input neuron. Additionally, max pooling layer then selected the best prominent feature from the convolution operation and minimized the time of computation of each layer. Down sampling was performed in this layer, so, max pooling was one of the ways of down sampling. An input image was divided into several pooling regions and extreme value was calculated of each region. Stride showed the learning rate during the training. The size of the spatial window specified the width (W) of the area to be target. On the other hand, the value of the Stride (S) marked the step size of the sliding window. The output volume size of max-pooling layer was calculated as:

$$(\text{Input window size} - \text{Pool size} + 2 * P) / S + 1 \quad (3.4)$$

Six Max Pooling Layer has the stride value set to '2' called step size. For adding the pixels to the input images padding is added with the stride value set as '1', and finally the Layer-29, Layer-30 of the proposed architecture is softmax, and Fully Connected Layer applied for classification in layer -31. While kernel values are specified from 2 to 64 in our proposed network.

The network is trained further by specifying the learning rate and epoch value of the network using the sophisticated gradient descent. For the training of the network, the learning rate gets off 0.01 whereas the epoch value is 30. During the training, the validation data and frequency are observed. The proposed network will shuffle the data with each epoch. Epoch and learning rates both minimize the error rates of the network for optimization of the network during training. Training data is used for training the network by MATLAB software and validation data is used for accurate calculation using the training plot. Based

Table 2. Filter size using every Conv layer and Max Pooling layer

Layer. No	CNN Layer Structure	Filter size after every layer
Layer 1	Image Input Layer	[(227 227 3)]
Layer 2	Convolutional	(3,2,'Padding',1)
Layer 3	BatchNormalization	-
Layer 4	ReLU Layer	-
Layer 5	Max Pooling Layer	(2,'Stride',2)
Layer 6	Convolutional	(3, 4, 'Padding', 1)
Layer 7	BatchNormalization	-
Layer 8	ReLU Layer	-
Layer 9	Max Pooling Layer	(2,'Stride',2)
Layer 10	Convolutional	(3, 8, 'Padding', 1)
Layer 11	BatchNormalization	-
Layer 12	ReLU Layer	-
Layer 13	Max Pooling Layer	(2,'Stride',2)
Layer 14	Convolutional	(3, 16, 'Padding', 1)
Layer 15	BatchNormalization	-
Layer 16	ReLU Layer	-
Layer 17	Max Pooling Layer	(2,'Stride',2)
Layer 18	Convolutional	(3, 32, 'Padding', 1)
Layer 19	BatchNormalization	-
Layer 20	ReLU Layer	-
Layer 21	Max Pooling Layer	(2,'Stride',2)
Layer 22	Convolutional	(3, 32, 'Padding', 1)
Layer 23	BatchNormalization	-
Layer 24	ReLU Layer	-
Layer 25	Max Pooling Layer	(2,'Stride',2)
Layer 26	Convolutional	(3, 64, 'Padding', 1)
Layer 27	BatchNormalization	-
Layer 28	ReLU Layer	-
Layer 29	Fully Connected Layer (2)	
Layer 30	softmax layer	
Layer 31	Classification Layer	

3.2.5 Classification Layer

This study used a softmax linear classifier for a deep and optimize features classification and depicted the separation among healthy and unhealthy (tumor) pictures. The softmax linear classifier was commonly used to perceive the classes in profound learning. In our study, we differentiated these two classes including normal or tumor i.e., Benign, Malignant through a softmax linear classifier.

Softmax layer's output contains positive values and these values were summed up to get one. After that, it can be taken by the classification layer for creating classification probabilities. The output unit activation function of the softmax function was like the categorical probability distribution that showed the probability of all groups as valid. The mathematical equation of softmax function is shown below:

$$\text{Softmax}(x_j) = \frac{\exp(x_j)}{\sum_{j=1}^K \exp x_j} \quad (3.5)$$

In equation 3.5, for each $\mathbf{x}$ value is the input vector for the output unit (if there have ten outputs units, there are ten components in $\mathbf{x}$). Then, j metrics the output units, this $j = 1, 2, \dots, K$.

This final layer was the layer of classification of the proposed approach. For every input class, this classification layer utilized the probabilities received from the previous softmax layer and allowed them to the mismatched classes and total loss was calculated in this layer. The final classification layer measured the cross-entropy loss or sigmoid cross-entropy for binary-label classification with equally exclusive groups. In this layer, train Network contained the values from softmax layer and applied every input to a few of the equally exclusive K groups using the sigmoid cross-entropy for 1 of $-K$ coding scheme.

$$\text{loss} = - \sum_{i=1}^N \sum_{j=1}^K t_{ij} \ln y_{ij}, \quad (3.6)$$

In Equation 3.6, N is the total number of variables, K is set of classes, t_{ij} is the predictor that it's the i th

sample place to the j th group, and y_{ij} is the result for the i sample for neuron j , which in this case is the output of the softmax function. The classification layer predicted the final validation accuracy of the trained network. To validate the results of our model, we used the Alex Net network by altering its two layers. This architecture saved the state-of-the-art result that validates the results obtained from our main proposed framework.

4 Experimental Results and Discussion

4.1 Results Evaluation

The performance of our presented technique for CT scan Lung tumor classification explains for Classification Accuracy Rate (CAR). On average, there was a gain of final ACC = 98.74%. An era or epoch many times holds a full detailed guide to the algorithm. Thus, each time the computation observed all the samples in the database, an epoch ended. We benefit ourselves with 31 layers of CNN design or architecture with 5 number epochs for each iteration, which is cycle operating in the neural network system and the learning rates set are defined as 0.01. The Table 3 shows the number of parameters of "Convolutional Neural Networks" (CNN).

Table 3: The Number of Parameters of CNN

Classifier	Number of Epoch	Learning Rate	Number of Layers
CNN	5	0.01	31

Thus, the framework can cover undetectable Lung tumors. Taking care of the medical expert's problem is a miraculous scale among the screening methods of the Lungs.

4.2 Performance Matrix

A performance matrix is a table that is frequently used to define the efficiency and accuracy of a classification system on a collection of test data in which true labels are familiar. The predicted True-positive (TP), and True-negative (TN) in a binary

performance matrix determined the proper predication of the Positive and Negative label class. On the other hand, FP and FN present False-Positives and False- Negatives. False-positive (FP) is specified as the number of positive incorrect labeling, and False-negative (FN) is the number of negative class errors. Predictive Accuracy was determined using Equation (4.1),

$$\text{Accuracy (ACC)} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (4.1)$$

Confusion Matrix		
Output Class	Normal	Tumor
Normal	198 22.6%	3 0.3%
Tumor	8 0.9%	666 76.1%
		Target Class
		Normal
		Tumor
		98.7% 1.3%

Figure 6. Confusion Matrix of proposed method in lung tumor detection task

The Confusion Matrix of our proposed architecture displays in Figure 6. The amount of TP class from the figure-5 is 198, and the FP is 3. Therefore, the total number of TN is 666 and FN is 8. Consequently, the likelihood of True-positive is 0.226, and the likelihood of False-positive is 0.3. The likelihood of TN is 0.761.

4.3 Evaluation during Validation and Training Graph Results:

The error in the training dataset is called the training loss and the verification or validation loss is generated by the information prepared by the system.

The graph below shows that the detection and final accuracy of the system is 98.74%, and it also shows the validation and training loss.

Our proposed CNN model extracted features from the pre-processing CT SCAN images and predicted scanning labels as Normal / Tumor. Out of the 874 test set of both normal and tumor cases, our model correctly estimated 864. But the network missed predicting 11 cases properly. Figure 7 shows 11 errors during our test set of our proposed model. There are 3 False-positives (FPs) out of 11 and 8 False-negatives (FNs) error.

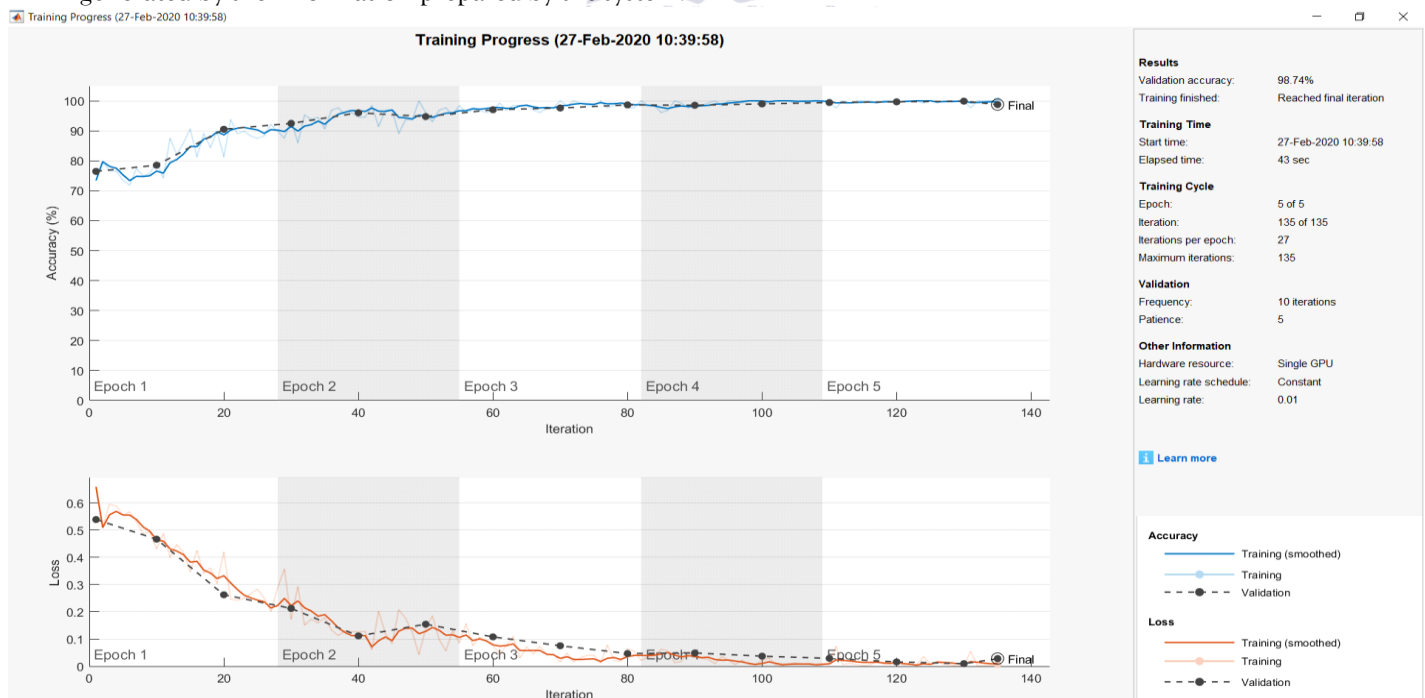


Figure 7: Predicated Accuracy using Each Epoch and Total of Loss Estimated During Training

4.4 Classification Accuracy

The convolutional operation, batch normalization layer, and Softmax strategies classifier coordinate with the Alex Net architecture to confirm the

planned design and can view the tumor with the perfect manual assessment. The convolutional neural networks obtained 98.74% accuracy.

Table 4: Classification Results Of Our CNN Model Compared With Other Related Work

Work	Database (Samples)	Methods	Accuracy (%)
(Setio, 2016) [18]	LUNA 16 (1,186)	Multi-scaled CNN	90.1%
(Kuruvilla, 2014)[13]	LIDC (110)	ANN	93.30%
(Kumar, 2015)[16]	LIDC(4,323)	5-layered trained through L-BFGS for denoisingautoencoder	75.01%
(Alakwaa, 2017)[23]	LUNA16 Challenge	3D CNN using U-Net	86.6%
(Song, 2017)[19]	LIDC-IDRI (9,106)	3-Kinds Deep Neural Networks (e.g CNN)	84.15%
(Tran, 2019)[22]	LUN16 (1,186)	15-layer 2D CNN	97.2%
Our Proposed CNN method	4,373 CT SCAN	31-layers 2-d CNN	98.74%

Unfortunately, it is very difficult to compare previously reported CAD systems due to various datasets due to patient policies and privacy. Since, some researchers reported experimental results using their private databases or local hospitals that are openly available and assessable. We picked out few CAD systems that are related to our work, to compare their efficiency, as shown in Table 4. Some of them [13, 16, 18, 19] used the LIDC-IDRI datasets. While others used their LUNA 16 databases [22, 23].

Work on (Setio, 2016) [18], the accuracy of the Multi-scale convolutional neural networks (MCNN) is 90.1%. The accuracy of the 3-D CNNs (U-Net prepared on LUNA 16 challenge with labeled candidates) is 86.6% in (Alakwaa, 2017) and the Artificial Neural Network (LIDC dataset with 110 nodule samples) is 93.30% (Kuruvilla, 2014). The experiment results suggest (Song, 2017) in which the

accuracy of deep neural architecture such as convolutional neural network architecture has recorded the highest precision, with 84.15% accuracy in [19]. A work presented by (Kumar, 2015) had revealed this great efficiency can be gained that utilized deep features derived from an autoencoder among (5-layered trained through L-BFGS for denoising autoencoder). The system had an accuracy rate of 75.01 percent, 83.35 percent sensitivity and 0.39 per patient False-positive rate across 10-fold cross-validation on the diagnostic database. Table 4 indicates

a comparative comparison of our proposed CNN network with other related works in the literature review and also shown in Figure 8. When the results are evaluated, our presented method is efficient with high accuracy 98.74% to our own collected CT image dataset in class structure for the characterization of healthy and Lung tumor disease.

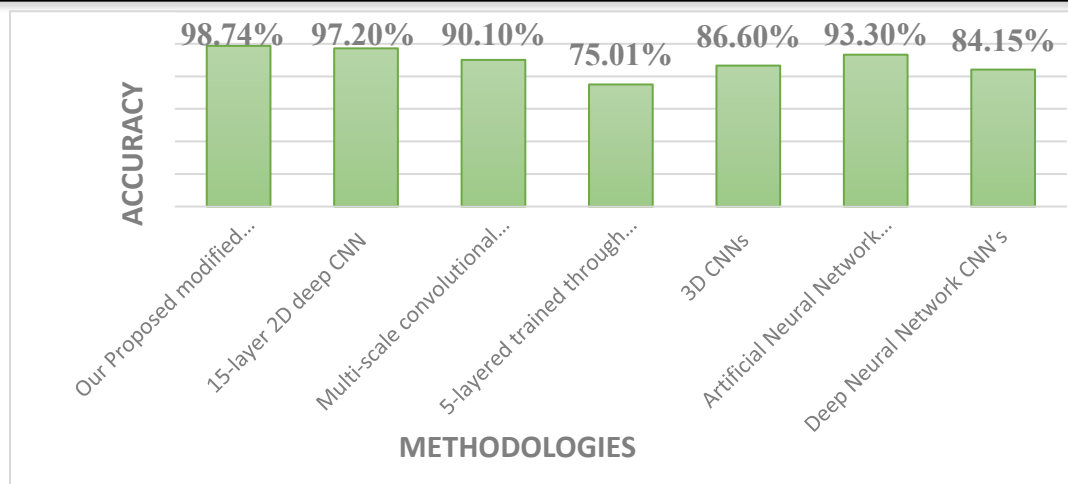


Figure 8: Comparison of CT Scan Lungs Tumor Classification with Different Methodologies

5 Conclusion and Future Work

Our study obtained the best detection performance and summarized the techniques of processing in Lung CT SCAN images and modified 2-dimensional Convolutional Neural Network (CNN) for lung tumor detection. The dataset consisted of 4,337 Lung CT SCAN image with 1028 normal images and 3345 tumors i.e., Malignant or Benign.

The proposed method consisted of two main stages: Image Pre-processing phase to enhance the quality of the CT SCAN image data, and classification in which a CNN model was created for accurate lung tumor detection on the basis of healthy and tumor infected labels. Our CNN classifier was trained using 80% of the dataset and evaluated using remaining the 20% of available data. The network is trained further by specifying the learning rate and epoch value of the network using the sophisticated gradient descent. For the training of the network, the learning rate gets off 0.01 whereas the epoch value is 30. We use a softmax linear classifier for a deep and optimize features classification, to best depict the separation among healthy and unhealthy (tumor) pictures. The classification layer predicts the final validation accuracy of the trained network. Accuracy can be in the form of a fraction of image labels that the convolutional neural network properly predicts. To validate the result of our proposed Convolutional Neural Network model, we used the Alex Net architecture for classification by alternating its two layers and obtained 98.74% classification accuracy

rate. This study is used to detect lung tumors in the early stage.

Through, there is support for future research on this issue. We have detected lung tumors in our research, but we have not seen the lung tumor position. In the future, our focus will be to identify benign and malignant cancerous tumor as well as size of the cancerous tumors. The dataset used in this study is small. Yet, we assume that by collecting more dataset, the efficiency of our CNN model can be enhanced and our CNN model can be used to detect and diagnose other types of cancer like breast cancer, colon cancer etc.

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