INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 4.295
(Volume 5, Issue 4)
Available online at: www.ijariit.com

Lung cancer detection using Convolutional Neural Network (CNN)

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ABSTRACT

Lung cancer is a dangerous disease that taking human life rapidly worldwide. The death of the people is increasing exponentially because of lung cancer. In order to reduce the disease and save a human's life, the automated system is needed. The purpose of the lung cancer detection system is able to detect and provide reliable information to doctors and clinicians from the medical image. To minimize this problem, many systems have been proposed by using different image processing techniques, machine learning, and deep learning techniques. A computed tomography (CT) imaging modality is an efficient technique for medical screening used for lung cancer detection and diagnosis. Physician and radiologist use the CT scan images to analyze, interpret and diagnose the lung cancer from lung tissues. However, in most cases, obtaining an accurate diagnosis result without using the extra medical tool known as a computer- Aid detection and Diagnosis (CAD) system is tedious work for many physicians. To obtain an accurate result from computer-aided diagnosis system lung segmentation methods are basic once. So in this project, we have used different lung segmentation and nodules segmentation methods. Our work has consisted of preprocessing, and lung segmentation by using thresholding, and also used the U-net model for detection of the candidate nodules of the patient's lung CT scan and classification methodology. We have used a convolutional neural network and designed a 3D CNN model that has a 0.77% accuracy performance.

Keywords*— Lung cancer, Cancer classification, Nodule detection, 3D CNN, Deep learning*

1. INTRODUCTION

Lung cancer is one of the dangerous diseases in the world that taking human life rapidly. The death of the people is increasing exponentially because of lung cancer. In order to reduce the disease, wrong interpretation of the radiologist, and save a human's life, the lung cancer detection and diagnosis system are needed. According to global cancer statistics report in 2012, around 1.83 million new lung cancer cases has enrolled and over 1.5 million deaths are estimated [12], and according to the latest World Health Organization data published in 2017 Lung Cancers Deaths in Ethiopia reached 1,584 or 0.25% of total deaths [13]. Medical imaging system produces a large amount of medical image containing the relevant information related to diseases. The medical image is one of the interesting research fields in medical problem domains to detect and diagnosis numerous diseases. Medical image analysis is used to analyzing and solving medical problems by using different medical image analysis techniques to detect relevant and hidden information or knowledge from any medical images. There are various medical imaging modalities that used to screening the from our body, those are Computed Tomography (CT scan), Positron Emission Tomography (PET), mammography, X-ray, and Magnetic Resonance Image (MRI), ultrasound and so on, that used for early detection and diagnosis of disease [12]. But one of the best imaging technique is Computed Tomography (CT scan) imaging are efficient for lung cancer detection and diagnosis because it can disclose every suspected and unsuspected lung cancer nodules from CT images [1].

Computer-Aided Diagnosis (CAD) has become a complementary and promising tool, to helping radiologists and physicians detect diseases accurately [1]. There are various ways that used to Lung cancer detection such as image processing, pattern recognition, and Artificial Neural Network (ANN) to implement the Computer-Aided Diagnosis (CAD). A lung nodule shows a range of abnormalities in lung tissue considered as small, round opacity, roughly spherical, restricted on abnormal lung tissue. To detect lung nodules from lung tissue radiologists, use chest Computed Tomography (CT) scans imaging modality.

Recently, deep learning has attracted much attention in many fields, such as image recognition and biomedical image analysis. Convolutional Neural Network (CNN) is an algorithm that most used and popular model in various research fields. CNN has been successfully applied to various research areas and has achieved state-of-the-art performance in video classification, natural language processing, image recognition and classification [2]. But there is still room for improvement on performance. We believe that enhancing the invariance of image features is a way to improve performance. We have used a convolutional neural network for classification due to the popularity of image and video classification, natural language processing and pattern recognition, etc. The main advantage of a convolutional neural network can extract and detect importance features from a given data automatically without any expert control. It has a special convolutional and pooling layer that perform parameter sharing operations. This parameter sharing operation makes the convolutional neural network most popular Algorithms. As compared as fully connected ANN, weight sharing in Convolutional Neural Network (CNN) facilitating in learning a feature regardless of its position in the image, along with having the added advantage of reduced computations. After convolution operation the Pooling operation is performed, this pooling operation is used to reduce the dimension and number of parameters used in our model. This makes training time shorten and reduce overfitting. The pooling layer operation consists of max pooling and means pooling. Mean pooling calculates the average neighborhood within the feature points, and max pooling calculates the neighborhood within a maximum of feature points. The error of feature extraction mainly comes from two aspects: the neighborhood size limitation caused by the estimated variance and convolution layer parameter estimated error caused by the mean deviation. Mean pooling can reduce the first error, retaining more image background information. Max pooling can reduce the second error, retaining more texture information. After the convolution layer and pooling layers, we should be using fully connected layers. The fully connected layers used for classification of the given patient medical CT scan images, whether the patient has cancer or non-cancer. And the final layer is dropout layer this layer is mainly used to reduce the overfitting problems. In this paper, we proposed a 3-dimensional convolutional neural network that helps to detect the small nodules in the CT scan data and classify whether the patient has cancer or not. If we use the 2D image the important and valuable information about the nodule may be missed out. Due to this, we are proposed a 3D Convolutional Neural Network is built for 3-dimensional images with RGB channels. 3D-CNN model projects feature map onto a 3D map via a 3D filter [3]. The 3D filter produces 3D images with different color channels. In 3D Convolutional Neural Network 3-Dimensional input images are used. Then several hidden layers comprised of Convolution Layer, Max pooling Layer, fully connected Layers generates Different images with different sizes, which are used for learning. Convolution layer is used to extract features from a given image by producing feature maps by applying convolution operation on different sub-region of the image with a learned filter/ kernel. In this paper we have used two different datasets (kaggle data science Bowel 2017 and Lung nodule analysis 2016), that is a help to increase the performance of training of our model. In this project, we are preprocessed and segmented the nodules from a given dataset that will help the future thesis works and our model evaluated by using the accuracy metrics. Hence our lung cancer detection system pipeline consists of preprocessing, lung segmentation, candidate nodule segmentation, nodule detection, and classification.

2. LITERATURE REVIEW

As we reviewed, many lung cancer detection system and diagnosis system have been proposed to the help of radiologist and clinician to detect and classifies the disease with the better result by using different approaches of image processing, machine learning, and deep learning. But the deep learning techniques are the current state-of-art methods for lung cancer detection system. We summarize these systems based on the methods they adopt.

2.1 Image processing approaches

Image processing technique has a great role in medical image analysis and it makes the classification processes more accurate. Image processing techniques have been greatly explored in nodule classification for lung CT images. Numerous studies adopted segmentation, morphological operations, and contour filter approaches for better nodule detection [5]. By using those approaches several researchers have proposed and implement lung cancer detection system with good accuracy. Neelima Singh et al[6] has been proposed lung cancer detection systems by using image processing techniques. The system is used image preprocessing, and after preprocessing of an image, a canny filter is used for Edge Detection. Superpixel Segmentation has been used for segmentation, and Gabor filter is used for denoise the medical images.

2.2 Machine learning approaches

Machine learning is studying methods that give computers the ability to solve problems by learning from experiences. The goal is to create mathematical models that can be trained to produce useful outputs when fed input data. Machine learning models are provided experiences in the form of training data and are tuned to produce accurate predictions for the training data by an optimization algorithm [7]. In recent years Machine learning techniques have played an important role in the medical field like medical image processing, computer-aided diagnosis, image interpretation, image registration, image segmentation, image retrieval, and analysis. These techniques composed of conventional algorithms without learning like Support Vector Machine (SVM), Neural Network (NN), and KNN, etc. Suren Makajua et al. [8] proposed a model that detect the cancerous nodule form CT scan image by using watershed segmentation for detection. In this proposed system Gaussian filter method is implemented in the pre-processing stages and using SVM for classification of the nodule as Malignant or benign. Qing. W et al. [9] proposed a system that detects small cell lung cancer (SCLC) form computed tomography (CT) scan images. The system proposed a novel Neural-Network Based algorithm, refers to an entropy degradation method (EDM) and use the vectorized histogram as training inputs.

2.3 Deep learning approaches

Machine learning is algorithms are limited in processing the natural images in their raw form, time-consuming, based on expert knowledge and requires a lot of time for tuning the features. Due to this limitation machine learning is overwhelming by deep learning techniques. Deep learning is fed with raw data, automatic features learner and fast. These algorithms try to learn multiple levels of abstraction, representation, and information automatically from a large set of images that exhibit the desired behavior of data. Deep learning-based algorithms showed promising performance as well as speed in different domains like speech recognition, text recognition, lips reading, computer-aided diagnosis, face recognition, drug discovery. Now a day deep learning algorithm has got great interest in each and every field and especially in medical image analysis due to the representation of multiple levels of abstraction and extraction of features from large dataset automatically.

Winona et al. [10] are proposed an Automatic Lung Cancer Detection and Diagnosis Using Handcrafted and Deep Learning Features. The system uses both handcrafted features such as the suspected nodule location, radius of the nodule, spectral signatures, taxonomic diversity and distinctness, and deep learning features were obtained with Inception-v3, a pre-trained network trained on ImageNet, which is currently the state-of-the-art Convolutional Neural Network (CNN) architecture. This system was trying to compare the results based on their features including handcrafted features (Bag of frequencies and taxonomic indices), deep learning features and use both of them by concatenating. The result shows the promising results but it needs a room of improvement for both handcrafted features. The Combined results were obtained by concatenating the feature vectors (handcrafted and deep learning), but the extreme disparity in size led to lower accuracy than expected.

Allison et al. [1] are to develop a Deep Learning for Categorization of Lung Cancer CT Images. The system has been present ensemble methods of Convolutional Neural Network (CNN) using multiple preprocessing methods to improving the accuracy of the system. This system uses both un-smoothing and smoothing images in separate networks to improve the classification. The result predicted by using both networks in a combined manner by applying voting systems rather than using average values. The smoothing network uses Gaussian filter methods to the testing and training images to create a second smoothed training-testing set.

Rotem et al [11] have been proposed Lung Nodule Detection in CT Images using Deep Convolutional Neural Networks. The system was proposed by using the publicity available Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI) database, which consists of CT scan images with different shape and size, and the system uses a deep Convolutional Neural Network (CNN), which is trained, using the back-propagation algorithm to extract lung nodules in sub-volumes of CT images. The system has a 78.9% sensitivity (True positive rate) with 20 False Positives (FPs) per scan. This proposed system has been achieved the result without using any segmentation methods and any FPS reduction process.

Albert C. et al [5] has been proposed Deep Convolutional neural networks for lung cancer detection system. This system has used a linear classifier as a baseline, a vanilla 3D CNN, and a Googlenet-based 3D CNN. Each classifier uses weighted softmax cross-entropy loss (weight for a label is the inverse of the frequency of the label in the training set) and Adam Optimizer, and the CNNs use ReLU activation and dropout after each convolutional layer during training. **Hongtao et al.**[4] Has proposed an automated pulmonary nodule detection in CT images using deep convolutional neural networks. **Wafaa A. et al** [12] has proposed Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN). **Prajwal R. et al** [3] has proposed Convolutional Neural Networks for Lung Cancer Screening in Computed Tomography (CT) Scans.

Emre Dandil [13] has been proposed a computer-aid pipeline for automatic lung cancer classification on Computed Tomography (CT) scan. The system used a private dataset that consists of 47 CT scans from 47 different patients. This proposed pipeline has composed on four stages: (1) Image preprocessing stage, in this stage, CT scan images are enhanced, and lung volume are extracted from the image, (2) Nodule detection stage. (3) Feature computation stage that used to extract features from lung image, and Principal Component Analysis (PCA) is used for feature reduction. The final stage is classification, in this stage the system, in this stage, the system has been used Probabilistic Neural Network (PNN) that used for benign and malign nodules.

2.4 Research Gap

A various researcher has been proposed their new work by using different machine algorithms and deep learning algorithms and also the obtained different system performance. Machine learning is algorithms are limited in processing the natural images in their raw form, time-consuming, based on expert knowledge and requires a lot of time for tuning the features. Due to this limitation machine learning is overwhelming by deep learning techniques. This deep learning algorithm is currently the state-of-art Computer-Aided Detection (CAD) system. Many researchers proposed their work on 2D CT scan images with the 3D model but this 2D can image is not providing the important and valuable information about the nodule may be missed out. In order to get those important and valuable information about nodules, we should be used, 3D model. A 3-dimensional convolutional neural network has helped to detect the small nodules in the CT scan data and classify whether the patient has cancer or not. As we have seen many researchers focus on the detection of pulmonary nodules from the lung image, but they are not focusing on for classifying a patient has cancer or non-cancer. Our work is focused on the classification of the patients whether the patient has cancer or not by using Three-Dimensional Convolutional Neural Network (3D-CNN).

3. PROPOSED METHODOLOGY

In our proposed system has five stages as shown below in figure 1. The basic idea is to leverage the information given from LUNA 16 dataset to predict the nodule Locations in the Kaggle dataset. Since we use two datasets, a pre-processing step ensures that they are in the same field. The segmentation of lung tissues on chest images is an important step to reduce the search space. The two steps are common for both the LUNA and Kaggle datasets. Next, detection and segmentation of lung nodules from the available search space. This is achieved by using LUNA dataset, as it provides us with cancerous regions in the lungs. This is then fed to the Kaggle dataset to locate cancerous regions. Finally, the classification of the detected nodules into malignant and benign is the final step. The details of each step are discussed below. This pipeline include data collection, image preprocessing, lung segmentation (including nodule segmentation) and classification (CNN model that classify whether the patients have cancer or non-cancer) pipelines of our lung cancer detection model that include data collection, image preprocessing, lung segmentation (including nodule segmentation) and classification (CNN model that classify whether the patients have cancer or non-cancer).

3.1 Data Source

The main challenges of many machine learning algorithms are luck of enough amount of data for trained the model, in order to reduce this challenge in this proposed system we are used two datasets from different online computation (Kaggle's data science bowl 2017 and lung nodule analysis 2016 dataset). The primary dataset we are used for this our proposed system is the patient lung CT scan dataset on Kaggle's data science Bowl 2017 (KDSB). This dataset contains labeled data for 2101 patients, where a label 0 is for the patient with no cancer and 1 is for the patient with cancer. For each patient, the CT scan comprises a variable number of images (normally around 100–400, each image is a 2-D axial slice) of 512×512 pixels. This dataset does not have labeled nodules. The slices are provided in the DICOM files. The 70% of the data provided is labeled in 0, and the remaining 30% are labeled in 1, so we use the loss function to address the imbalance problems.

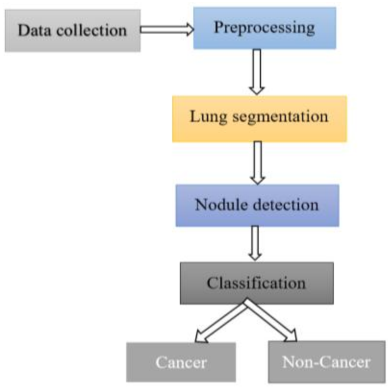

Fig. 3.1: Pipeline of Proposed Methodology

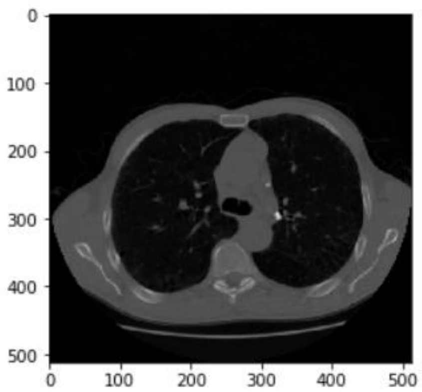

Fig. 3.2: The original 2D lung CT scan image

Since the Kaggle dataset alone is insufficient to provide accurately classify the validation set, so we used patient lung CT scan dataset with a labeled nodule from the lung nodule analysis 2016 (LUNA 2016) challenges. This dataset comprises labeled data for 888 patients. For each patient, the data consists of CT scan data and a nodule label (list of nodule center coordinates and diameter). For each patient, the CT scan data consists of a variable number of images (typically around 100-400, each image is an axial slice) of 512 x 512 pixels. Lung Nodule analysis 2016 (LUNA16) and Kaggle data science Bowl 2017 (KDSB 2017) are used for our proposed work.

	id	cancer
0	0015ceb851d7251b8f399e39779d1e7d	1
1	0030a160d58723ff36d73f41b170ec21	0
2	003f41c78e6acfa92430a057ac0b306e	0
3	006b96310a37b36cccb2ab48d10b49a3	1
4	008464bb8521d09a42985dd8add3d0d2	1
5	0092c13f9e00a3717fdc940641f00015	0
6	00986bebc45e12038ef0ce3e9962b51a	0
7	00cba091fa4ad62cc3200a657aeb957e	0
8	00edff4f51a893d80dae2d42a7f45ad1	1
9	0121c2845f2b7df060945b072b2515d7	0

Fig. 3.3: Sample labeled patients with their id numbers

As we have seen in the above figure the labeled data consists of the patient's ID and their cancer status 0's the patient has not cancer and 1's the patient has cancer.

3.2 Preprocessing and segmentation

A Computed Tomography (CT) scan images not containing the lung only, it is surrounded by other substances like tissues, bones, air, blood, and water. The presence of this substance is not important. It affects the ability that the model characterizes the nodules and the performance of the detection system, and thus we need to exclude them in order to achieve high accuracy. As mentioned above, since there are two datasets, one has to make sure that the pixels are in the same range to ensure that the information from one dataset is transferred to the other. To express CT numbers in a standardized and convenient form, Hounsfield unit (HU) is a quantity commonly used in Computed Tomography (CT) scanning[17]. The Kaggle dataset is by default not in this unit. The images are scaled to HU units by multiplying with rescale slope and adding the intercept, that is stored in the metadata of the scans. The LUNA dataset is by default in HU units. The advantage of bringing in to HU units is twofold. Firstly, the datasets are in the same range. Secondly, the range of values in HU units represents a physical property like air, lungs, fat, and bone. The first task of our preprocessing is loading the dataset. The whole image data were kept in a directory in the secondary memory. The directory contains the images of the instances used for training and testing. The directory contains the images of each instance are named by the patient's id. The images for an instance are first loaded into a List for further manipulation, and then we convert the pixel value of each image to Hounsfield Units (HU), a measurement of Radiodensity. The sample patients' distribution HU at different axial slices are shown in *Fig*, and typical radiodensities of the various part that comprises in the CT scan is showed in Table . And we stack 2D axial slices to the 3D image, we use segmentation to exclude the surrounding substance such as lung tissues, outside air, bone, and other substances those makes the data noisy, and leave the lung only for classify. There are many commonly used segmentation methods like thresholding, watershed, and cluster methods (k-means and Meanshift)[18].

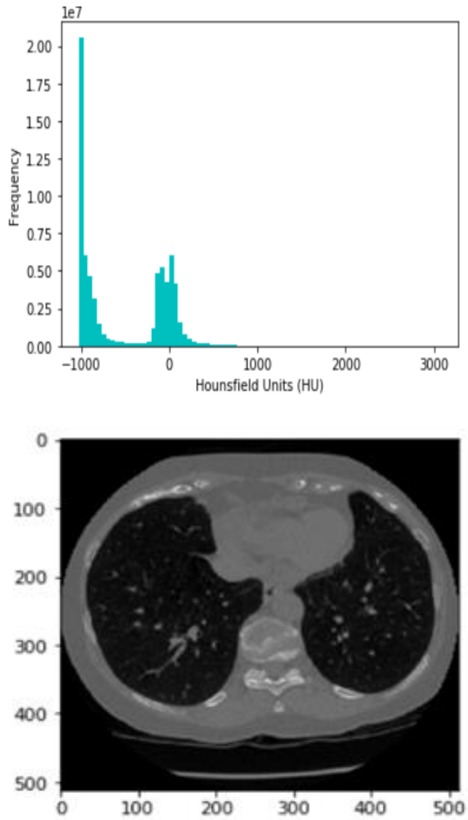

Fig. 3.4: Patients image with a Hounsfield unit (HU) pixel distribution at different axial.

The instance images are converted to Hounsfield unit as shows on in Figure 5. And the Histogram representation shows the CT image is surrounded by different substances. From Histogram, there are a lot of lung tissues, bones, and livers, etc. from the tiny line 700 HU and 3000 HU represents bones. Each individual slices has different thickness, this can be problematic for automatic analysis due to this after converted each slice to Hounsfield unit, the slices are resampled to the same size the size of each slice thickness. Using the metadata from the DICOM header we can see that the size of each voxel as the slice thickness. For visualization purpose, images then resampled in 1x1x1 mm pixels and slices. Also, different voxel for different images can be problematic for 3D Convolutional Neural Network.

Table 2: Typical radiodensity in Hounsfield unit (HU) of various substances in lung CT scan [5], [18].

Substances	Radiodensity (HU)
Air	-1000
Lung tissue	-500
Water	0
Bone	+700 to 3000
Kidney	+30
liver	+40 to +60
Blood	+30 to +45

3.3 Resampling

After converting each slice into Hounsfield Unit (HU) we are resampled the given slices because it is not clear how much the image is thick. By using the metadata from the DICOM header we can see that the size of each voxel as the slice thickness. For visualization, we are resampled the image into in 1mm × 1mm × 1mm pixels and slices. The difference slice spacing between with different slice can be problematic for our designed 3D convolutional neural network the resampled 3D image is shown below Fig. For resampling slice thickness of 0.69 is used and the pixel spacing is also used 0.69.

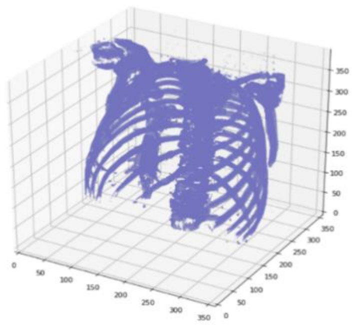

Fig. 3.5: Sample patient 3D image with pixels values greater than 400 HU reveals the bone segment

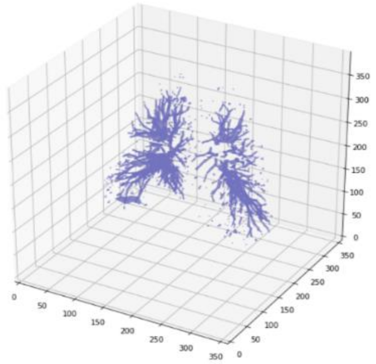

Fig. 3.6: Sample patient bronchioles within the lung

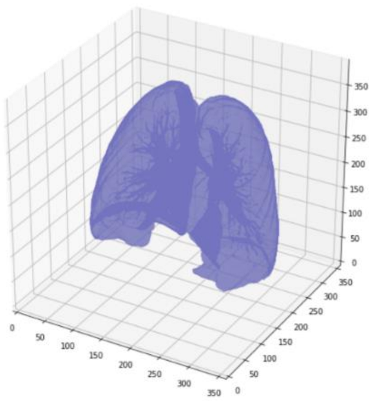

Fig. 3.7: Sample patient initial mask with no air

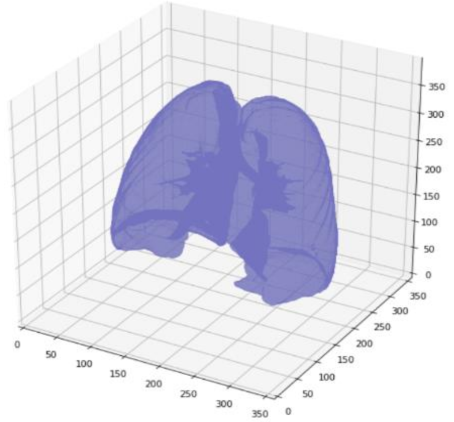

Fig. 3.8: Sample patient final mask in which bronchioles are included

3.4 Lung Segmentation

Segmentation of lung form CT image is the major challenging work due to heterogeneity in lung region and similar densities in pulmonary structures such as arteries, veins, bronchi. Thresholding methods are used for our work to isolate the regions within the image and then separate only the lungs. The threshold is not fixed and can vary across different lung images, this is due to certain images have a background around a grey circular region while others do not.

The threshold was chosen between the lung pixel values and dense tissue pixel value. The pixels are rested with the minimum value to the average pixel value of the image (lung region) and perform k-means clustering to get two clusters. Morphological operation erosion and dilation are applied to the binary image. All the above methods are applied and working well in the given dataset (Kaggle data science bowl 2017) as shown below *Fig*. We used a threshold of 604(-400 HU) at all places because it was found in experiments that it works just fine. We segment lung structures from each slice of the CT scan image and try not to lose the possible region of interests attached to the lung wall. There are some nodules which may be attached to the lung wall.

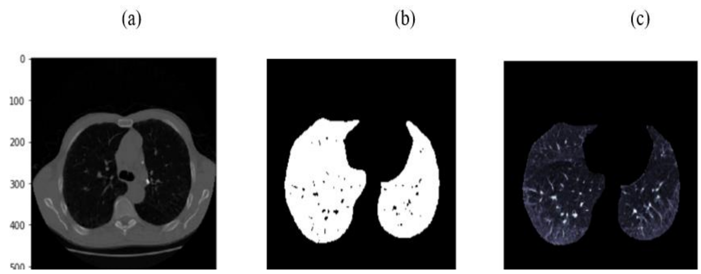

Fig. 3.9: (a) Original 2D CT slice of a sample patient, (b) its segmentation mask by thresholding and (c) is lung volume segmentation by using thresholding.

3.5 Lung Candidate Nodule Detection

After segmenting the lung structures from the CT Scanned images, our task is to find the candidate regions with nodules since the search space is very large. Also, the whole image can't be classified directly using 3D CNNs due to limit on computation, we need to find possible regions of cancer and then classify them. It was found in experiments that all the region of interests has intensity > 604(-400 HU). So, we used this threshold to filter the darker regions. This reduces the number of candidates by a large number and preserves all the important regions with high recall. We then classify all the candidate points to reduce the False Positives [19].

Fig. 3.10: The original image of the 2D slice of sample patients (right) and the segmented mask by thresholding (middle), and the detected candidate nodules using the region of interests have intensity > 604(-400 HU) on the left.

3.6 Downsampling

The size of the image is inconsistence, this inconsistency size of the image is stressed our memory in the time of feed the data in our model. So, we are downsampling our give images into the volume of [96x96x20]. First, the images are loaded and the volume size of 96x96x20 values are divided respectively by X, Y, Z-axis voxel size of the images to calculate the resize factor. Then by the images are resized by using resize factor and the new image size is 96x96x20. Finally, the labeled data are attached to the resized image that identifies whether the patient is cancer or non-cancer. The data is ready to feed into the 3D-convolutional neural network that we are proposed for the classification of the patient cancer status.

4. CLASSIFICATION

4.1 Deep learning

Deep learning is a machine learning technique that focuses on an algorithm inspired by the function and structure of the human brain called Artificial Neural Network (ANN). Deep learning algorithms such as convolutional neural network, recurrent neural network, deep neural network and deep belief network[20]. Deep learning-based algorithms showed promising performance as well as speed in different domains such as computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection, and board game programs [20]. Machine learning is algorithms are limited in processing the natural images in their raw form, time-consuming, based on expert knowledge and requires a lot of time for tuning the features. Deep learning algorithms are fed with raw data, automatic features learner and fast. These algorithms try to learn multiple levels of abstraction, representation, and information automatically from a large set of images that exhibit the desired behavior of data. Although automated detection of diseases based on conventional methods in medical imaging has been shown significant accuracies around for decades, new advances in machine learning techniques have ignited a boom in deep learning. Now a day deep learning algorithm has got great interest in each and every field and especially in medical image analysis due to the representation of multiple levels of abstraction and extraction of features from large dataset automatically. More specific uses of deep learning in the medical field are segmentation, diagnosis, classification, prediction, and detection of various anatomical Regions of Interest (ROI). Compared to traditional machine learning, deep learning is far superior as it can learn from raw data and has multiple hidden layers which allow it to learn abstractions based on inputs. The key to deep learning capabilities lies in the capability of the neural networks to learn from data through a general-purpose learning procedure.

4.2 Convolutional Neural Networks (CNNs)

A convolutional neural network is a neural network architecture that efficiently exploits the spatial correlation of the input data. Moreover, weight sharing in CNN facilitates in learning a feature regardless of its position in the image, along with having the added advantage of reduced computations as compared to a fully connected ANN. The convolution layer of a CNN produces a feature map by convolving different sub-regions of the image with a learned kernel (learned during the training process). Further, non-linear activation functions such as a sigmoid, tanh or rectified linear (ReLu) can also be applied. The ReLu layer is also known to improve the convergence properties when the error is low, leading to stagnation in the traditional sigmoid activation function [1]. The main advantage of a convolutional neural network can extract and detect importance features from a given data automatically without any expert control. It has a special convolutional and pooling layer that perform parameter sharing operations. This parameter sharing operation makes the convolutional neural network most popular Algorithms. As compared as fully connected ANN, weight sharing in Convolutional Neural Network (CNN) facilitating in learning a feature regardless of its position in the image, along with having the added advantage of reduced computations. CNN containing different layers like Convolution layer, pooling layer, and fully connected layer. Convolution layer is used to extract features from a given image by producing feature maps by applying convolution operation on different sub-region of the image with a learned filter/ kernel.

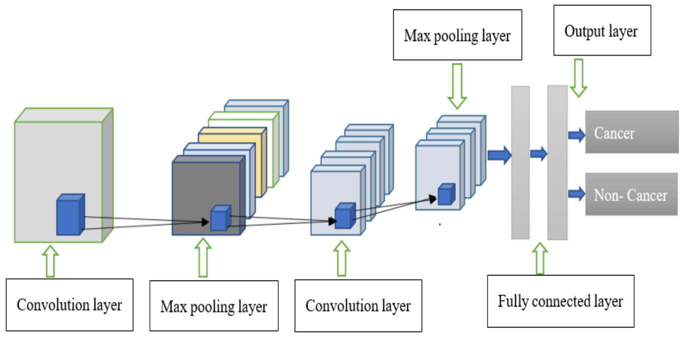

Fig. 4.1: A common 3D-CNN architecture

4.3 Our proposed 3D-CNN models

The size of each cancer nodules is different, at the first stage, the size of the nodule is very small. So, to detect them we used 3D convolutional neural network. If we use the 2D image the important and valuable information about the nodule may be missed out. Due to this, we are proposed a 3D Convolutional Neural Network is built for 3-dimensional images with RGB channels. 3D CNN model projects feature map onto a 3D map via a 3D filter [3]. The 3D filter produces 3D images with different color channels. In 3D Convolutional Neural Network 3-Dimensional input images are used. Then several hidden layers comprised of Convolution Layer, Max pooling Layer, Fully Connected Layers generates Different images with different sizes, which are used for learning. In the Convolutional Layers, Weights with 3-dimensional sizes are used. Biases define the number of output image or output neuron from each layer. Initially hidden layers which comprised with Convolution layer and max-pooling layer generates 3D images with different color channels of the input image or images for the layer[3]. A proposed a 3D CNN classifier has 3 convolutional layers followed by 3 max-pooling layers and 2 fully- connected layers. Our proposed system totally consists of 9 layers that including input and output layers. This model takes the input size 96x96x20 of the lung CT scan Image.

The convolution layer accepts the volume size of (W x H x D x C), where W is the width size of the image, H is the height of the image, D is the depth of the image and the last is C is the channel of the image either RBG (3) or grayscale (1) image, but to training our model we are used the grayscale image so the value is 1. In the first convolution layer we have (W1 x H1 x D1) volume size, where: W1 is Width of the Input image in the Convolution Layer. H1 is Height of the Input image in the Convolution Layer. D1 is Depth of the Input image in the Convolution Layer. In convolution layer we have four hyperparameters such as the number of kernels F, the size of kernels K, the striding S and the number of zero paddings P. the general formula used to find the output size of the tensor (image) f in the convolution layer is:

$$Output\ Tensor\ Size(O) = \frac{W-K+2P}{S} + 1 \qquad (4.1)$$

The number of channels is the output image size is equal to the number of kernels K. The Max Pooling Layer accepts the volume size (W3 x H3 x D3) as input: where W3 is Width of the input image in the Max Pooling Layer, H3 is Height of the input image in the Max Pooling Layer, and D3 is Depth of the input image in the Max Pooling Layer.

In the Max Pooling Layer, two hyperparameters require: The spatial extent/pooling size k and the stride S the general formula of the output tensor (image) size in map pooling layer is:

$$Output\ Tensor\ Size(O) = \frac{W-K}{S} + 1 \qquad (4.1)$$

Convolution layer 1: firstly, we are fed the input data size (64x64x32) into the convolution layer and in the convolution, a layer is used the kernel size (3, 3, 3) and the stride is (1, 1, 1) and the padding is "SAME". This layer used rectified linear unit (ReLu) activation function and this activation function is defined as:

$$f(x) = \max(0, x) \qquad (4.2)$$

Where, f(x) is the rectified linear unit activation function, and x is the input data. This activation function is if the input data is negative return 0, else return the original positive value and this makes our model more efficient in computation.

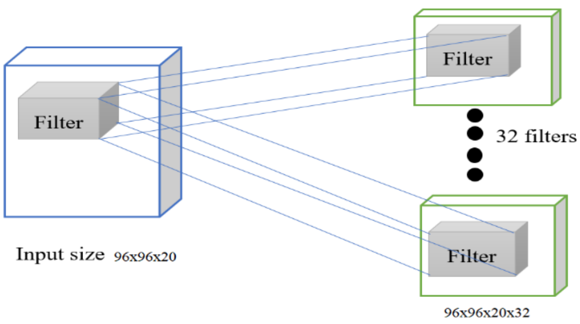

Fig. 4.2: 3D convolution layer filters

Max pooling layer 1: after first convolution layer comes max-pooling layer. in this layer, the kernel size is (3,3,3) and the stride is (2,2,2) and the padding is "SAME" used. The max-pooling layer is used to reduce the computational by reducing the dimensions of the images. **Convolution layer 2**: the output of the first max-pooling layer directly fed into the second convolution layer, and in this layer the kernel size is (3, 3, 3) and the stride is (1, 1, 1) and the zero paddings is "SAME" are used and use rectified leaner unit (ReLu) activation function. **Max pooling layer2**: the output of the convolution layer2 is directly fed into this layer, and this layer is used the kernel size of (3, 3, 3) and the stride of (2, 2, 2) and the zero-paddings of "SAME". And use rectified leaner unit (ReLu) activation function. **Convolution layer 3**: the output of the first max-pooling layer directly fed into the second convolution layer, and in this layer the kernel size is (3, 3, 3) and the stride is (1, 1, 1) and the zero paddings is "SAME" are used and use Rectified Linear unit (ReLu) activation function.

Max pooling layer 3: the output of the convolution layer2 is directly fed into this layer, and this layer is used the kernel size of (3, 3, 3) and the stride of (2, 2, 2) and the zero-padding of "SAME". And use rectified leaner unit (ReLu) activation function. **Fully connected layer**: after the last max-pooling layer the output is flattened from 3D- one-dimensional vector. This fully connected layer is used to classify the patient's cancer status weather the patients has cancer or not. Rectified Linear Unit (ReLu) activation function is used on each layer. The number of output class is two which is also known as binary classification.

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.

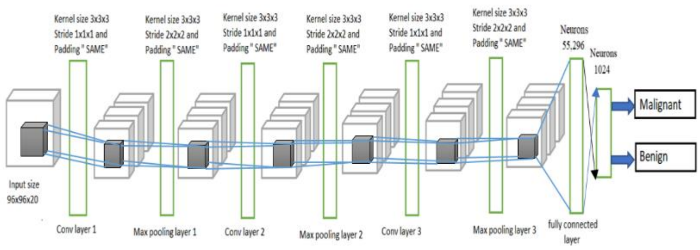

Fig. 4.3: The architecture of our 3D CNN

Table 4: Parameters of 3D CNN model

Layers	Parameters	Activation	Output
Input			96x96x20
Layer 1(Conv1)	Kernel size 3x3x3, stride 1x1x1	ReLu	96x96x20x32
Layer 2 (Max pooling 1)	Kernel size 3x3x3, stride 2x2x2		48x48x10x32
Layer 3 (Conv2)	Kernel size 3x3x3, stride 1x1x1	ReLu	48x48x10x64
Layer 4 (Max pooling 2)	Kernel size 3x3x3, stride 2x2x2		24x24x5x64
Layer 5 (Conv3)	Kernel size 3x3x3, stride 1x1x1	ReLu	24x24x5x128
Layer 6 (Max pooling 3)	Kernel size 3x3x3, stride 2x2x2		12x12x3x128
Fully connected Layer	Input Neurons 12x12x3x128= 55, 296)		Output Neurons (1024)
output	Input neurons (1024)		Output 2

As we saw in table 4, the model takes 96x96x20 pixel size of the image as input. And in the first convolution layer, we used 3x3x3 kernel and stride 1x1x1 size with the number of kernels of 32, and relu activation function then produces 96x96x20x32 based on equation 4.1. The next layer is max pooling layer, in this layer we are used 3x3x3 kernel size and stride 2x2x2 size, and it produces 48x48x10x33 based on equation 4.2. And the second convolution layer we are used 3x3x3 kernel size and stride 1x1x1 size, and it produces 48x48x10x64. And the second max-pooling layer we are used kernel size of 3x3x3 and stride size of 2x2x2 and ReLu function is applied and produce 24x124x5x64. And the final convolution layer used 3x3x3 kernel size and stride 2x2x2 size and it has 24x24x5x128 output, and the final max-pooling we used a kernel size of 3x3x3 and stride 2x2x2 size and ReLu activation function is applied, and it produces 12x12x3x128 output. After the max-pooling layer, we are flattened our 3D image shape into 1D and produce 55,296 neurons. Those neurons are directed feed to our fully connected layer and it produces 1024 neurons in the hidden layers. In the hidden layer, we have used the dropout layer with a keep rate of 0.8 to reduce the model overfitting during training the model. The hidden layer is produced 2 output/ class which the patients have cancer or non-cancer.

5. RESULT AND DISCUSSION

Initially, we had used raw image data without using lung segmentation, nodule detection, but the performance is very poor. Due to the CT, scan image is surrounded by other substances like blood, bone, liver and other tissues without removing their substance our model does not provide good performance. Then we have removed their substances and trained our 3D- CNN model, still we obtained a bad result. Hence in order to improve our model performance, we are applied lung segmentation and nodule detection on raw CT scan image data. For lung segmentation, we have used thresholding and to detect lung nodules U- the net model was applied. As an experimental result shows using thresholding and U-net model has improved the performance of our 3D convolutional neural network. The trained U-net model is used to detect the location of the malicious nodules and we are used a KDSB dataset.

For train our model we have used a labeled CT scan image in DICOM file format from KDB dataset. We have used 1439 patient's dataset to train our model and 100 patients image data to validate our model and 50 patients image data for testing. To evaluate our model, we have used accuracy metrics. Early experimentation suggested that the number of filters and neurons per layer were less significant than the number of layers[12]. In our model, we have used 32 filters in the first convolution layer and 64 filters in the second convolution layer and 128 filters for the final convolution layer. We have reshaped our dataset into [-1, 96, 96, 20, 1] tensor sizes and we used Adam Optimizer with learning rate 0.0003 and a dropout 0.8 and we trained our model with 50 epochs and it takes a couple of an hour. The final accuracy of our 3D CNN model is 0.77 and the final error rate is 0.24.

Table 0: Accuracy comparison of before and after preprocessing the data on our 3D-CNN

	Accuracy
Before preprocessing	0.645
After preprocessing	0.77

After preprocessed our dataset we have to get 0.1105 accuracy difference. This shows preprocessing the CT scan data is a necessary phase for improving our model performance.

5.1 Performance Evaluation

To evaluate our model performance, we are used accuracy metrics. This accuracy matrix is used to show the correctness of the model by dividing the number of correctly predicted to a total number of prediction.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \qquad (0.1)$$

As we have seen in the above table the accuracy of our 3D CNN model is 0.77 and error rate is 0.23. Our designed 3D CNN has consisted of three convolution layers and max-pooling layers, and one fully connected layer. We have also used a ReLu activation function and dropout layers with a keep rate of 0.8. Our model has achieved 0.77 accuracies with 0.23 error rate. The performance of the current state of the art model is 0.84. The performance of our model is good enough but not achieved the performance of the state-of-art model accuracy because the dataset we used is not enough to train the model and our dataset also highly imbalanced data. Due to those problems, our model has not achieved a state of art model performance.

5.2 Comparable work

We had been reviewed many works of literature including the current state-of-art lung cancer detection and classification system. We are compared our work with their work as we have seen below table.

Table 5.2: A comparable literature work include our work

Model	Accuracy
Deep learning for lung cancer detection system.[5]	Linear: 0.665 Vanilla 3D CNN: 0.70 3D Googlenet: 0.75
Lung cancer detection and classification using 3D-CNN.[11]	0.866
Our designed work	0.76

The accuracy of our 3D CNN model is 0.76 and error rate is 0.24. Our designed 3D CNN has consisted of three convolution layers and max-pooling layers, and one fully connected layer. We have also used a ReLu activation function and dropout layers with a keep rate of 0.8. Our model has achieved 0.76 accuracies with 0.24 error rate. The performance of the current state of the art model is 0.84. The performance of our model is good enough but not achieved the performance of the state-of-art model accuracy because the dataset we used is not enough to train the model and our dataset also highly imbalanced data.

6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this paper, we have been analysis various lung cancer detection system and they used different methodologies for preprocessing, lung segmentation (including nodule segmentation and candidate nodule detection), and classification of lung CT scan images in order to improve the performance of the detection of lung cancer. We are used CT scan image for this project, because Computed Tomography (CT) is the most effective method of lung nodule detection for its ability to form three-dimensional (3D) images of the chest, resulting in greater resolution of nodules and tumor pathology. We are implemented preprocessing and lung segmentation by using thresholding and also used U-net model for detection the candidate nodules of the patient's lung CT scan that is used for our classification model. We are proposed 3D-CNN classifiers that have 3 convolutional layers, 3 max-pooling and one fully connected layers that including output layers. We have also used a ReLu activation function and dropout layers with a keep rate of 0.8. Our model has achieved 0.77 accuracies with 0.23 error rate. The performance of the current state of the art model is 0.84. The performance of our model is good enough but not achieved the performance of the state-of-art model accuracy because the dataset we used is not enough to train the model and our dataset also highly imbalanced data. Due to that problem, our model has not achieved the state of art model performance.

6.2 Future work

In our proposed system we describe the techniques used in the preprocessing of the CT scan image and the 3D-convolutional neural network model that used to classify the patient's cancerous status. However, our model can classify detect cancer from the CT scan but not detect the location of the cancerous nodule and the size of the cancerous nodules. For our future work, we will detect the cancerous nodule location and also their sizes. And also, the dataset that used to train our model is very small and to achieve a good accuracy needs more dataset, so by using an extra dataset from the different source, we can improve the performance of our model.

The main challenges in our work are data-imbalance problems. The dataset we were used has consist of 70% of non-cancerous and the remaining 30% is cancers. Due to this the machine learning model will predict belongs to one class, so for the future, we will use different mechanism (resampling the dataset and by using balanced datasets) that used to reduce data imbalance problem.

7. REFERENCES

[1] A. M. Rossetto and W. Zhou, "Deep Learning for Categorization of Lung Cancer CT Images," Proc. - 2017 IEEE 2nd Int. Conf. Connect. Heal. Appl. Syst. Eng. Technol. CHASE 2017, pp. 272–273, 2017.

[2] Q. Song, L. Zhao, X. Luo, and X. Dou, "Using Deep Learning for Classification of Lung Nodules on Computed Tomography Images," J. Healthc. Eng., vol. 2017, pp. 1–7, 2017.

[3] P. Rao, N. A. Fereira, and R. Srinivasan, "Convolutional neural networks for lung cancer screening in computed tomography (CT) scan," Proc. 2016 2nd Int. Conf. Contemp. Comput. Informatics, IC3I 2016, pp. 489–493, 2016.

[4] H. Xie, D. Yang, N. Sun, Z. Chen, and Y. Zhang, "Automated pulmonary nodule detection in CT images using deep convolutional neural networks," Pattern Recognit., vol. 85, pp. 109–119, 2019.

[5] P. L. Albert, Chon, and Niranjan Balachandar, "Deep Convolutional Neural Networks for Lung Cancer Detection," no. November, pp. 1–9, 2009.

[6] N. Singh and A. Asuntha, "Research Article Image Processing used for Lung Cancer Detection in Medical Imaging," vol. 8, no. 4, pp. 1044–1049, 2016.

[7] M. B. A. Miah and M. A. Yousuf, "Detection of lung cancer from CT image using image processing and neural network," 2nd Int. Conf. Electr. Eng. Inf. Commun. Technol. iCEEiCT 2015, no. December 2015.

[8] S. Makaju, P. W. C. Prasad, A. Alsadoon, A. K. Singh, and A. Elchouemi, "Lung Cancer Detection using CT Scan Images," Procedia Comput. Sci., vol. 125, no. 2009, pp. 107–114, 2018.

[9] Q. Wu and W. Zhao, "Small-Cell Lung Cancer Detection Using a Supervised Machine Learning Algorithm," Proc. - 2017 Int. Symp. Comput. Sci. Intell. Control. ISCSIC 2017, vol. 2018-February, pp. 88–91, 2018.

[10] W. Richey, N. Khosravan, U. Bagci, and S. Member, "Automatic Lung Cancer Detection and Diagnosis Using Hand Crafted and Deep Learning Features," no. 1, pp. 1–4, 2016.

[11] R. Golan, J. Christian, and D. Jorg, "Lung nodule detection in CT using deep convolutional neural networks," 2016 Int. Jt. Conf. Neural Networks, 2016.

[12] W. Alakwaa, M. Nassef, and A. Badr, "Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN)," Int. J. Adv. Comput. Sci. Appl., vol. 8, no. 8, 2017.

[13] E. Dandıl, "A Computer-Aided Pipeline for Automatic Lung Cancer Classification on Computed Tomography Scans," J. Healthc. Eng., vol. 2018, pp. 1–12, 2018.

[14] M. Javaid, M. Javid, M. Z. U. Rehman, and S. I. A. Shah, "A novel approach to a CAD system for the detection of lung nodules in CT images," Comput. Methods Programs Biomed., vol. 135, pp. 125–139, 2016.

[15] E. Rendon-Gonzalez and V. Ponomaryov, "Automatic Lung nodule segmentation and classification in CT images based on SVM," 9th Int. Kharkiv Symp. Phys. Eng. Microwaves, Millim. Submillim. Waves, MSMW 2016, no. June, pp. 1–4, 2016.

[16] E. Matsuyama and D.-Y. Tsai, "Automated Classification of Lung Diseases in Computed Tomography Images Using a Wavelet-Based Convolutional Neural Network," J. Biomed. Sci. Eng., vol. 11, no. 10, pp. 263–274, 2018.

[17] "Data Science Bowl 2017 | Kaggle." [Online]. Available: https://www.kaggle.com/c/data-science-bowl-2017/data. [Accessed: 21-Jul-2019].

[18] W. J. Sori, J. Feng, and S. Liu, "Multi-path convolutional neural network for lung cancer detection," Multidimens. Syst. Signal Process., 2018.

[19] "Candidate Generation and LUNA16 preprocessing | Kaggle." [Online]. Available: https://www.kaggle.com/arnavkj95/candidate-generation-and-luna16-preprocessing. [Accessed: 21-Jul-2019].

[20] "Deep learning in neural networks: an overview.," Deep learning, 30-Jan-2019. [Online]. Available: https://en.wikipedia.org/wiki/Deep_learning. [Accessed: 21-Jul-2019].

