A Thesis/Project/Dissertation Report

on

LUNGS CANCER DETECTION USING FILTER WITH CNN

Submitted in partial fulfillment of the
requirement for the award of the degree of

Btech in Computer Science

Under The Supervision of
Dr. N. Gayathri
Assistant Professor

Submitted By

Ayush Chauhan
19021011445/19SCSE1010256
Ayush Pandey
19021011415/19SCSE1010226

SCHOOL OF COMPUTING SCIENCE AND ENGINEERING
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
GALGOTIAS UNIVERSITY, GREATER NOIDA
INDIA
DECEMBER, 2021

SCHOOL OF COMPUTING SCIENCE AND ENGINEERING
GALGOTIAS UNIVERSITY, GREATER NOIDA

CANDIDATE'S DECLARATION

We hereby certify that the work which is being presented in the thesis/project/dissertation, entitled **"LUNGS CANCER DETECTION USING FILTER WITH CNN"** in partial fulfillment of the requirements for the award of the Btech submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of July, 2021 to December,2021 under the supervision of Dr. N. Gayathri (Assistant Professor), Department of Computer Science and Engineering, of School of Computing Science and Engineering , Galgotias University, Greater Noida

The matter presented in the thesis/project/dissertation has not been submitted by me/us for the award of any other degree of this or any other places.

Ayush Chauhan(19SCSE1010256)

Ayush Pandey(19SCSE1010226)

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Dr. N. Gayathri

Assistant Professor

CERTIFICATE

The Final Thesis/Project/ Dissertation Viva-Voce examination of Ayush Chauhan(19SCSE1010256) & Ayush Pandey(19SCSE1010226) has been held on _____ and his/her work is recommended for the award of Btech.

Signature of Examiner(s) **Signature of Supervisor(s)**

Signature of Project Coordinator **Signature of Dean**

Date: December, 2021

Place: Greater Noida

Abstract

Lung cancer is one of the most prevalent cancer-related diseases with a high mortality rate, and this is largely due to the lateness in detecting the presence of malignancy. Again, the conventional methods used in the diagnosis of lung cancer have had their shortfalls. While the effectiveness of computerized tomography in detecting this malignancy, the large volumes of data that radiologists have to process not only present an arduous task but may also slow down the process of detecting lung cancer early enough for treatment to take its course. It is against this backdrop that computer-aided diagnostic (CAD) systems have been designed. One of such is the convolutional neural network, a method that best describes a group of deep learning models featuring filters that can be trained with local pooling operations being incorporated on input CT images in an alternating manner to create an array of hierarchical complex features.

The need to have this type of data-driven technique is further informed by the attempt to ensure successful segmentation of lung nodules, a step that cannot be overruled when striving for a good model of detection or diagnosis. There are variations and models of the convolutional neural networks that have been effectively put to use in the lung nodule detection. The 2D CNN model has been utilized in the medical field for quite a while now, and as it has displayed its many strengths, so could the limitations not be hidden. It is in addressing these limitations and improving on the detection prowess of the convolutional neural network that the 3D model is now fast gaining traction.

The 3D models have been reported to return pronounced sensitivity and specificity in detection of lung nodules, but the issues of time consumption, training complexities and hardware memory usage could make it difficult to implement the 3D model in the medical field. In this paper, review the advances that have been made in the area of adopting 3D CNN model in the diagnosis of lung cancer.

Cellular breakdown in the lungs is one of the darkest deadly disease in the world . Earlier treatment recognition identification are hardly more crucial for patient. Medical expert use some biological picture just like histological image of Adencarcinoma of biopsy tissue from possible lungs images for analysis. Now onwards than not the analyzation of cellular breakdown In the lungs liver are hardly And Deadly .CNN means convolutional neural organization could be distinct different characterize in lungs type with more than prominent pression. Cellular breakdown in a limited time which is really hardly and crucial for deciding patient good

treatment method and their success rate very lesser in harmless tissue in biological term Adenocarcinoma, and squamous.

Keywords - Convolution Networks; Lung cancer; Nodules; CT images; 2D CNN, Segmentation; Classification.

Table of Contents

Title		Page No.
Candidates Declaration		**I**
Certificate		**II**
Abstract		**III**
Contents		**IV**
List of Table		**V**
List of Figures		**VI**
Acronyms		**VII**
Chapter 1	**Introduction**	**1**
	1.1 Introduction	**2**
	1.2 Formulation of Problem	**3**
	1.2.1 Tool and Technology Used	
Chapter 2	**Literature Survey/Project Design**	**5**
Chapter 3	**Functionality/Working of Project**	**9**
Chapter 4	**Results and Discussion**	**11**
Chapter 5	**Conclusion and Future Scope**	**41**
	5.1 Conclusion	**41**
	5.2 Future Scope	**42**
	Reference	**43**
	Publication/Copyright/Product	**45**

List of Table

S.No.	Caption	Page No.
1		

Research Study	Dataset	No. of Samples	Acc. (%)	Spe. (%)	Sen. (%)
[10]	Private	128	90.63	89.47	92.30
[9]	Private	120	90	93.33	86.66
[6]	LIDC	2545	-	78.70	73.30
[13]	LIDC-IDRI	33	90.91	94.74	85.71
[7]	LIDC	4323	75.01	-	83.35
[8]	LIDC	110	93.30	100	91.40
[11]	LIDC	73	92.78	97.89	85.64
[12]	NBIA-ELCAP	113	-	52.17	96.15
[5]	Private	3278	-	89.56	91.38
Proposed Work	LIDC-IDRI	8296	97.2	95.6	96.1

List of Figures

S.No.	Title	Page No.
1		

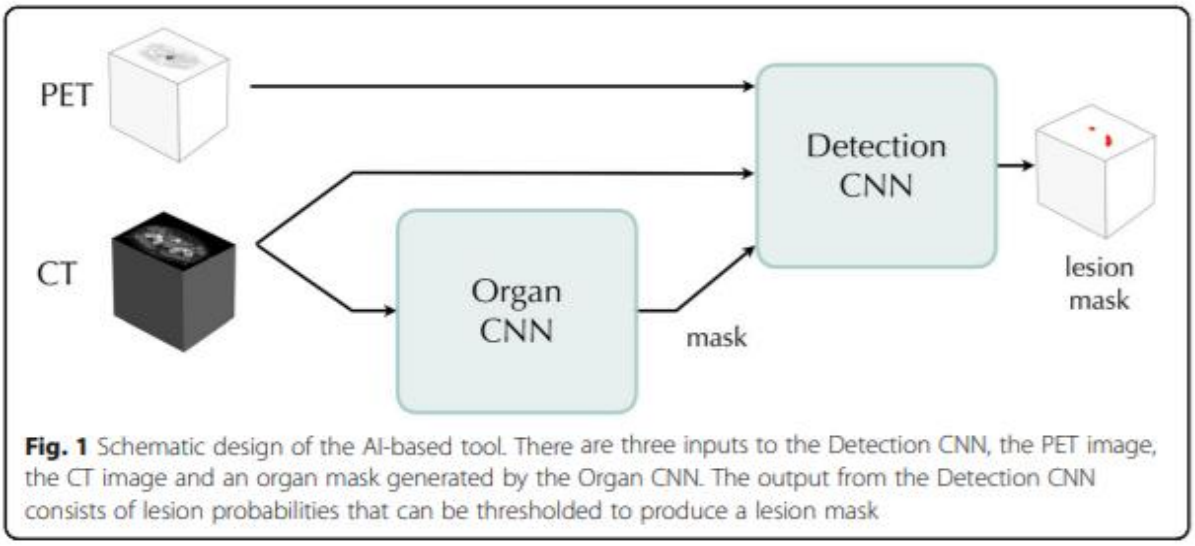
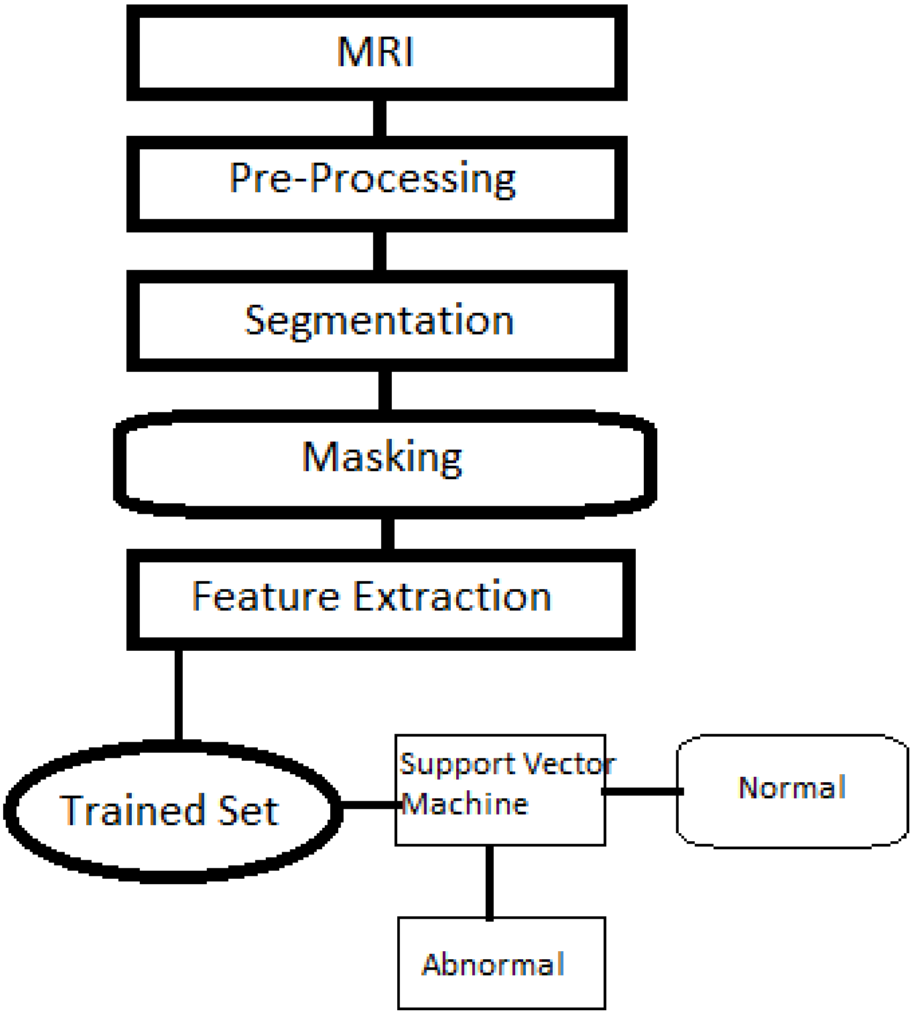


Fig. 1 Schematic design of the AI-based tool. There are three inputs to the Detection CNN, the PET image, the CT image and an organ mask generated by the Organ CNN. The output from the Detection CNN consists of lesion probabilities that can be thresholded to produce a lesion mask


MRI
Pre-Processing
Segmentation
Masking
Feature Extraction
Trained Set
Support Vector Machine
Normal
Abnormal

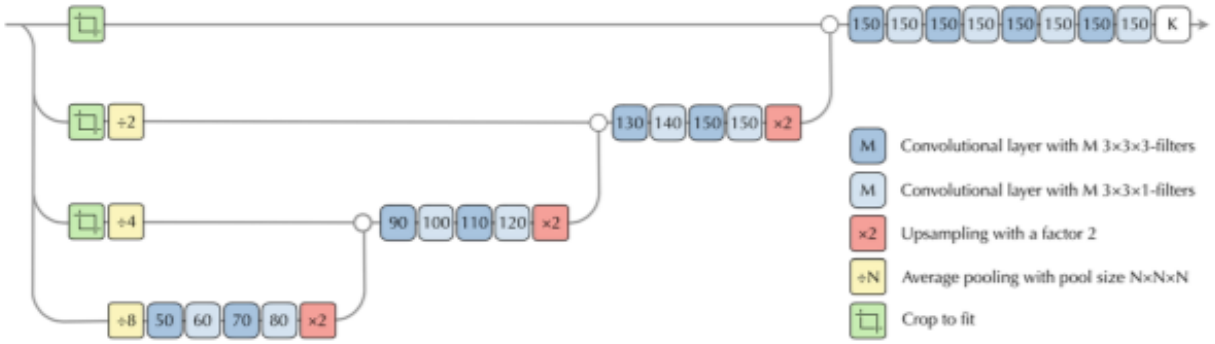


Fig. 2 Structure of the networks. Due to the pooling layers the network works on four different resolutions. This allows a large receptive field at low memory cost during training. All convolutional layers use rectified linear unit activations apart from the last one using a softmax activation to produce the final output probabilities

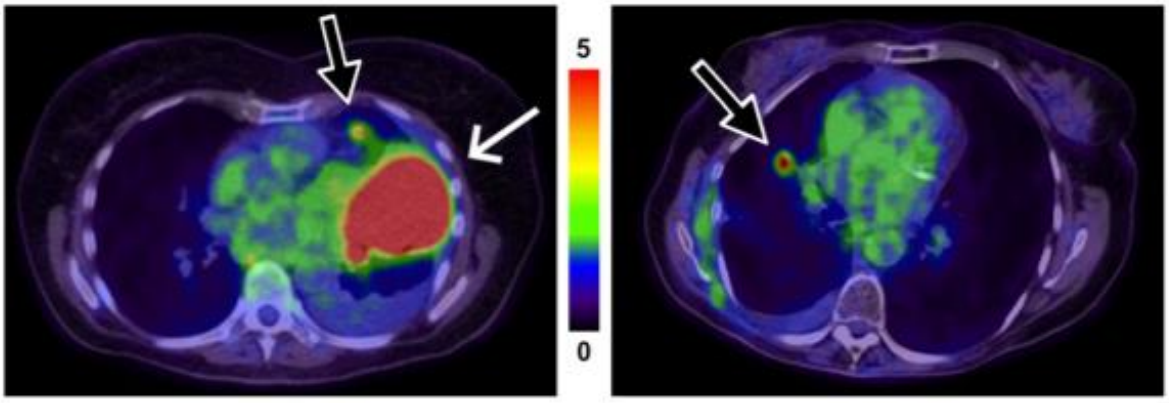


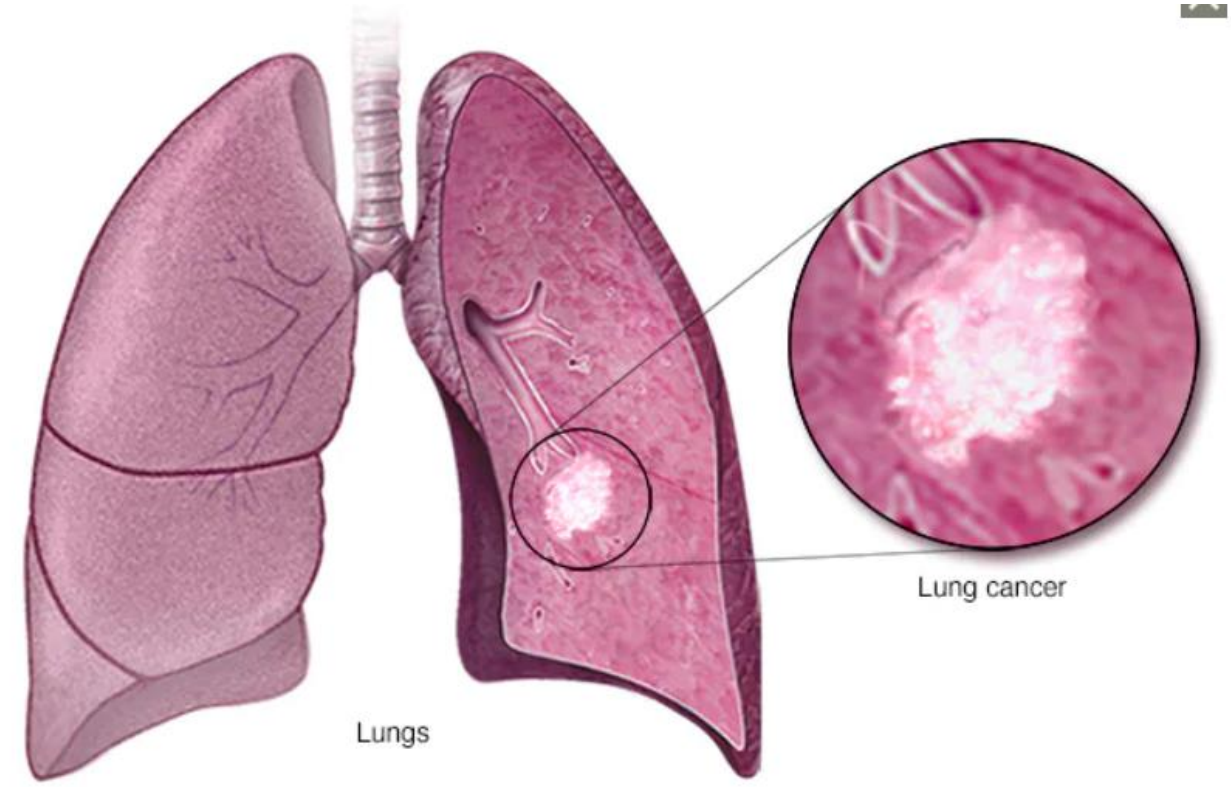
Fig. 3 Two patients (left and right respectively), each with a missed lung lesion (black arrow) by the AI-model. Both were less than 1 mL and therefore removed in the post-processing. The larger lesion in the left image (white arrow) was detected correctly. Segmentations are not shown

CHAPTER-1

Introduction

1.1 Introduction

Lung cancer is a type of cancer that begins in the lungs. Your lungs are two spongy organs in your chest that take in oxygen when you inhale and release carbon dioxide when you exhale. Lung cancer is the leading cause of cancer deaths worldwide. People who smoke have the greatest risk of lung cancer, though lung cancer can also occur in people who have never smoked. The risk of lung cancer increases with the length of time and number of cigarettes you've smoked. If you quit smoking, even after smoking for many years, you can significantly reduce your chances of developing lung cancer.



Lung cancer

Lung cancer begins in the cells of your lungs.

Lung cancer typically doesn't cause signs and symptoms in its earliest stages. Signs and symptoms of lung cancer typically occur when the disease is advanced.

Signs and symptoms of lung cancer may include:

- A new cough that doesn't go away
- Coughing up blood, even a small amount
- Shortness of breath
- Chest pain
- Hoarseness
- Losing weight without trying
- Bone pain
- Headache

Make an appointment with your doctor if you have any persistent signs or symptoms that worry you. If you smoke and have been unable to quit, make an appointment with your doctor. Your doctor can recommend strategies for quitting smoking, such as counselling, medications and nicotine replacement products.

Smoking causes the majority of lung cancers — both in smokers and in people exposed to second hand smoke. But lung cancer also occurs in people who never smoked and in those who never had prolonged exposure to second hand smoke. In these cases, there may be no clear cause of lung cancer. Doctors believe smoking causes lung cancer by damaging the cells that line the lungs. When you inhale cigarette smoke, which is full of cancer-causing substances (carcinogens), changes in the lung tissue begin almost immediately.

At first your body may be able to repair this damage. But with each repeated exposure, normal cells that line your lungs are increasingly damaged. Over time, the damage causes cells to act abnormally and eventually cancer may develop.

Doctors divide lung cancer into two major types based on the appearance of lung cancer cells under the microscope. Your doctor makes treatment decisions based on which major type of lung cancer you have.

The two general types of lung cancer include:

- **Small cell lung cancer.** Small cell lung cancer occurs almost exclusively in heavy smokers and is less common than non-small cell lung cancer.
- **Non-small cell lung cancer.** Non-small cell lung cancer is an umbrella term for several types of lung cancers. Non-small cell lung cancers include squamous cell carcinoma, adenocarcinoma and large cell carcinoma.

A number of factors may increase your risk of lung cancer. Some risk factors can be controlled, for instance, by quitting smoking. And other factors can't be controlled, such as your family history.

Lung cancer can cause complications, such as:

- **Shortness of breath.** People with lung cancer can experience shortness of breath if cancer grows to block the major airways. Lung cancer can also cause fluid to accumulate around the lungs, making it harder for the affected lung to expand fully when you inhale.
- **Coughing up blood.** Lung cancer can cause bleeding in the airway, which can cause you to cough up blood (hemoptysis). Sometimes bleeding can become severe. Treatments are available to control bleeding.
- **Pain.** Advanced lung cancer that spreads to the lining of a lung or to another area of the body, such as a bone, can cause pain. Tell your doctor if you experience pain, as many treatments are available to control pain.
- **Fluid in the chest (pleural effusion).** Lung cancer can cause fluid to accumulate in the space that surrounds the affected lung in the chest cavity (pleural space).

Fluid accumulating in the chest can cause shortness of breath. Treatments are available to drain the fluid from your chest and reduce the risk that pleural effusion will occur again.

- **Cancer that spreads to other parts of the body (metastasis).** Lung cancer often spreads (metastasizes) to other parts of the body, such as the brain and the bones.

  Cancer that spreads can cause pain, nausea, headaches, or other signs and symptoms depending on what organ is affected. Once lung cancer has spread beyond the lungs, it's generally not curable. Treatments are available to decrease signs and symptoms and to help you live longer.

There's no sure way to prevent lung cancer, but you can reduce your risk if you:

- **Don't smoke.** If you've never smoked, don't start. Talk to your children about not smoking so that they can understand how to avoid this major risk factor for lung cancer. Begin conversations about the dangers of smoking with your children early so that they know how to react to peer pressure.
- **Stop smoking.** Stop smoking now. Quitting reduces your risk of lung cancer, even if you've smoked for years. Talk to your doctor about strategies and stop-smoking aids that can help you quit. Options include nicotine replacement products, medications and support groups.
- **Avoid secondhand smoke.** If you live or work with a smoker, urge him or her to quit. At the very least, ask him or her to smoke outside. Avoid areas where people smoke, such as bars and restaurants, and seek out smoke-free options.
- **Test your home for radon.** Have the radon levels in your home checked, especially if you live in an area where radon is known to be a problem. High radon levels can be remedied to make your home safer. For information on radon testing, contact your local department of public health or a local chapter of the American Lung Association.
- **Avoid carcinogens at work.** Take precautions to protect yourself from exposure to toxic chemicals at work. Follow your employer's precautions. For instance, if you're given a face mask for protection, always wear it. Ask your doctor what more you can do to protect yourself at work. Your risk of lung damage from workplace carcinogens increases if you smoke.

- **Eat a diet full of fruits and vegetables.** Choose a healthy diet with a variety of fruits and vegetables. Food sources of vitamins and nutrients are best. Avoid taking large doses of vitamins in pill form, as they may be harmful. For instance, researchers hoping to reduce the risk of lung cancer in heavy smokers gave them beta carotene supplements. Results showed the supplements actually increased the risk of cancer in smokers.
- **Exercise most days of the week.** If you don't exercise regularly, start out slowly. Try to exercise most days of the week.

In cellular breakdown in the lungs is deadly disease among most of the people. Particular 28% of all death of lungs. They was not the patients of lung cancer .The most of the death from cellular breakdown in the lungs approximately 70% is from smoking and all knows smoking is injurious to health also. Cellular breakdown in lungs in non smokers people can be patients of lung cancer probably and now air pollution is been high level . Cellular breakdown can be caused due to exposure to container or smoke and various element or harmful element present in the atmosphere. this is ideally in this research different or many kinds of image , X-ray. In lung cancer detection many types of test are perform to detect presence of harmful elements. Now onward we are performing biological images just as an input we give .In phase of biopsy when lab technician study these reports is a right way or simply way to analysis. After recognizing it forward image, X-ray ,CT-PET to next process and once access the result of cellular breakdown in the lungs. For pathologists and other clinical experts diagnosing cellular breakdown in the lungs and the sorts is a tedious interaction. There is a critical change the malignant growth types are not readable and understand .some coordinates which are part of this process .these don't works direct to incorrect fully treatment because for this special work probably it may take money to patients (men, women). AI and deep learning is a part of computer science .Both of technology is most trending terminology because these are co-related with each other as well and .Ml is a application of AI which allow to work to learn from data with performed program

respectively by giving of information. Data To keep to safe. This is ideally main work of AI & Ml the part of considered taking X-ray, CT-PET and images with AI strategies like Convolutional neural network CNN, SVM, RF random forest, navee bycee algorithm. for Cellular breakdown in the lungs discovery. And acknowledgement reason a few papers likewise preferred taking biological pictures .But it recognize carcinomas and non carcinomas images and it is having a lower precisiom and also having lower frequency as well .We are doing main work in the research paper. And This research paper already have a thought about talking X-ray, image ,CT-PET and to forward next process this pictures belongs to biology pictures (Adencarcinoma and Carcinomous) in this paper convolutional neural network CNN engineering to Character the harmful .And we can find the accuracy of given image which is discussed already .And we don't have observe different paper .but i do not know the reason .In another word can say the main approach of this research paper to solve the accuracy with using CNN convolutional neural network and Then find the lung cancer is present or not .So that is why it is preferred method .that is simple or single conclusion belong to this research paper in cellular breakdown in lung cancer most of the benefial thing is about classification research paper in the terms of Convolutional neural network and getting ready to get of all neural network with association shapes for justifying behind the ml based on work and AI base on work ,this paper represent a Convolutional neural network (CNN) based each techniques in cellular breakdown in the lung cancer.

1.2 Problem Formulation

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.

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.

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. 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. 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 Mean shift).

The instance images are converted to Hounsfield unit. 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.

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.

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.

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.

Down sampling 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 down sampling 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.

CLASSIFICATION

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. 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. 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.

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. 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.

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. 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. 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.

ALGORITHM

- Stage 1: START The primary structure block in our arrangement of assault is convolution activity. In this progression, we will address include locators, which essentially fill in as the neural organization's channels.

- Step 1(b): DATA COLLECTION The second piece of this progression will include the Rectified Linear Unit or ReLU. We will cover ReLU layers and investigate how linearity capacities with regards to Convolutional Neural Networks.

- Step 1(c): input Image

- Step 2(a):Detect X-Ray

- Stage 2: PRE PROCESSING In this part, we'll cover pooling and will get to see precisely how it by and large functions. This part will end with an exhibit made utilizing a visual intuitive apparatus that will figure the entire idea out for you.

- Stage 3: IMAGE SEGMENTATION This will be a concise breakdown of the straightening system and how we move from pooled to smoothed layers when working with Convolutional Neural Networks. In this part it is used to bitwise addition to convert the binary images

Ya= CNN(xa)

Where , xa = input of CNN network

Ya = output of CNN network Further to the next LSTM networks and RNN

- Stage 4: CNN For gaining knowledge from 2D model of any input scanned input image we mostly used CNN , it’s structure used to perform such acts. The model was built from 22 layer deep CNN. More than 8 inception module as a group are stored in Googlenet. Every module has it’s convolutions at various measures, some pooling and integration operations.

Stage 4.1 : CONVOLUTIONAL LAYER Transformation of segmented images into a set of feature maps is the goal of convolutional layer .We perform this act using convolution operation which is the sum of dot product of two terminology after the reversiol and shifting of first terminology , For filtering the input segmented images we use cernal images and hence feature maps are produced as an output using the resulting convolved

F(a,b) = (I*K)(a,b)

Where, F(a,b) = set of feature maps

I(a,b) = input (segmented) image

K = kernel filter

Stage 4.2: MAX POOLING LAYER

In this layer taking the maximum value from a small window layer map which gives down sampling of the feature maps

F = max{F(a,b)}

Where, F(a,b) = Set of feature maps produced by conventional layer maps

5. RNN (LSTM)

The last layer of the CNN -LSTM is the LSTM layer. The LSTM consists of four gates, the equations of 4 gates are given below:

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$$
$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$
$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$$

Where,

It = indicates the input gate,

ft = indicates the forget gate,

ot = indicates the output gate,

sigma = indicates the activation function,

wx = indicates the weights for the respective gates

h(t-1) = output of previous lstm block,

x(t) = current input

bx = bias for the respective gates

The LSTM networks major purpose is to map the features extracted from the previous layer to their appropriate class. The classification of the extracted features is done using softmax activation function.

6. OUTPUT LAYER

The final result is obtained in the form of label or class i.e. normal and cancer.

1.2.1. TOOLS AND TECHNOLOGY USED

TOOLS AND TECHNOLOGY USED

1. PYTHON

Python is an interpreted high-level general-purpose programming language. Its design philosophy emphasizes code readability with its use of significant indentation. Its language constructs as well as its object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically-typed and garbage-collected. It supports multiple programming paradigms, including structured (particularly, procedural), object-oriented and functional programming. It is often described as a "batteries included" language due to its comprehensive standard library. Guido van Rossum began working on Python in the late 1980s, as a successor to the ABC programming language, and first released it in 1991 as Python 0.9.0.[33] Python 2.0 was released in 2000 and introduced new features, such as list comprehensions and a cycle- detecting garbage collection system (in addition to reference counting). Python 3.0 was released in 2008 and was a major revision of the language that is not completely backward-compatible. Python 2 was discontinued with version 2.7.18 in 2020.

Python consistently ranks as one of the most popular programming languages. Python was conceived in the late 1980s by Guido van Rossum at Centrum Wiskunde & Informatica (CWI) in the Netherlands as a successor to the ABC programming language, which was inspired by SETL, capable of exception handling and interfacing with the Amoeba operating system. Its implementation began in December 1989. Van Rossum shouldered sole responsibility for the project, as the lead developer, until 12 July 2018, when he announced his "permanent vacation" from his responsibilities as Python's "benevolent dictator for life", a title the Python community bestowed upon him to reflect his long-term commitment as the project's chief decisionmaker. In January 2019, active Python core developers elected a five-member "Steering Council" to lead the project. Python 2.0 was released on 16 October 2000, with many major new features, including a cycle-detecting garbage collector (in addition to reference counting) for memory management and support for Unicode. Python 3.0 was released on 3 December 2008. It was a major revision of the language that is not completely backward-compatible. Many of its major features were backported to Python 2.6.x and 2.7.x version series. Releases of Python 3 include the 2to3utility, which automates the translation of Python 2 code to Python 3. Python 2.7's end-of-life date was initially set at 2015 then postponed to 2020 out of concern that a large body of existing code could not easily be forward-ported to Python 3. No more security patches or other improvements will be released for it. With Python 2's end-of-life, only Python 3.6.x and later are supported. Python 3.9.2 and 3.8.8 were expedited as all versions of Python (including 2.7) had security issues, leading to possible remote code execution and web cache poisoning.

2.GOOGLE COLAB

You will quickly learn and use Google Colab if you know and have used Jupyter notebook before. Colab is basically a free Jupyter notebook environment running wholly in the cloud. Most importantly, Colab does not require a setup, plus the notebooks that you will create can be simultaneously edited by your team members – in a similar manner you edit documents in Google Docs. The greatest advantage is that Colab supports most popular libraries which can be easily loaded in your notebook.

3. Kaggle (For dataset)

Kaggle, a subsidiary of Google LLC, is an online community of data scientists and machine learning practitioners. Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges.

CHAPTER 2- LITERATURE SURVEY

The author S. Sasikala, B. R. Sowmiya proposed a modal using CNN on CT scan images to check weather the cancer is present in the lungs or not. Using they work and find two different phases in training volumetric features from input data as the first phase and classification as the second phase. The system proposed by them could classify the cancerous and non-cancerous cells with accuracy of 98%. T. Atsushi, T. Tetsuya, K. Yuka, and F. Hiroshi applied Convolutional Neural Network on cytological images to lung cancer type classification. They considered little cell carcinoma, Squamous cell , Adenocarcinoma images in maintained dataset. The DCNN architecture of 3 convolution and pooling layers

The area of research on the application of 3D convolutional neural network in detecting lung nodule is gradually becoming a beehive of activities with a good number of researchers have

already directed their attention - and one can be certain that there are more to come - there. Because of this, it becomes pertinent to explore some of the works that have been done so far. designed a method of classifying lung nodule using 3D deep CNN and an ensemble technique. The 3D CNN models employed in this research were of two types - one with dense connections, and another with shortcut connections. These two connections allowed the direct and quick passage of gradient thus solving the gradient vanishing issue that is capable of making the training process less efficient due to poor backpropagation. More so, with these connections, it was easy to capture the unique and generic features of candidate nodules from the network. The researchers reported that their model gave a progressive performance in distinguishing nodules from non-nodules. proposed a multi-scale 3D CNN model using three different architectural frameworks that were trained and optimized for LUNA 16 challenge dataset. The extracted 3D patches with scales, 40 X 40 X 26, 30 X 30 X 10 and 20 X 20 X 6 for each of the candidate nodules. Label prediction values were incorporated from scale patches with a weighted sum, and weighting was manually achieved. This model was able to encode contextual information thus addressing the challenges of large variation feasible with lung nodules; this encoding measure specifically resulted in the model reflecting higher discriminatory capability which must have impacted its sensitivity - one of the variants was reported to have a sensitivity of 84% at 1 false positive. Using 3D volumetric patches as input, created a 3D CNN model that significantly reduced false positives. They designed the model's framework through the application of a deep CNN technique for the identification of nodules, and for detecting candidate nodules. This framework design entailed the design of a deconvolutional CNN architecture for the detection of candidate nodules on axial CT slices while a 3D deep CNN was directed at a false-positive reduction. The sensitivity of this model in detecting lung nodule was observed to be 91.3% - this

is traceable to the pronounced reduction in false positives. An augmented method of lung cancer detection was designed by. This model involved three phases namely segmentation, detection of nodule and classification of the malignancy. To actualize the segmentation of lung tissue from CT scan, thresholding was used at the initial stage - through the researchers later used the watershed method to capture voxels that were not obtainable using thresholding since they (i.e. the voxels) were present at the edge of the lung. The Kaggle Data Science Bowl data set and Lung Nodule analysis 2016 (LUNA 16) were used for training the classifier

The latter (data set) was however found to be more effective for achieving a more accurate validation set. The preprocessing measure and the feeding of U-Net architecture - having 2D CT image slices segmentation of 256 X 256 - into the 3D CNN system appreciably took care of the issues of interference from other nodules; allowing for the accurate detection of candidate nodules. Regarding the results from the simulation experiment; the CAD method proposed here by showed an accuracy rate of 86.6%, the falsenegative rate being 14.7% while the false-positive rate was 11.9%. The 3D image was then normalized using linear scaling model to obtain pixels that are squeezable to values between 0 and 1; this was followed by the down-sampling of the 3D image - each dimension measuring 0.5 in scale - and zero-centring. Using a 3D multi-view CNN with chain and directed acyclic graphic (DAG) architectural frameworks, and CT dataset obtained from Lung Image Database Consortium/Image Database Resource Initiative (LIDCIDRI), was able to establish the superiority of Multiview one-network strategy over the one-view-one network strategy with the former showing to be more significant in improving the output of the 3D convolutional neural networks

The authors classified the nodules based on two categories: Binary-benign and malignant; and ii) Ternarybenign, Primary malignant and metastatic malignant. Upon application of data

augmentation and balancing strategy on the dataset; the authors discovered a total of 7,440 benign lesions (from 29 patient cases) and 7,080 malignant lesions (from 67 patient cases) under the binary classification while for the general classification; a total of 3,348 benign lesions (from 29 patient cases), 3,380 primary malignant cases (from 25 patient cases) and 3,368 metastatic malignant lesions (from 42 patients cases) were realized. The 3D multi-view CNN model proposed by [20] gave a specificity rate of 93.32 - 94.51 % and sensitivity rate of between 95.48 - 95.68% on the 3D multi-view CNN model with the DAG architectural framework while for the one with chain architecture gave a specificity rate of ranging between 89.73 - 93.94% and sensitivity of between 94.17 - 98.49%. More specifically, the effectiveness of the multi-view one network strategy was reflected by the fact that one of its variants showed the lowest error is generated. With this model, the binary classification error rate was 4.59% while the ternary classification error rate was 7.70%. [34] [38] created the CCE large Cube CNN, a 3D CNN model for the detection of lung nodule; this model is set on addressing the challenges arising from data resolution, hardware memory consumption and time-consumption, and the design is modelled after the Extended-Caffe framework. It features down-sampling and up-sampling sections; the combination of these sections enables the capture of local and global information from the original input data. The researchers trained the network for 100 epochs and found it to be stable at 60 epochs, even as learning rate was reduced by 0.1 at epoch value of 50 and 80. In this model, the network was trained with LUNA 16 data set, and a combination of stochastic gradient descent and step-wise learning rate strategies was also used in the training process. 3D convolution was optimized in two different ways: through the single-precision general matrix multiply (SGEMM) process and the Intel Math Kernel Library for Deep Neural Networks (MKL-DNN) which is renowned for its pronounced performance due to the influence of the Intel

AVX512 architecture. Summarily, the performance of the CCE large Cube CNN was quite notable as the Free-response Receiver Operating Characteristic (FROC) analysis gave a value of 0.833, and it was yet effective in detecting candidate nodules that are of small or large sizes. Breaking down further; a proportionality was observed between data resolution and performance - as better and/or improved performances were derivable from higher resolution. More so, it was reported that higher resolution brought about the conspicuousness and distinctiveness of the features of small candidate nodules. This, coupled with the FROC value, could highlight the importance of this model in detecting/predicting lung cancer at the early stage. Additionally, the efficiency of the model is brought to the fore in that training for 100 epochs of one-fold data set is actualized in nearly 61 hours which is about 5 times lesser what is attainable without optimization. Again, optimization of batch normalization using the MKL2017 resulted in 3.42 times higher performance ratio than the normalization that was not optimized. Another significant observation from this research concerns the variations in memory consumption as realized with both CPU and GPU; for the former, the model could receive a maximum input data of 448 X 448 X 448 pixels consuming 378.7GB RAM with a batch size of 1 - this is a sharp contrast to the 128X128X128 pixels with memory consumption being 11.9GB possible on GPU with the same batch size. used series of prior knowledge to propose a model that was effective for adequately detecting nodules from a limited data - the sensitivity rate was 90% while 5 false positives generated per CT scan - scans sourced from LIDC were used in validating the model. A Bayesian model was used to capture candidate nodules as the preset parameters filtered out contravening voxels - those whose clusters were not 23mm. The reduction of variability of the input fed into the 3D CNN was ensured by aligning the candidate nodules to principal directions

through the application of intensity-weighted principal component analysis. The accuracy of this model was further boosted by the data augmentation and weight regularization
- achieved through a hyper-parameter of 0.0005 - that were carried out in the developmental stage. The network was trained to 10 epochs and model selection was triggered when there was a loss on validation data set. Another interesting aspect of the observations from this research is the significance of the alignment to principal directions with a marked reduction in detection performance reported when the model was not aligned; this further buttress the role played by principal direction alignment in addressing the issues evolving from generalization errors. This model yet highlighted the influence of the dense evaluation of candidate clusters with a single evaluation being more prone to errors at the stages of generation and extraction of candidate cube. The authors classified using preprocessing then segmentation and used CNN architecture 2,2,1 convolution, max pool and fully connected layers respectively. The sizes should be 50x50 and 32 features and 3x3 convolution kernels and LUNA16 datasets used and implemented with the tensor flow and vanilla 3D CNN classifier for lung cancer detection with accuracy 80%.[40]. To detect the lung cancer first we need to identify lung nodules. A solid shape is made around the knobs with the knob as the middle. A 3D Convolutional Neural Network (CNN) is utilized to recognize knobs utilizing these blocks. The predicted nodules coordinates are used to make cubes around nodules as the same size as before and a second 3D CNN is used to predict cancer using it. The model achieves precision and recall of 89.24% and 82.17% respectively [41]. Using 3D CNN with shortcut connections and dense connection we can classify nodule and non-nodule with LUNA 16 dataset and checkpoint ensemble method will give a better performance that gives highest completion performance metric (CPM) score 0.910

The Various CNN methods used as mentioned in the comparison Table 1. we have done the comparison of lung detection methods and result. In the result, we have considered accuracy, precision, recall, sensitivity, specificity, AUC, CPM, classification rate. we have compared with consideration of various CNN architectures. The various datasets used LUNA16, LONI, LIDC-IDRI, General public data etc. Jakimovski & Davcev et al Double deep CNN is more connection and dense connection also giving high Competition performance metric (CPM) score:0.910 with LUNA 16 DATASET . 3D multi-view CNN (with chain e accurate compared to all other CNN methods with 99.6% accuracy with LONI data set.3D CNN with shortcut architecture, and with DAG architecture) chain architecture will give high sensitivity and specificity than DAG Architecture. Ensemble and False positive reduction methods also giving effective results on public data. Deep CNN (executed based on the center of ROI) will give less false positive rate .

Reference

[1] Siegel RL, Miller KD, Jemal A. (2016). Cancer statistics, 2016. CA Cancer J Clin. 66(1):7–30.

[2] JC. (2000). Surgical management of early stage lung cancer. SeminSurgOncol 18:124–136. [PubMed: 10657914].

[3] Liu X, Hou F, Qin H, Hao A (2018). Multi-view multi-scale CNNs for lung nodule type classification from CT images. Pattern Recognition; 77:262–275.

[4] Jenuwine NM, Maheshb SN, Furstc JD, Raicu DS (n.d.). Lung nodule detection from CT scans using 3D convolutional neural networks without candidate selection.

[5] J. Fan, W. Xu, Y. Wu, and Y. Gong (2010). Human tracking using convolutional neural networks. IEEE Transactions on Neural Networks, vol. 21, no. 10, pp. 1610–1623.

[6] Teramoto A, Fujita H, et al. (2016). Automated detection of pulmonary nodules in PET/CT images: Ensemble false positive reduction using a convolutional neural network technique. Medical Physics, vol. 43, no. 6, pp. 2821–2827.

[7] Shen D, Wu G, Suk HI (2017). Deep Learning in Medical Image Analysis. Annual Review of Biomedical Engineering, 19:221–248.

[8] Kakinuma R, Noguchi M, Ashizawa K et al. (2016). Natural history of pulmonary subsolid nodules: a prospective multicenter study. J ThoracOncol 11:1012–1028

[9] Alakwaa W, Nassef M, Badr A (n.d.). Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN).

[10] Valente IRS, Cortez PC, Neto EC, Soares JM, de Albuquerque VHC, Tavares JMRS (2016). Automatic 3D pulmonary nodule detection in CT images: a survey. Comput Methods Programs Biomed; 124:91– 107.

[11] Kubota T, Jerebko AK, Dewan M, Salganicoff M, Krishnan A (2011). Segmentation of pulmonary nodules of various densities with morphological approaches and convexity models. Med Image Anal; 15:133–54.

[12] Baldwin DR, Callister ME (2015). The British Thoracic Society guidelines on the investigation and management of pulmonary nodules. Thorax 70:794–798

[13] Diciotti S, Lombardo S, Falchini M, Picozzi G, Mascalchi M (2011)Automated segmentation refinement of small lung nodules in CT scans by local shape analysis. IEEE Trans Biomed Eng; 58(12):3418–28.

[14] Roth HR, Lu L, et al. (2015). Deeporgan: Multi-level deep convolutional networks for automated pancreas segmentation in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 2015, pp. 556–564.

[15] Huang X, Shan J, Vaidya, V. (2017). Lung Nodule Detection In CT Using 3D Convolutional Neural Networks. IEEE 379 - 383

[16] Ji S, Xu W, Yang M, Yu K (2017). 3D Convolutional Neural Networks for Human Action Recognition. (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 8, No. 8.

[17] Gavrielides M, Kinnard LM, Myers KJ, et al. (2009). Noncalcified lung nodules: volumetric assessment with thoracic CT. Radiology; 251: 26–37.

[18] Ding J, Li A, Hu Z, Wang L (2017). Accurate Pulmonary Nodule Detection in Computed Tomography Images Using Deep Authorized licensed use limited to: Carleton University. Downloaded on June 02,2021 at 11:10:53 UTC from IEEE Xplore. Restrictions apply. 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN) 768 Convolutional Neural Networks. arXiv preprint arXiv:1706.04303, pages 1–9.

[19] Dou Q, Chen H, Yu L, Qin J, Heng, PA (2017). Multi-level Contextual 3D CNNs for False Positive Reduction in Pulmonary Nodule Detection. IEEE, Transactions on Biomedical Engineering, 64(7):1558 – 1567.

[20] Fetita CI, Prêteux F, Beigelman-Aubry C, Grenier P. 3D automated lung nodule segmentation in HRCT. In Medical Image Computing and Computer-Assisted Intervention—MICCAI. New York: Springer, pp. 626–634.

[21] Ge ZY, Sahiner B, Chan HP, Hadjiiski LM, Cascade PN, Bogot N et al. (2005). Computer-aided detection of lung nodules: False positive reduction using a 3-D gradient field method and 3-D ellipsoid fitting. Med. Phys., vol. 32, pp. 2443–2454.

[22] FirminoM,Morais AH, Mendona RM, Dantas MR, HekisHR, Valentim RA (2014). Computer-aided detection system forlung cancer in computedtomography scans: Review and futureprospects. Biomedical Engineering Online 13, 41.doi:10.1186/1475-925X-13- 41.

[23] Golan R, Jacob C, Denzinger J (2016). Lung nodule detection in CT images

[24] Havaei M, Davy A, et al. (2016). Brain tumor segmentation with deep neural networks. Medical Image Analysis.

[25] Jacobs C, van Rikxoort EM, Twellmann T, Scholten ET, de Jong PA, Kuhnigk JM et al. (2014). Automatic Detection of Subsolid Pulmonary Nodules in Thoracic Computed Tomography Images. Medical Image Analysis, 18(2):374–384, 2014.

[26] JakimovskiG, and Davcev D (2019). Using Double Convolution Neural Network for Lung Cancer Stage Detection. Appl. Sci. 9:427. doi:10.3390/app9030427

[27] Jung H, Kim B, Lee I, Lee J, and Kang J. (2018). Classification of lung nodules in CT scans using three-dimensional deep convolutional neural networks with a checkpoint ensemble method. BMC Medical Imaging (2018) 18:48. https://doi.org/10.1186/s12880-018-0286-0

[28] Kang G, Liu K, Hou B, Zhang N (2017). 3Dmulti-view convolutional neuralnetworks for lungnodule classification. PLoS ONE 12(11): e0188290.https://doi.org/10.1371/journal.pone.0188290

[29] Karpathy A, Toderici G, Shetty S, Leung T, Sukthankar R, Li F (2014). Large-scale video classification with convolutional neural networks. In Proceedings of the 27th IEEE Conference on Computer Vision and Pattern Recognition, (CVPR ’14), pp. 1725–1732, Columbus, Ohio, USA.

[30] Kobayashi Y, Mitsudomi T (2013). Management of ground-glass opacities: should all pulmonary lesions with ground-glass opacity be surgically resected? Transl Lung Cancer Res 2:354–363

[31] Li B, Chen Q, Peng G, Guo Y, Chen K, Tian L, Ou S, Wang L (2016). Segmentation of pulmonary nodules using adaptive local region energy with probability density function-based similarity distance and multi-features clustering. BioMedEngOnLine; 15:49; DOI 10.1186/s12938-016-0164-3.

[32] Li W, Cao P, Zhao D, Wang J (2016). Pulmonary Nodule Classification with Deep Convolutional Neural Networks on Computed Tomography Images.Computational and Mathematical Methods in Medicine Volume 2016, Article ID6215085, 7pages http://dx.doi.org/10.1155/2016/6215085.

[33] Liu M, Lu L, et al. (2011). Sparse classification for computer aided diagnosis using learned dictionaries. in MICCAI; vol. 14, pp. 41–8.

[34] Naidich DP, Bankier AA, MacMahon H et al (2013). Recommendations for the management of subsolid pulmonary nodules detected at CT: a statement from the Fleischner Society. Radiology 266:304–317.

[35] K. Rajkumar and V. Dhanakoti, “Methodological Survey to Improve the Secure Data Storage in Cloud Computing,” 2020 International Conference on Emerging Smart Computing and Informatics (ESCI), 2020.

[36] S. S. Sengar, U. Hariharan, and K. Rajkumar, “Multimodal Biometric Authentication System using Deep Learning Method,” 2020 International Conference on Emerging Smart Computing and Informatics (ESCI), 2020.

[37] U. Hariharan, K. Rajkumar, Nilotpal Pathak, “Enhancing the Energy Efficiency using AMH Protocol for Wireless Sensor Networks”, IJAST, vol. 29, no. 05, pp. 3607 - 3612, Apr. 2020.

[38] U. Hariharan and K. Rajkumar, “Prolong Network Lifetime Using Dynamic Routing for Wireless Sensor Networks,” INTERNATIONALJOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH, vol. 9, no. 3, pp. 7166–7169, Mar. 2020.

[39] Kuppusamy, P., Rajkumar, K., Maheswar, R., Sheeba Rani, S., & Amiri, I. (2020). A long-reach radio over free space optics (Ro-FSO) system using hybrid orthogonal frequency division multiplexing (OFDM)-multibeam concept with enhanced detection, Journal of Optical Communications (published online ahead of print 2020), 000010151520190292. doi: https://doi.org/10.1515/joc-2019-0292.

[40] Tasnim Ahmed, Mst. Shahnaj Parvin, Mohammad Reduanul “Lung Cancer Detection Using CT Image Based on 3D Convolutional Neural Network” Journal of Computer and Communications Vol.08 No.03(2020)

[41] M.Bikromjit Khumancha , Aarti Baraiy, C.B. Rama Raoz “Lung Cancer Detection from Computed Tomography (CT) Scans using Convolutional Neural Network” IEEE DOI: 10.1109/ICCCNT45670.2019.8944824

[42] Hwejin Jung, Bumsoo Kim, Inyeop Lee Junhyun Lee and Jaewoo Kang “ Classification of lung nodules in CT scans using threedimensional deep convolutional neural networks with a checkpoint ensemble method “BMC Medical Imaging (2018) https://doi.org/10.1186/s12880-018-0286-0

[43] Margarita Kirienko, Martina Sollini, Giorgia Silvestri, Serena Mognetti, Emanuele Voulaz, Lidija Antunovic, Alexia Rossi,Luca Antiga, and Arturo Chiti,"Convolutional Neural Networks Promising in Lung Cancer T-Parameter Assessment on Baseline FDG-PET/CT" Contrast Media & Molecular Imaging / 2018 / Article DOI:

[44] Sountharrajan S, Karthiga M, Suganya E, and Rajan C,"Automatic Classification on Bio Medical Prognosis of Invasive Breast Cancer" Asian Pac J Cancer Prev. 2017; 18(9): 2541–2544.

[45] Sountharrajan, S.; Thangaraj, P. "Optimized Feature Selection Technique for Automatic Classification of MRI Images for Alzheimer's Disease" Journal of Medical Imaging and Health Informatics, Volume 6, Number 8, December 2016, pp. 2057-2062(6)