Lung Cancer Detection and Classification using Deep Learning

Ruchita Tekade[1], Prof. Dr. K. Rajeswari[2]

Computer Department,
Pimpri Chinchwad College of Engineering
Savitribai Phule Pune University
Pune, India

[1]ruchitatekade@gmail.com, [2]kannan.rajeswari@pccoepune.org

***Abstract*— In recent years, so many Computer Aided Diagnosis (CAD) systems are designed for diagnosis of several diseases. Lung cancer detection at early stage has become very important and also very easy with image processing and deep learning techniques. In this study lung patient Computer Tomography (CT) scan images are used to detect and classify the lung nodules and to detect the malignancy level of that nodules. The CT scan images are segmented using U-Net architecture. This paper proposes 3D multipath VGG-like network, which is evaluated on 3D cubes, extracted from Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI), LUng Nodule Analysis 2016 (LUNA16) and Kaggle Data Science Bowl 2017 datasets. Prediction from U-Net and 3D multipath VGG-like network are combined for final results. The lung nodules are classified and malignancy level is detected using this architecture with 95.60% of Accuracy and 0.387732 of logloss.**

***Keywords*—- Computer Aided Diagnosis (CAD) systems, Image Processing, Deep Learning, Computer Tomography (CT), lung nodule, malignancy, U-Net, 3D multipath VGG-like network, 3D cubes, Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI), LUng Nodule Analysis 2016 (LUNA16), Kaggle Data Science Bowl 2017**

I. INTRODUCTION

According to the survey of World Health Organization (WHO), Lung cancer was the second most leading cause of death in 2015 and it is on fifth rank in 2017. It is most common in smokers accounting 85% of cases among all. So many Computer Aided Diagnosis (CAD) Systems are developed in recent years. Detection of lung cancer at early stage is necessary to prevent deaths and to increase survival rate. Lung nodules are the small masses of tissues which can be cancerous or noncancerrous also called as malignant or benign. Benign tissues are most commonly non-cancerous and does not have much growth where malignant tissues grows very fast and can affect to the other body parts and are dangerous to health.

For medical imaging so many different types of images are used but Computer Tomography (CT) scans are generally prefered beacause of less noise. Deep learning is proven to be the best method for medical imaging, feature extraction and classification of objects. Several types of deep learning architectures are introduced by so many researchers to classify the lung cancer. In this study, 3D multipath VGG-like network is proposed with 2 classifications. One classification is of lung nodules and non-nodules and other is of benign nodules and malignant nodules. This study also adapts U-Net architecture for segmentation of lung CT scans to detect the lung nodules from CT scans. The segmentation is done using image processing techniques as discuused in section III. This segmentation of ct scans gives the lung nodules which includes nodules connected to the lung boundaries too. Results from segmentation and our proposed network are combined to have more accurate results. Fig. 1 shows the proposed model. This approach is evaluated on Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) [2], LUng Nodule Analysis 2016 (LUNA16) [3] and Kaggle Data Science Bowl 2017 [4] datasets. More about these datasets is discussed in section III. Section IV discuss about the results and evaluation.

II. LITERATURE REVIEW

So many different architectures are proposed and compared in different studies. IT mainly included Convolutional Neural Network (CNN) and its variants. Convolutional Neural Network can be applied on 2D (known as 2D CNN/ConvNet) as well as 3D data (known as 3D CNN/C3D/3D ConvNet). These architectures are modified for several applications and datasets.

Hongyang Jiang et al., 2016 [5] gives the different approach of preprocessing the lung CT scan images before providing them to CNN architecture. This results in better results as there are so many non-imaging regions which can reduce the accuracy of feature extraction. In 2D images objects may overlap on each other, so that lung nodule detection may have high false positive rate.

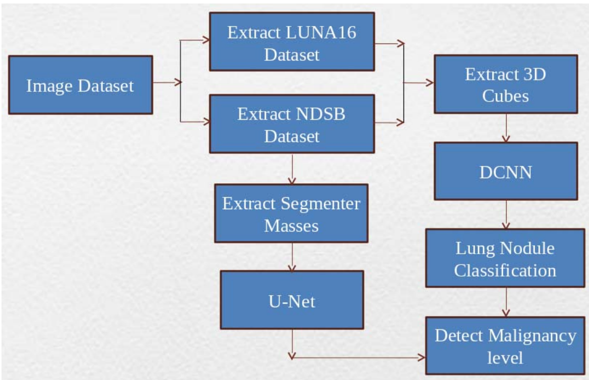

Fig. 1 Proposed Approach

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That is why, Xiaojie Huang et al., 2017 [6] proposes 3D CNN to detect lung nodules using 3D cubes from lung CT scans. As 3D images gives more clear idea about objects, 3D CNN performs relatively always good as compared to 2d CNN.

CNN has so many variants as, LeNet [7], AlexNet [8], ZFNet [9], VGGNet [10], GoogleNet [11], ResNet [12], etc. These architectures gives more deepness as they evolve. ResNet is 20 times deeper than AlexNet and 8 times deeper that VGGNet. VGGNet has two variants as VGG16 and VGG19. According to the application, depth required and considering time to train factor one can choose the architecture among them. Jia Ding et al., 2017 [13] have proposed an architecture which is based on R-CNN where Deconvolutional structure is added and uses first five groups of VGG-16 layers for lung nodule candidate detection. After that false positive rate is also reduced using 3D DCNN. Mohammad Tariqul Islam et al., 2017 [14] have combined AlexNet, VGGNet and ResNet together to have ensemble probabilities from different architectures for classification. And localization is done by overlapping occlusions.

For segmentation of images, CNN is modified and different architectures are formed as U-Net [15], SegNet [16], FCN [17], Enet [18], DenseNet [19], DilatedNet [20], PixelNet [21], ICNet [22], ERFNet [23], DeconvNet [24] and many more. Botong Wu et al., 2018 [25] gives Pulmonary Nodule Segmentation Attributes and Malignancy Prediction (PN-SAMP) approach using 3D U-Net architecture. In this work, lung nodule detection and malignancy prediction is done simultaneously by learning high level attributes from bottom of U-Net and from 3DCNN where segmentation is done. By this literature survey, this can be concluded that 3DCNN is always better to have good results of application. Combining different approaches gives some different way of handling data and also gives improved results.

III. Dataset and Methods

A. Dataset

Dataset used in this study is from TCIA repository named as, Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) [2]. This data contains 1010 patient cases and 1018 thoracic CT scans acquired from them in dicom format. Four radiologists have annotated lung lesions according it's size as nodules > = 3mm, nodules < 3mm and non-nodules > = 3mm. These annotations acquired from four radiologists are included as labels of the CT scan images in XML files. This dataset also contains the labels of malignancy level of lung nodules. There are 4 levels of malignancy included in this dataset as 0 = Unknown, 1 = Benign or non-malignant disease, 2 = Malignant, Primary lung cancer, 3 = malignant metastatic. Benign are the lung tissues which grows gradually and this growth stop at certain point. These tissues are commonly non-cancreous and does not affect seriously to health. And malignant tissues are cancerous and grows very fast. These tissues can affect to other body parts also.

LUng Nodule Analysis 2016 (LUNA16) [3] was a competition held in 2016-2017 which mainly focus on pulmonary nodules by screening CT scan images from LIDC-IDRI dataset. The list of patient ids and the location of lung nodules in respective CT scan is provided in this competition. X, Y and Z coordinates of lung nodules and it's diameter are included in the dataset. As LIDC-IDRI dataset is created with the help of four radiologists, some nodules are annotated by more than one radiologist. This redundancy is removed in LUNA16 dataset and redundant data is excluded. Also the CT slices having thickness more than 2.5mm are excluded. This dataset contains total 888 CT scans in mhd and raw format.

Kaggle Data Science Bowl 2017 [4] was a competition held in 2017 to increase the effiency of algorithms to classify the cancer and to detect if lung nodules in the CT scans are malignant i.e. cancerous. This dataset has two stages but only first stage is used in this study. This stage 1 data contains 1595 patient cases with 285380 CT scans in dicom format. This dataset contains the labels of benign and malignant forms of tissues. If nodule is benign then value is 0 and if it is malignant then it 1. These labels are used to classify the cancer. Some information of lung nodules from LIDC-IDRI and some from LUNA16 and Kaggle Data Science Bowl 2017 are combined to detect lung nodules location in CT scans and to classify the cancer types respectively.

B. Deep Learning Architectures

So many different types of deep learning architectures are proposed in recent researches for image segmentation and object classification in images. Some architectures are also proposed for medical imaging disease diagnosis. Two architectures among them are adapted and modified in this study.

Convolutional Neural Network is also known as CNN and ConvNet. CNN is useful for feature extraction and classification of objects in the image. This CNN is nothing but a stack of different layers. Convolutional layer and pooling layer has the responsibility of feature extraction of objects provided to CNN where convolutional layer extract the features and pooling layer selects the important features from them also known as subsampling of convolved features. There are two types of pooling as max pooling and average pooling, but max pooling iswidely used in so many researches where maximum value among the values in pooling window is selected

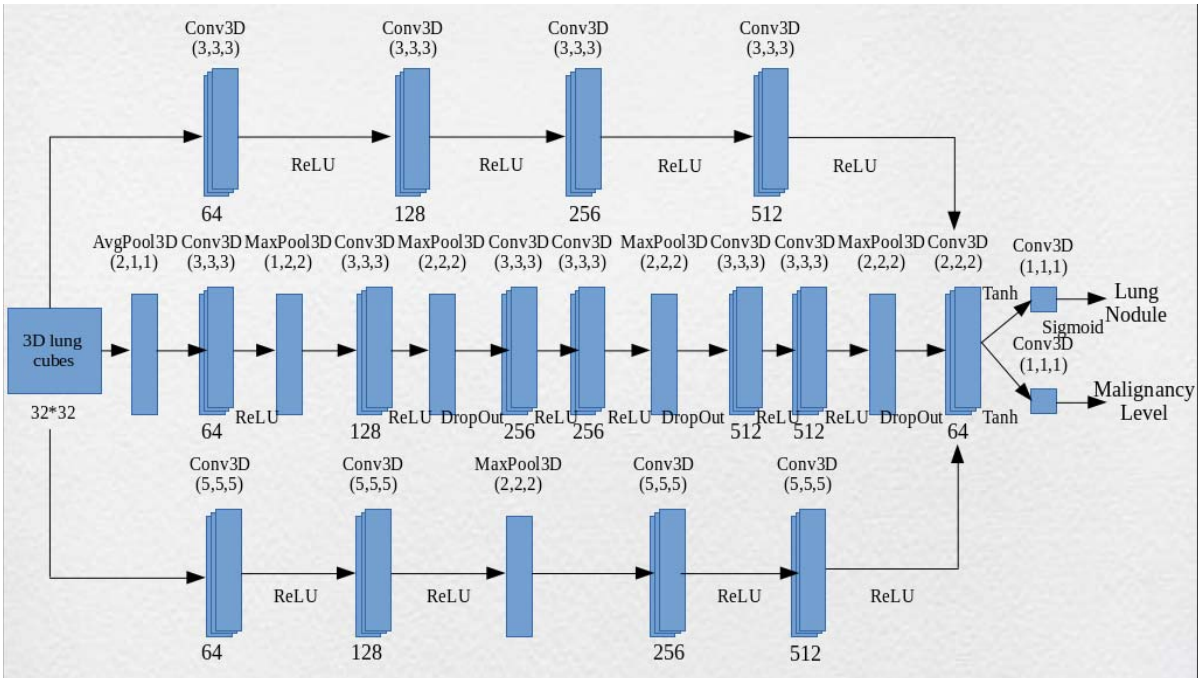

Fig. 2 3D multipath VGG-like Architecture

as sampled feature from convolved features. Activation function is used to determine output of neural nettwork. It squash input into the desired range according to the function. ReLU (Rectified Linear Unit) is most commonly used activation function which converts all negative values into 0 and keep positive values as they are. After conventional and pooling layers, classifier is applied to find probabilities of classes and loss is calculated using loss functions to back propagate the weights. And optimizers are used to select weights after back propagation which has less loss.

This study proposes 3D multipath architecture which uses VGG-16 like structure of convolutional and pooling layers. After comparing other architectures, VGGNet is chosen as it is light weight and trains faster. Fig. 2 shows the proposed 3D multipath VGG-like architecture. It has VGG-16 structure and fully convolutional layers from different paths, which are concatenated for final output. Lung nodules and

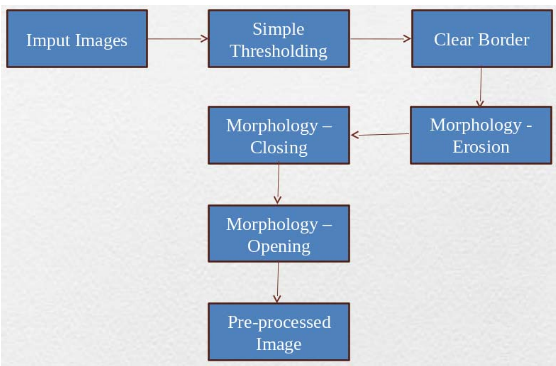

Fig. 3 Image Preprocessing

malignancy level classifications are done at last layer using softmax classifier. Adam optimizer is used to optimize the weights selection for convolutional kernel. Predictions from this architecture are further combined with segmentation model.

Segmentation of lung nodules is additional part adapted from (Julian De Wit, 2017). Before segmentation, lung CT scan images are preprocessed using image processing techniques as shown in Fig. 3. Using U-Net architecture as shown in Fig. 4 segmentation masses are generated for lung CT scan images and lung nodules are segmented. Using this model we get another approach of lung nodule detection. After segmentation and classification all results from all models are combined to have more accurate results for lung nodule detection and maliganncy prediction.

IV. Results and Evaluation

As discussed in previous section, Data from LIDC-IDRI, LUNA16 and Data Science Bowl 2017 are collected which has lung CT scan images. The lung CT scan images from LUNA16 and Data Science Bowl 2017 are used and labels from all three datasets are used which has positive, negative as well as false positive data. 3D cubes from LUNA16 and Data Science Bowl 2017 are extracted including positive, negative and falsepositive samples and provided to our proposed architecture. Segmentation of lung nodules is done over Data Science Bowl 2017 dataset. The predictions from both the approaches are combined and test set is predicted over all the models.

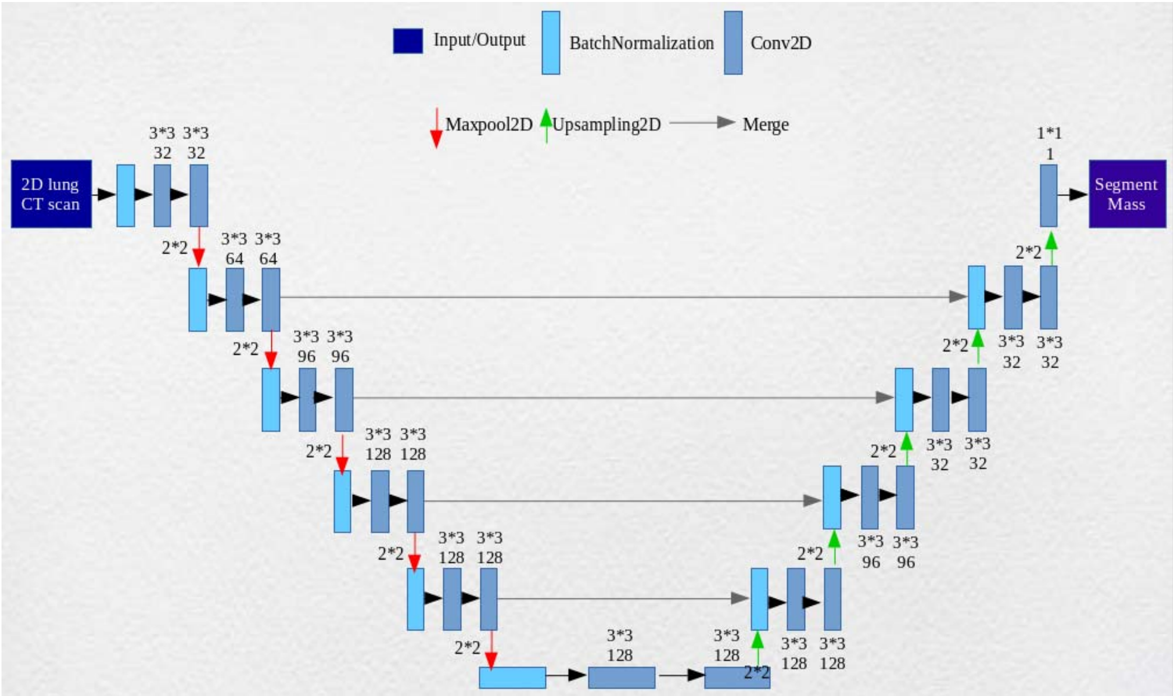

Fig. 4 U-Net Architecture with Batch Normalization

This proposed approach is evaluated on Nvidia Tesla K20 GPU for fast processing with CUDA 9.0 and CuDNN 7.0 for fast neural network operations. Keras library with tensorflow at backend is used for CNN model in Python3.5. The features are extracted from lung CT scan images and model is learned over 35000 3D cubes extracted from LUNA16 and Data Science Bowl 2017 dataset. And predictions are done over Data Science Bowl 2017 dataset. For calculating results performance metricssuch as binary accuracy and log loss are used for 3D multipath VGG-like architecture and Dice coeficient for U-Net segmentation as shown in equation (1), (2) and (3) respectively,

$$Accuracy = \frac{No.of\ truly\ classified\ samples}{Total\ no.\ of\ samples}$$

...Equation (1)

$$LogLoss = -\frac{1}{n}\sum_{i=1}^{n}\left[Y_{True}\log\left(Y_{Pred}\right)+\left(1-Y_{True}\right)\log\left(Y_{Pred}\right)\right]$$

...Equation (2)

$$Dice\ Coefficient = \frac{2\left|Y_{True} * Y_{Pred}\right|}{\left|Y_{True}\right|+\left|Y_{Pred}\right|}$$ ...Equation (3)

This approach gives the accuracy of 0.956 and loss of 0.09 for training of proposed architecture as shown in Fig. 5 and Dice Coeficient of 0.9 of U-Net architecture. For prediction of malignancy level, the logg loss is calculated as it is used in Data Science Bowl 2017 competition and this approach gives the log loss of 0.387732.

V. Conclusions

This study is conducted with the ultimate aim of improving efficiency of lung nodule detection and malignancy level prediction using lung CT scan images. This experiment is conducted using LIDC-IDRI, LUNA16 and Data Science Bowl 2017 datasets on CUDA enabled GPU Tesla K20. The Artificial Neural Networks plays very important role in better analyzing the dataset, extracting features and classification. The proposed approach contains mainly two architecture. U-Net architecture is adapted for segmentation of lung nodules from lung CT scan images and proposed 3D multipath VGG-like architecture is for classifying lung nodules and predict malignancy level. This is useful to predict whether the patient will have the cancer in next two years or not.

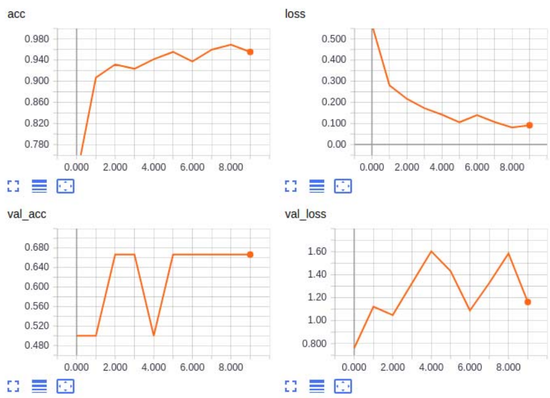

Fig. 5 Training and Validation Accuracy and Loss

Combining the two approaches as proposed architecture and U-Net segmentation has given the better results for predicting lung nodule detection and also further predicting malignancy level. This approach gives accuracy as 95.66% and loss 0.09 and dice coefficient of 90% and for predicting log loss is 38%.

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