

**Title Of Paper :** A 3D probabilistic deep learning system for detection and diagnosis of lung cancer using Low-Dose CT Scans

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## Dataset Used:-

We have used the dataset used in LUNA16 challenge.

Basically the LUNA16 challenge dataset contains images from LIDC-IDRI database. But not all annotations of LIDC-IDRI database are included here. Nodules having size less than 3mm and nodules annotated by only 1 or 2 radiologists are considered irrelevant and not included in LUNA16 dataset.

We are mainly interested in the 3-D voxels containing nodules and therefore we need to cut out parts from each scan.

The three dimensional candidate contains a lesion positioned in the centre but it also has a lot of background around it. Since nodules can be of a different size, some slices consist mainly of background and usually only the centre three-five slices have a nodule. Big lesions, on the other hand, can appear on many slices through Z plane. To work with two dimensional data we need to annotate as positive class only those slices from candidates that contain a nodule. To be certain that no incorrectly labelled samples are present in our training dataset, we use only middle slices to represent a volumetric candidate in two dimensions.

## **Feature Of Data:-**

CT images are stored in Metalmage (mhd/raw) format. Each .mhd file is stored with a separate .raw binary file for the pixel data.

## **Data Pre-processing :-**

There is a module for operation on raw CT scan images. This will include data reading, extraction of candidate patches, regions saving, augmentation and splitting of train and test data sets. We have written modules that include functions which will be used for reading images, converting them to different system of coordinates, extracting the needed ROIs and saving them. Data augmentation is used during the training of all our models.

## **Model Proposed in Paper:**

The system takes a raw 3D CT scan of the lung as input and provides as outputs a per-patient malignancy classification probability, per-nodule malignancy scores, and segmented lung nodule candidates. The system can refer patients or nodules whose results have a high degree of uncertainty to a radiologist for confirmation.

As first step, pre-processing of each 3D scan to a consistent format is done . The pre-processed scan is then fed into the CAdE module, which performs 3D segmentation. The goal of our CAdE module is to identify and localize lung nodules with the highest possible recall. The output of CAdE module is a list of identified lung nodules which are then fed into CAdX module. CAdX module uses two cascaded 3D deep learning models. The first model ranks the candidates based on their malignancy risk. The second model then uses that ranking to select the top-k candidates and perform multiple-instance classification to make a patient diagnosis.

The full system is developed and tuned simultaneously, since CAdX performance is dependent on CAdE performance . In particular , when the CAdX system is trained with candidates with a high FPR, it becomes much more robust to false positive candidates, resulting in improved performance regardless of the underlying CAdE system's FPR.

### **Model Implemented By Us:-**

At first pre-processing of each data is done which includes data reading, regions saving, augmentation and splitting of training and testing data sets. After pre-processing of data it goes through a training phase. In training phase, we check whether our model is giving correct result for this particular data or not. If the model does not give correct results, then we update the values of weights given to inputs. After the training phase is complete the data will be passed through a

test phase and the accuracy of model would be calculated. We have used both 2D and 3D CNN and created a model using each of them and have displayed their recall score and accuracy score. By comparing their recall score we can find out which of them is better.

## Result From Paper:-

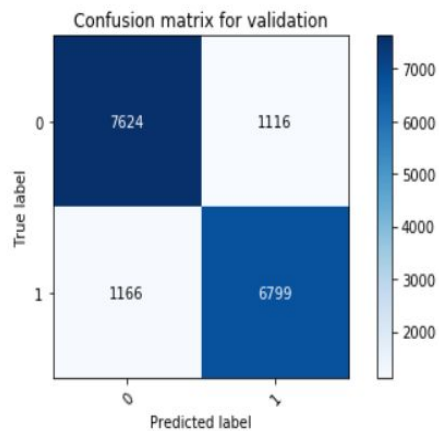
	LUNA16 CAdE	sensitivity	Kaggle Stage-2	CADx AUROC
CAdE FP/ patient	Primary arch. (V-Net based)	Comparison arch. (3D U-Net)	Evaluated on Primary arch.	Evaluated on Comparison arch.
1/8	0.832	0.839	0.867	0.869
1/4	0.879	0.888	0.868	0.868
1/2	0.920	0.917	0.863	0.863
1	0.942	0.941	0.868	0.863
2	0.951	0.950	0.866	0.858
4	0.959	0.952	0.869	0.858
8	0.964	0.952	0.869	0.859
average	0.921	0.920	0.867	0.864

The recall score of model proposed by paper is 92.1% which means that the model proposed by paper can find correct results for most of the patients.

## Result Obtained By Us:-

### Confusion matrix for 2D CNN :-

Out[11]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7fb381c66588>

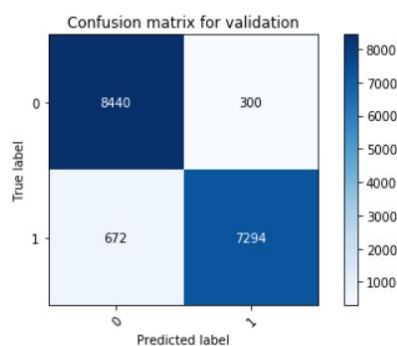


In [12]: `recall_score(np.argmax(Y_test, axis=-1), predicted), accuracy_score(np.argmax(Y_test, axis=-1), predicted)`

Out[12]: (0.8536095417451349, 0.8633941933552829)

### Confusion matrix for 3D CNN :-

Out[8]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7fe37a31b828>



In [9]: `recall_score(np.argmax(Y_test, axis=-1), predicted), accuracy_score(np.argmax(Y_test, axis=-1), predicted)`

Out[9]: (0.9156414762741653, 0.9418173111456961)

The recall score obtained by 2D CNN model is 85% while the accuracy score obtained by this model is 86%.

The recall score obtained by 3D CNN model is 91.5% while the accuracy score obtained by this model is around 94%.

This means that both the models can predict correct results for almost all the cases. But, the accuracy and recall of 3D CNN model is better than the 2D CNN model which implies that the 3D CNN model is better than the 2D CNN model.

### **Conclusion :**

We observe that, in lung nodule detection, the choice of CT scan image features impacts the results much more. Higher the number of features, more is the training time and epochs required to train the model.

Sources:

<https://github.com/rickbeeloo/CNN>

<https://github.com/junqiangchen/LUNA16-Lung-Nodule-Analysis-2016-Challenge>

Dataset link:- <https://luna16.grand-challenge.org/Data>

Journal link:- <https://drive.google.com/drive/u/0/my-drive>