

Image Processing based Lung Cancer Detection from a Low Dose CT Scan Image

Machine Perception
DS/NC/ESD 863/2016-T2-DNE863

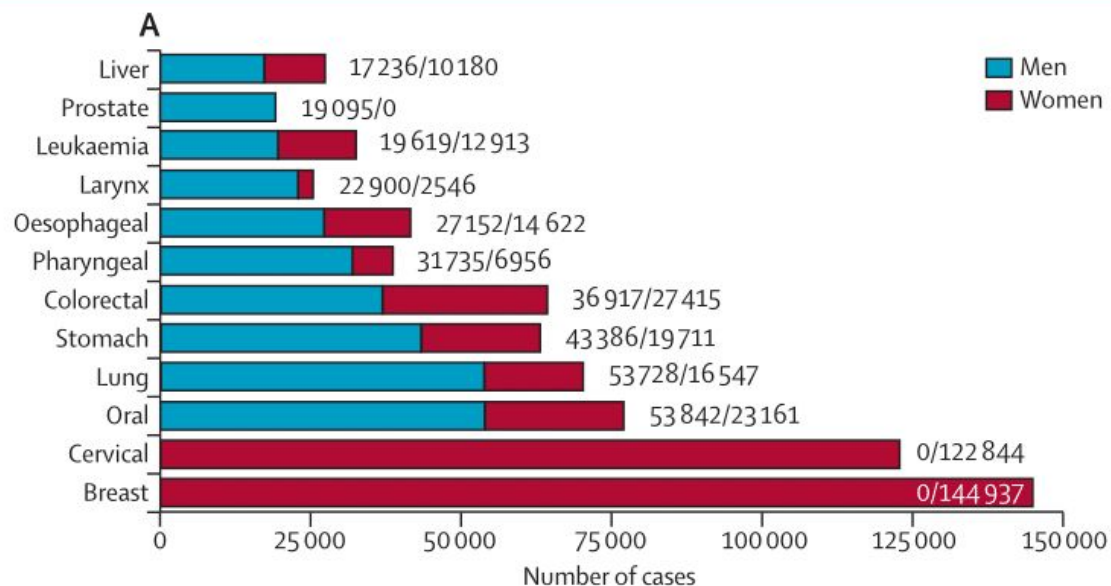
	Group 33	
Team 1	Team 2	Team 2
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Overview

- Motivation
- Problem Statement
- Dataset Description
- Our Approach
- Segmentation
- Blob Analysis
- Feature Extraction
- Classifier design
- Future Scope
- Conclusion

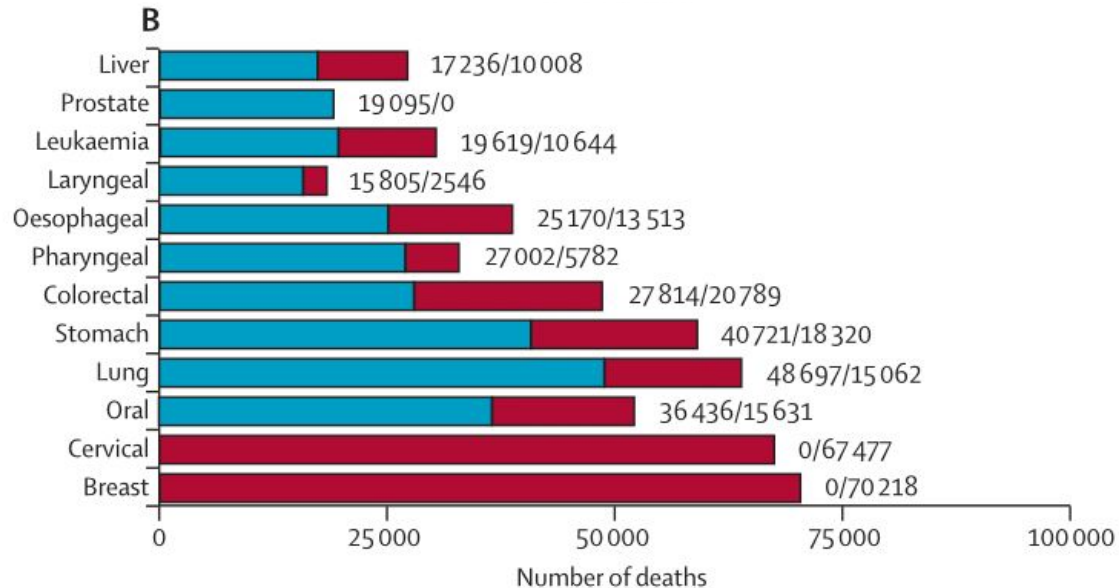
Motivation

Number of Cancer cases by type in India (2012)



Motivation

Number of deaths due to Cancer in India (2012)



Motivation

Most common cancers in Indian Men and Women

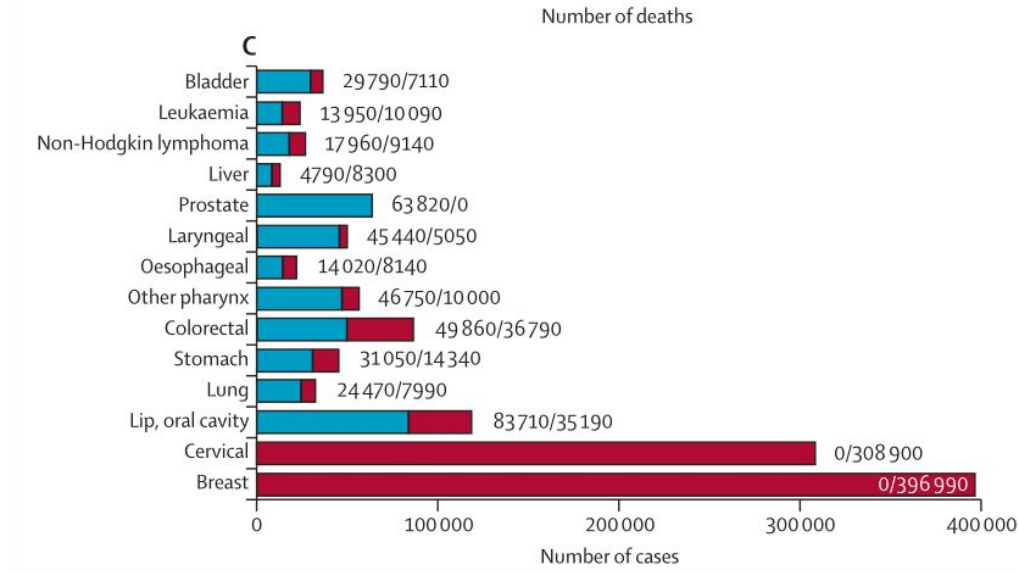


Image courtesy: Mallath MK, Taylor DG, Badwe RA, et al. The growing burden of cancer in India: epidemiology and social context. Lancet Oncol. 2014;15(6):e205-12.

Motivation

- One year ago, the office of the U.S. Vice President spearheaded a bold new initiative, the Cancer Moonshot, to make a decade's worth of progress in cancer prevention, diagnosis, and treatment in just 5 years.
- Data Science Bowl will be a critical milestone in support of the Cancer Moonshot by convening the data science and medical communities to develop lung cancer detection algorithms.
- Using a data set of thousands of high-resolution lung scans provided by the National Cancer Institute, participants will develop algorithms that accurately determine when lesions in the lungs are cancerous.
- Kaggle Dataset contains 2121 patient data with each patient containing approximately 200 images of CT scans.
- The dataset is quite extensive and is around 100GB in size.
- The problem and the dataset is quite promising to achieve meaningful result and contribute something to the community.

Problem Statement

- Low-dose computed tomography (CT) scans can reduce lung cancer deaths by 20 percent^[1]
- Challenge of reducing false positive rate
- Reducing patient anxiety, costly and unnecessary diagnostic work
- Develop algorithms that accurately determine when lesions in the lungs are cancerous.
- Get patients earlier access to life-saving interventions, and give radiologists more time to spend with their patients.

[1] Aberle DR, Adams AM, Berg CD, et al. Reduced lung-cancer mortality with low-dose computed tomographic screening. N Engl J Med. 2011;365(5):395-409.

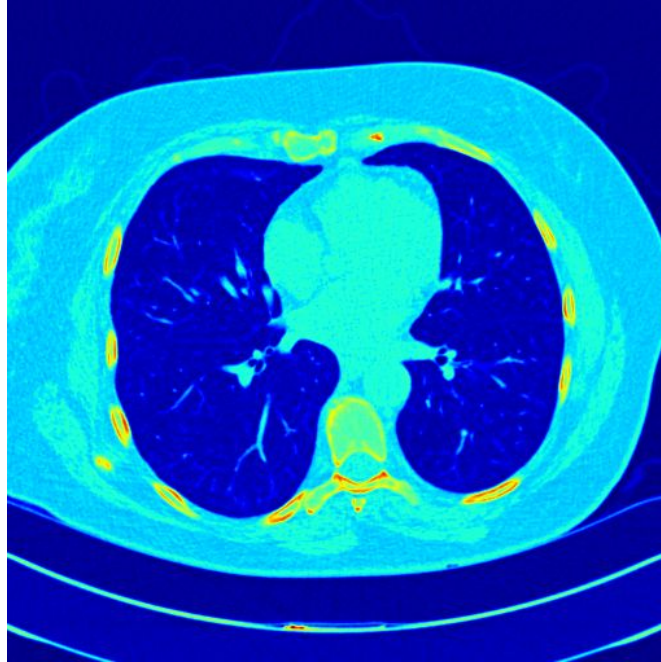
Dataset description

Kaggle Dataset:

- Over a thousand low-dose CT images from high-risk patients in DICOM format
- Each image contains a series with multiple axial slices of the chest cavity
- Each image has a variable number of 2D slices, which can vary based on the machine taking the scan and patient.
- The DICOM files have a header that contains the necessary information about the patient id, as well as scan parameters such as the slice thickness.
- The images in this dataset come from many sources and will vary in quality

Dataset description

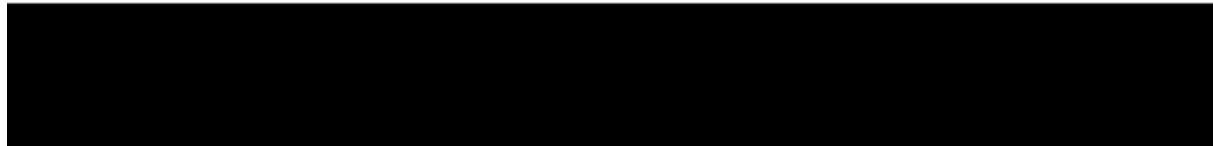
Kaggle Dataset:



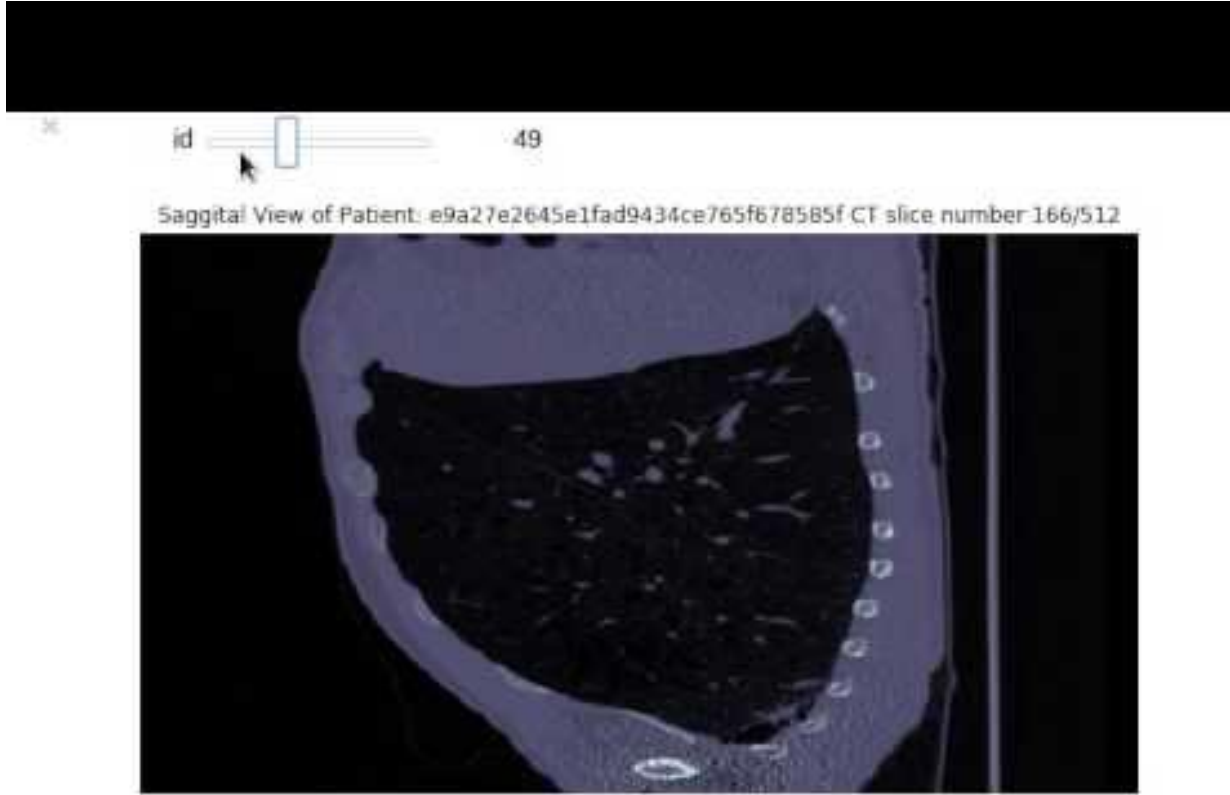
Axial view of CT scans



Axial View of Patient: e9a27e2645e1fad9434ce765f678585f CT slice number 120/288



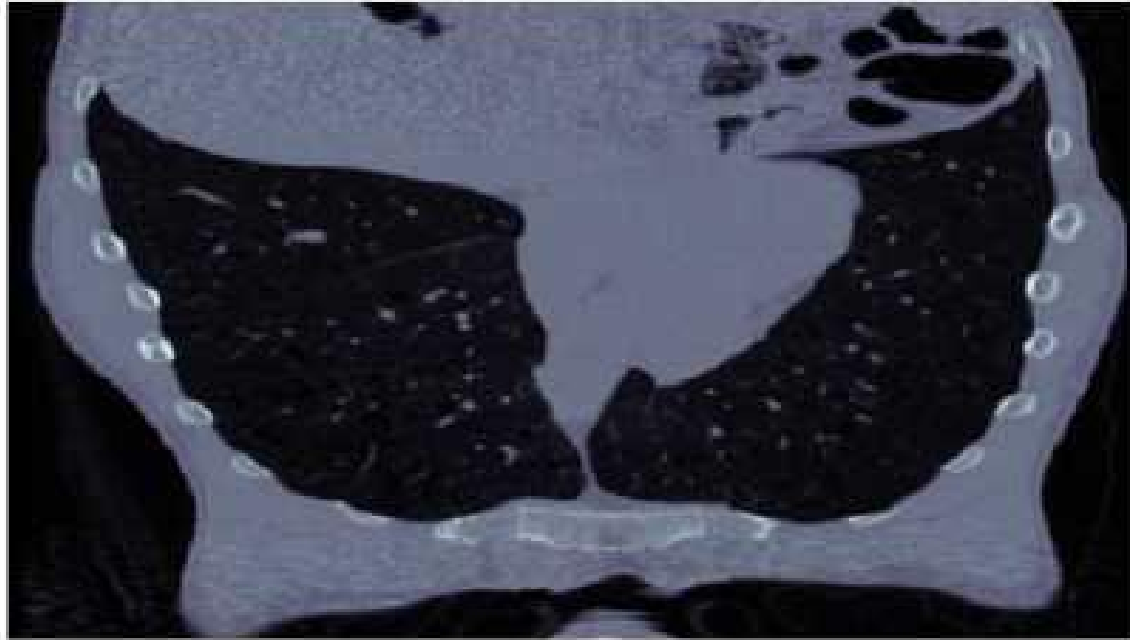
Sagittal View of CT scans

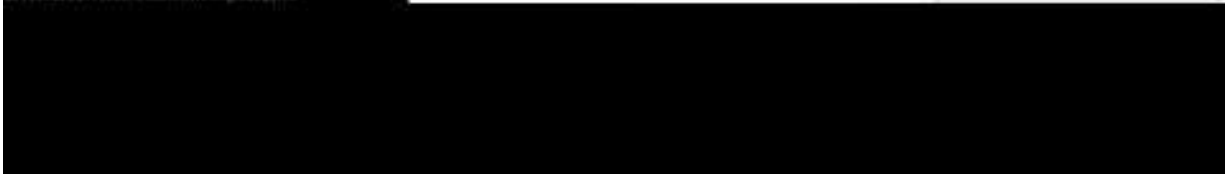


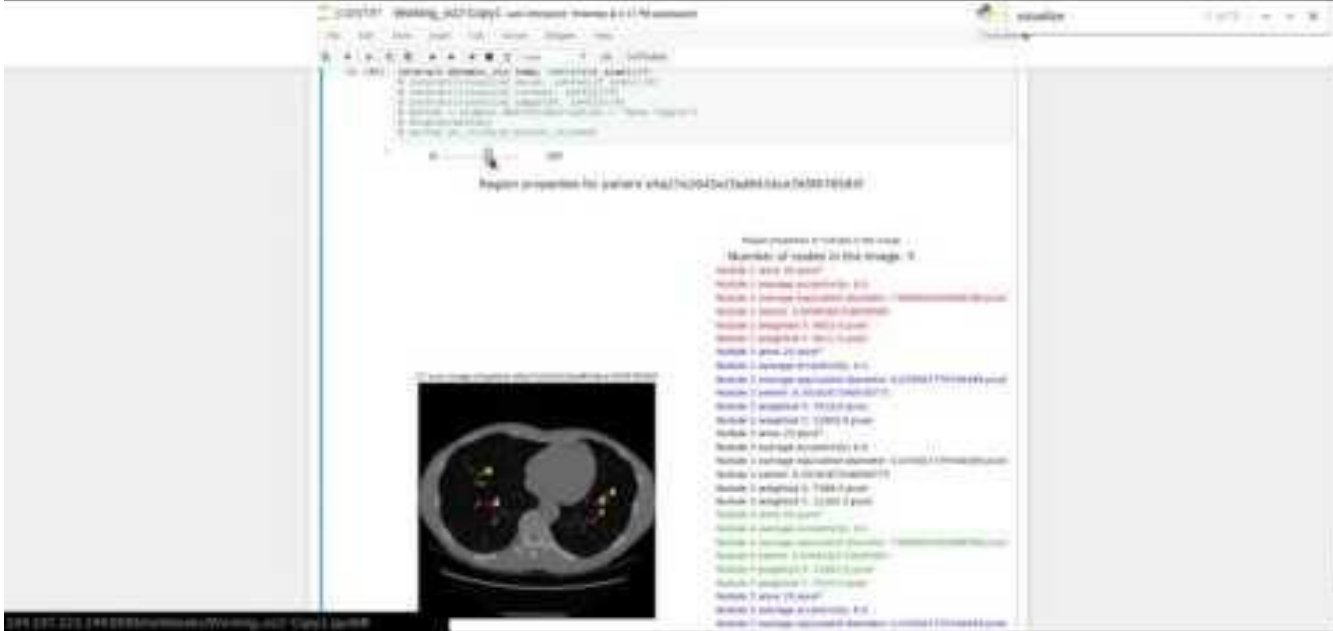
Coronal View of CT scans



Coronal View of Patient: e9a27e2645e1fad9434ce765f678585f CT slice number: 202/517





[illegible]

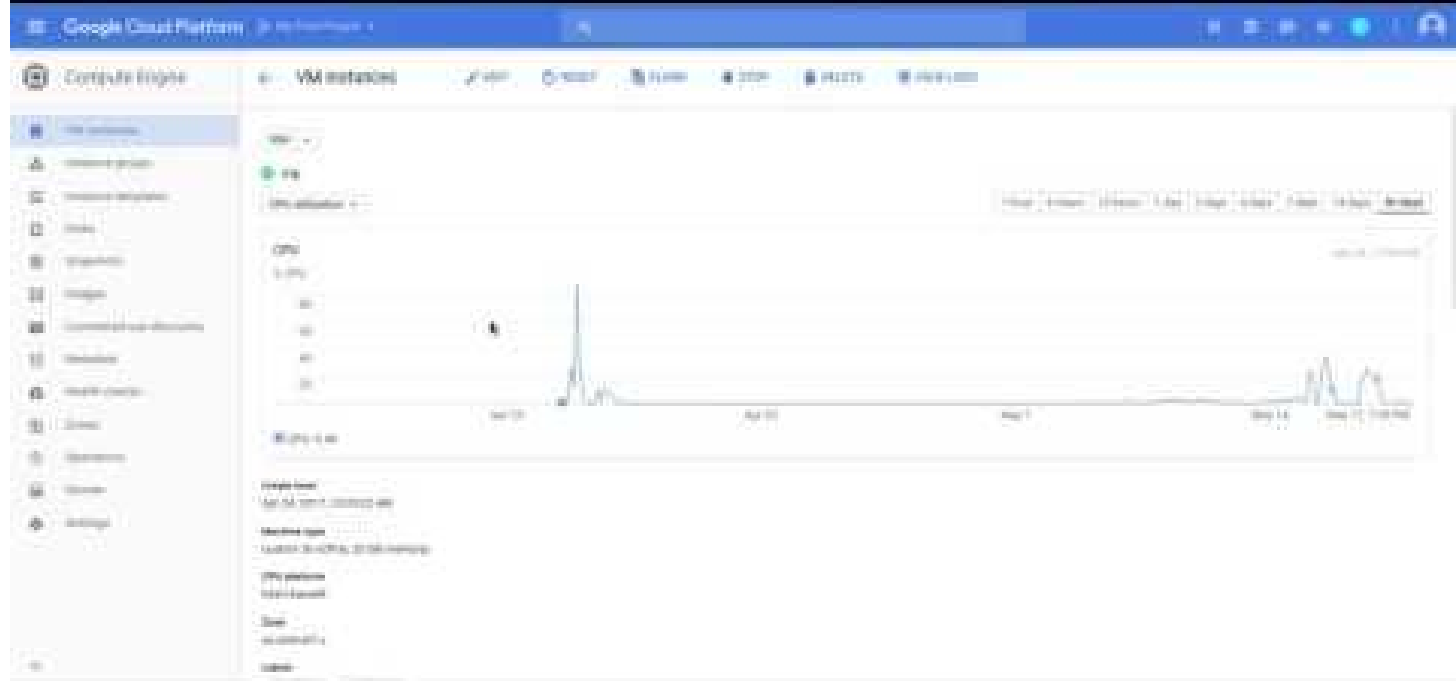
Feature extraction

```
[avg_area,max_area, avg_eccentricity,  
avg_equivalent_diameter,  
std_equivalent_diameter, total_extent,  
weightedX, weightedY, num_nodes,  
num_nodes_per_slice]
```

Feature extraction

```
regions = regionprops(labeled_image, image_nob, cache=True)
for rp in regions:
    total_area += rp.area
    areas.append(rp.area)
    avg_eccentricity += rp.eccentricity
    avg_equivalent_diameter += rp.equivalent_diameter
    eqi_diams.append(rp.equivalent_diameter)
    total_extent += rp.extent
    weightedX += rp.centroid[0]*rp.area
    weightedY += rp.centroid[1]*rp.area
    num_nodes += 1
weightedX = weightedX / total_area
weightedY = weightedY / total_area
avg_area = total_area / num_nodes
avg_eccentricity = avg_eccentricity / num_nodes
avg_equivalent_diameter = avg_equivalent_diameter / num_nodes
std_equivalent_diameter = np.std(eqi_diams)
max_area = max(areas)
num_nodes_per_slice = num_nodes * 1. / n_slices
return np.array([avg_area, max_area, avg_eccentricity, avg_equivalent_diameter, std_equivalent_diameter, \
                 total_extent, weightedX, weightedY, num_nodes, num_nodes_per_slice])
```

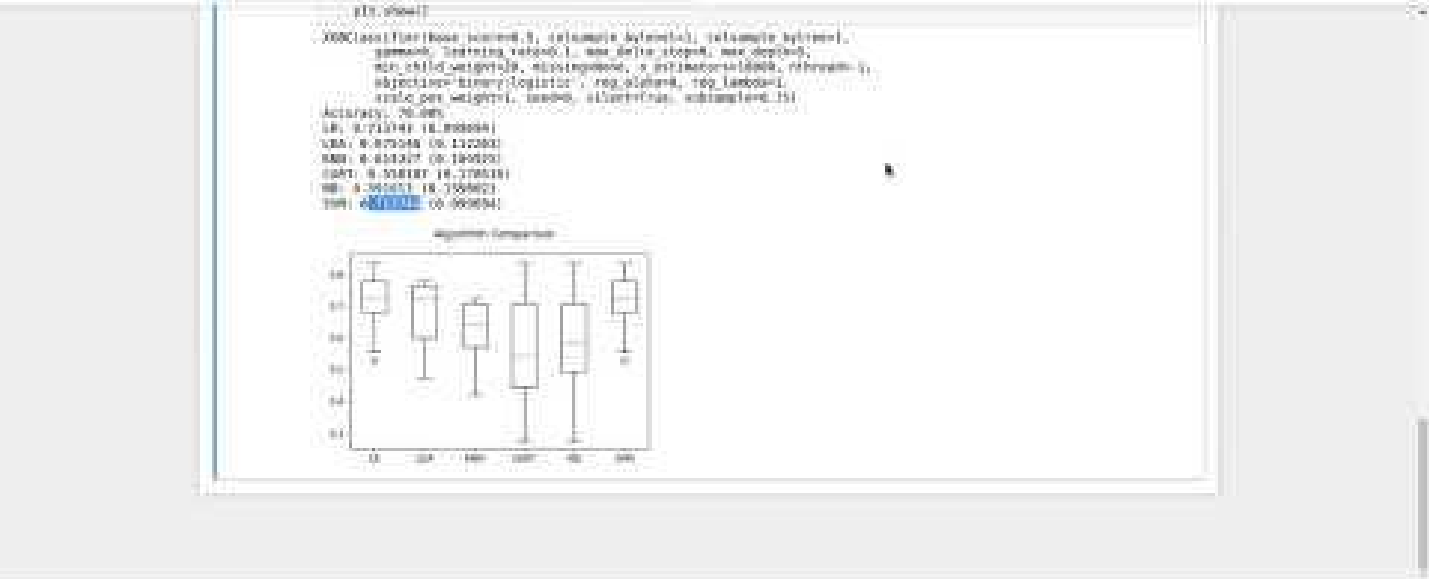

Google Cloud Dashboard



GCP ssh access

[illegible]

Classifier training and results



Future Scope

- Improvement in segmentation process using sophisticated machine learning techniques like CNNs (3D segment analysis using CNNs)
- Better segmentation using U-net
- Classification using 3D Convolutional Neural Networks
- Challenge of reducing false positive rate to a greater extent
- Training with more datasets like LUNA16

Conclusion

- An attempt to detect Lung Cancer lesions using Low Dose CT scan images
- Challenging problem both computationally and intellectually
- Contribution to the community
- Learning cloud tools for large scale Machine Learning tasks
- Testing with different models
- Exposure to Medical Imaging and challenges
- Satisfactory results using classical machine learning models
- Work on improving the accuracy using more sophisticated models in the future

Thank you

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