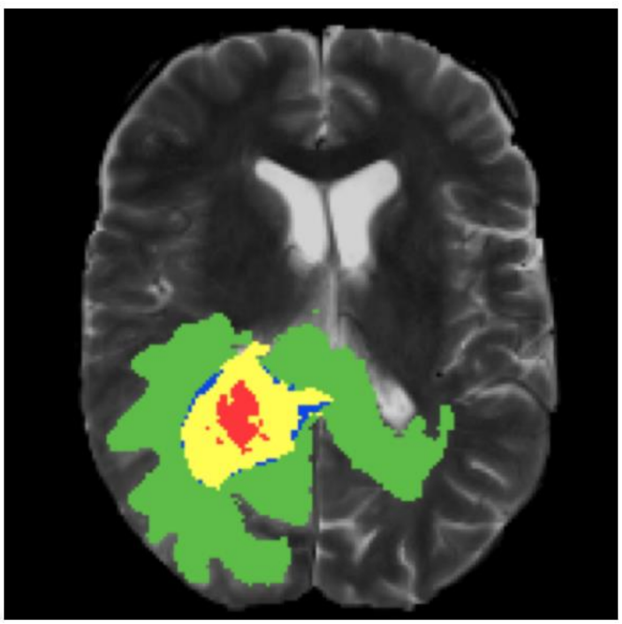


PROJECT REPORT ON USAGE OF DEEP LEARNING TECHNIQUES FOR MEDICAL IMAGE SEGMENTATION

ABSTRACT

The task of semantic image segmentation is to classify each pixel in the image. In this project, I have discussed how to use deep convolutional neural networks mainly concentrated on Image slicing technique for Medical Image segmentation.

Swathi SuragowniRavindranath
MSBA | Advanced Machine Learning Final Project

DEEP LEARNING TECHNIQUE FOR MEDICAL IMAGE SEGMENTATION

Summary:

What is Sematic Segmentation?

Semantic image segmentation is the task of classifying each pixel in an image from a predefined set of classes

Pixel-wise image segmentation is a well-studied problem in computer vision. The task of semantic image segmentation is to classify each pixel in the image. In this project, I have discussed how to use deep convolutional neural networks to do image segmentation.

Deep learning and convolutional neural networks (CNN) have been extremely ubiquitous in the field of computer vision. CNNs are popular for several computer vision tasks such as Image Classification, Object Detection, Image Generation, etc. Like for all other computer vision tasks, deep learning has surpassed other approaches for image segmentation.

There are several applications for which semantic segmentation is very useful.

As mentioned above most of the applications segment the images based on pixels but I have used slightly different approach in my project.

- I have used 2D U-net convolutional neural network (CNN) for **slice-wise tumor segmentation.**
- The **axial projection** was used to train the network due to the higher resolution of image representation in this plane.
- I have used CT scans of different patients to detect the tumor.

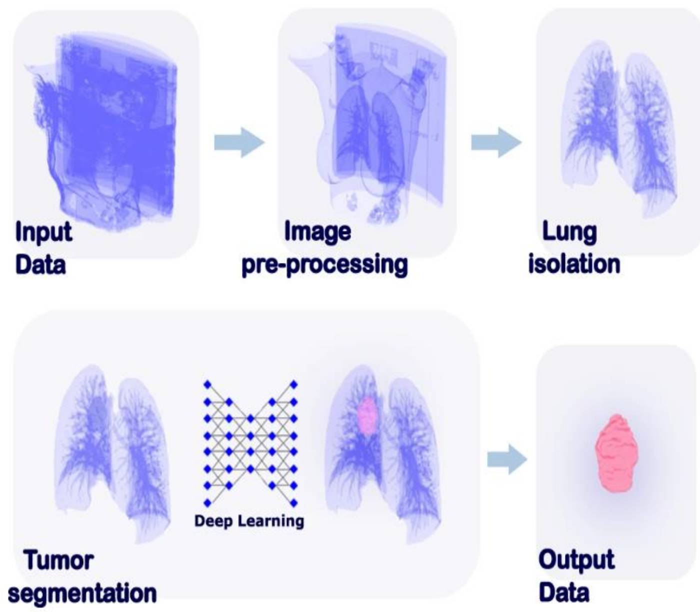
Problem Statement:

The Problems addressed in this project are listed below:

- Lung cancer is the deadliest of all cancers afflicting both sexes, accounting for 18.4% of the total cancer deaths worldwide in 2018, almost equal to breast and colon cancers combined.
- Automated detection and segmentation would immediately impact the clinical workflow in radiotherapy, one of the most common treatment modalities for lung cancer. Radiotherapy uses medical imaging, especially computed tomography (CT), to obtain accurate tumor localization and electron densities for the purpose of treatment planning dose calculations.
- Accurate segmentation of the tumor and organs at risk are also essential as errors might lead to over- or under-irradiation of both the tumor and/or healthy tissue.
- It has been estimated that a 1 mm shift of the tumor segmentation could affect the radiotherapeutic dose calculations by up to 15%.
- Therefore, automated accurate segmentation can significantly reduce the time needed by clinicians to carryout treatment planning, and adaptive re-planning of treatment depending on the changes in the tumor.

Techniques Used:

- I have implied the below techniques for slice-wise tumor segmentation.
- The Process projected in the below image was followed to get the desired results.



Proposed workflow is fully automatic and due to preprocessing step can handle variability in CT scans.

1. Description of data:

- The pretreatment CT scans of Lung cancer patients were retrospectively collected and anonymized by each center.
- CTs of lung abnormalities other than NSCLC were included in the training dataset as negative examples, allowing our method to exclude them from the detection and segmentation process
- lung CT slices without contours were also used in the training process as negative samples, thereby increasing the number of unique training samples and decreasing the false-positive rate of the model

2. <u>Image preprocessing:</u>

A harmonization routine for the preprocessing of CT scans in order to more comprehensively unify patterns on the images for the models to learn from.

3. <u>Lung region isolation:</u>

- First, the CT couch is detected and removed from the image volume. Air-filled connected volumes are detected and region growing and morphological operations are applied in order to remove small vessels and to connect adjacent regions, resulting in a 3D binary lung mask.
- The spine axis is identified and the lung mask is halved and symmetrically flipped about the sagittal plane, keeping the union of the flipped and the original lung masks.
- By doing so, the algorithm is optimized for handling lung abnormalities such as atelectasis, pulmonary infiltration, consolidation, and fibrosis.

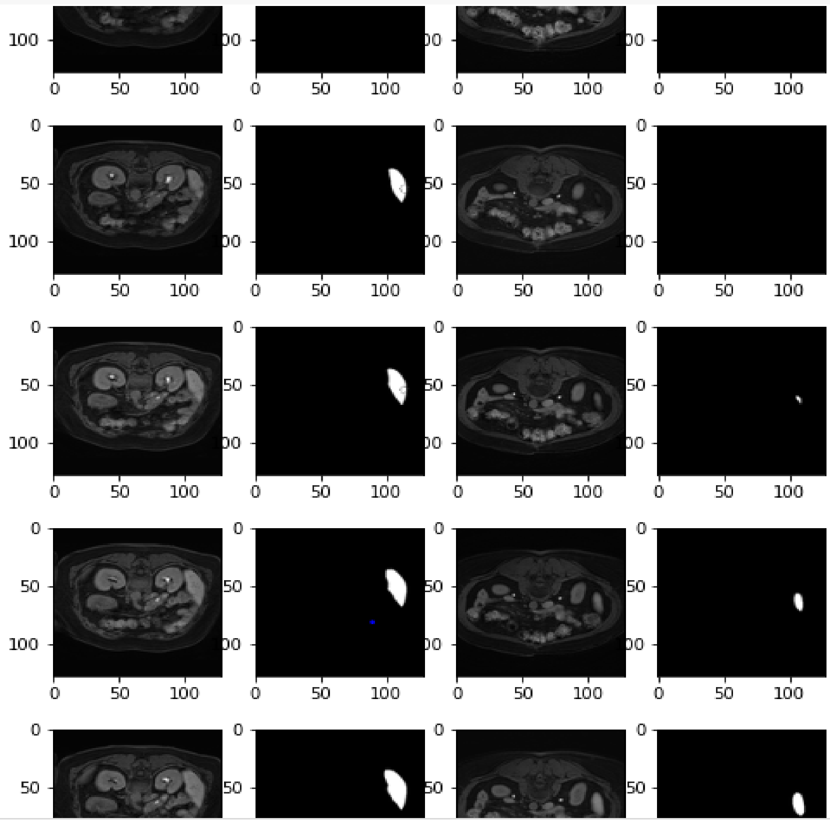
4. Tumor detection and segmentation:

- The widely used 2D U-net convolutional neural network (CNN) was employed for **slice-wise tumor segmentation.**
- The axial projection was used to train the network due to the higher resolution of image representation in this plane.

```
#show 1st 20 slices

for i in range(20):
    fig, ax = plt.subplots(1,4, figsize = (8,4))
    ax[0].imshow(x_data[i], cmap='gray')
    ax[1].imshow(y_data[i], cmap='gray')
    ax[2].imshow(x_test[i], cmap='gray')
    ax[3].imshow(y_test[i], cmap='gray')

plt.show()
```



A 2D CNN architecture was chosen for several reasons:

(1) by using a 2D input the training dataset can be increased by more than a factor of 60, as overall more than 60,000 unique slices were available in the training set.

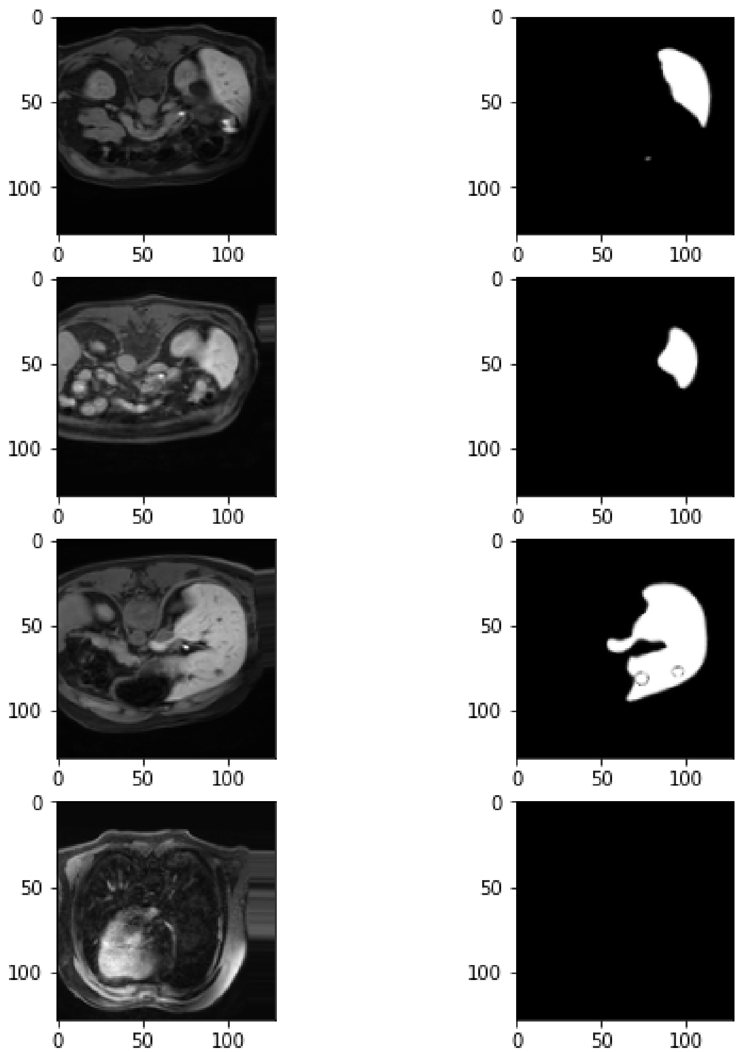
2) due to calculation costs, most present deep 3D architectures could analyze only a sub volume of the medical image , or they require a dimensionality reduction using interpolation or other image processing methods. 2D architectures do not have this problem and can process CT scans in the original resolution

5. Data Augmentation:

In order to increase the robustness of the system to a wide range of imaging parameters, the training dataset was expanded using augmentation techniques with the following parameters.

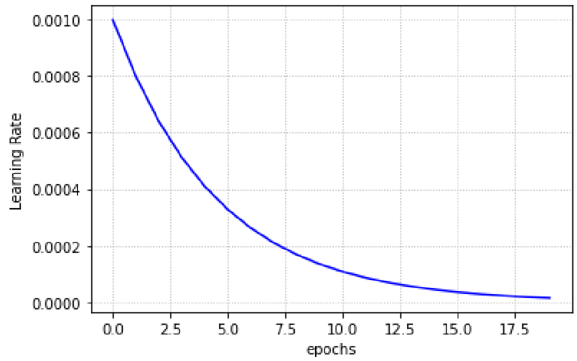
```
def my_generator(x_train, y_train, batch_size):
    data_generator = ImageDataGenerator(
            width_shift_range=0.1,
            height_shift_range=0.1,
            rotation_range=10,
            zoom_range=0.1).flow(x_train, x_train, batch_size, seed=42)
    mask_generator = ImageDataGenerator(
            width_shift_range=0.1,
            height_shift_range=0.1,
            rotation_range=10,
            zoom_range=0.1).flow(y_train, y_train, batch_size, seed=42)
    while True:
        x_batch, _ = data_generator.next()
        y_batch, _ = mask_generator.next()
        yield x_batch, y_batch
```

```
image_batch, mask_batch = next(my_generator(x_train, y_train, 8))
fix, ax = plt.subplots(8,2, figsize=(8,20))
for i in range(8):
    ax[i,0].imshow(image_batch[i,:,:,0], cmap='gray')
    ax[i,1].imshow(mask_batch[i,:,:,0], cmap='gray')
plt.show()
```



6. Results:

```
plt.plot(hist.history['lr'], color='b')
plt.xlabel("epochs")
plt.ylabel("Learning Rate")
plt.grid(linestyle='dotted')
plt.show()
```

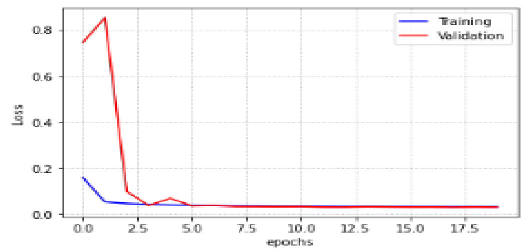


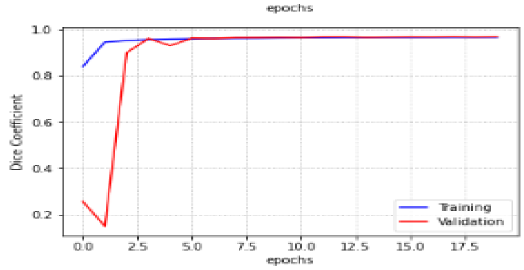
7. Loss Function and Dice co-efficient.

The loss function was calculated by combining the Dice co-efficient loss and the binary cross-entropy, and privilege was given to the Dice co-efficient loss during the first 50 epochs. The privilege was defined by the coefficients before the Dice co-efficient and cross-entropy terms in the loss function. By adding the binary cross-entropy component to the loss function, negative samples (slices without contour) could also contribute to the training.

```
plt.plot(hist.history['loss'], color='b', label='Training')
plt.plot(hist.history['val_loss'], color='r', label='Validation')
plt.legend(loc='upper right')
plt.xlabel("epochs")
plt.ylabel("Loss")
plt.grid(linestyle='dotted')
plt.show()

plt.plot(hist.history['dice_coef'], color='b', label='Training')
plt.plot(hist.history['val_dice_coef'], color='r', label='Validation')
plt.xlabel("epochs")
plt.ylabel("Dice Coefficient")
plt.legend(loc='lower right')
plt.grid(linestyle='dotted')
plt.show()
```





Contributions:

- Though the techniques used were already studied in class. We have learnt about Image segmentation using pixels. In this method we have learnt that in an image with various entities, we want to know which pixel belongs to which entity, for example in an outdoor image, we can segment the sky, ground, trees, people, etc.
- My contribution to the class was to use new method i.e., Slice wise tumor segmentation.
- Slicer wise tumor segmentation is the automated detection and segmentation method that mainly helps doctors to identify the tumor without any manual intervention.
- As per my knowledge we learnt about convolution network methods, and I have used this new technique for Medical Image segmentation.
- This method is applied as follows:
- I have used Ct scan as input.
- This complex CT scan image was divided into slices as shown in above results.
- I have Reshaped input data to feed into the network with shape (depth*#image, width, height, channel)
- Convolution 2d, U-net and many other methodologies were used to determine the efficiency.
- A robust algorithm for the isolation of the lung region was developed to allow the use of CT scans as input.
- First, the CT couch is detected and removed from the image volume. Air-filled connected volumes are detected and region growing, and morphological operations are applied in order to remove small vessels and to connect adjacent regions, resulting in a 3D binary lung mask.
- The spine axis is identified, and the lung mask is halved and symmetrically flipped about the sagittal plane, keeping the union of the flipped and the original lung masks.
- By doing so, the algorithm is optimized for handling lung abnormalities such as atelectasis, pulmonary infiltration, consolidation, and fibrosis.To accurately identify the spine axis, a further algorithm was developed which identifies the center of the spine using the stored preprocessed image with Lung window A "Lung Image" slice containing the lung is projected onto the coronal plane and filtered with a seventh-order moving average filter.
- This is repeated for the first five slices in which the lung mask is present in order to find a starting point for the center spine position S0S0. The axis of the spine is positioned normally to this point.
- S0=1n∑z=0nPzS0=1n∑z=0nPz
- Where P is a central spine point for the current axial slice, *n* is the number of slices (=5).
- Due to irregularities in patient positioning and anatomy, the central spine position S_t is recalculated slice-wise by using exponential smoothing:
- St=∝·xt+(1−∝) ·St−1St=∝·xt+(1−∝)·St−1

- Where xx is a central spine point based on the filtered signal for the current axial slice, and α is the weighting coefficient (=0.3).
- This method of flipping the lung mask allows for the inclusion of regions that contain large-sized abnormalities, such as lung collapse, which obscure parts of the lung, whereas commonly used methods exclude those regions
- A morphological dilation with the circle kernel (r =−5) is applied to the resulting lung mask to have a margin around the lung area. The final binary lung mask is used to isolate the lung region within the original image by setting all the voxel values outside the mask to the normalized air value.

Conclusion:

Detection and segmentation of abnormalities on medical images is highly important for patient management including diagnosis, radiotherapy, response evaluation, as well as for quantitative image research. In this Project I have presented a fully automated pipeline for the detection and slice wise segmentation of lung cancer developed and validated on multiple thoracic CT scans. Along with quantitative performance detailed by **image slice thickness, tumor size, image interpretation difficulty, and tumor location**. I have demonstrate that on average, radiologists & radiation oncologists preferred automatic segmentations in 56% of the cases.