Univ.AI

BRAIN TUMOR SEGMENTATION AND CLASSIFICATION

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PROBLEM STATEMENT

- Segment the tumour part from the MRI scans of brain.
- Identify the kind of tumour from categories: Meningioma, Glioma, Pituitary tumour

ABOUT DATA SET

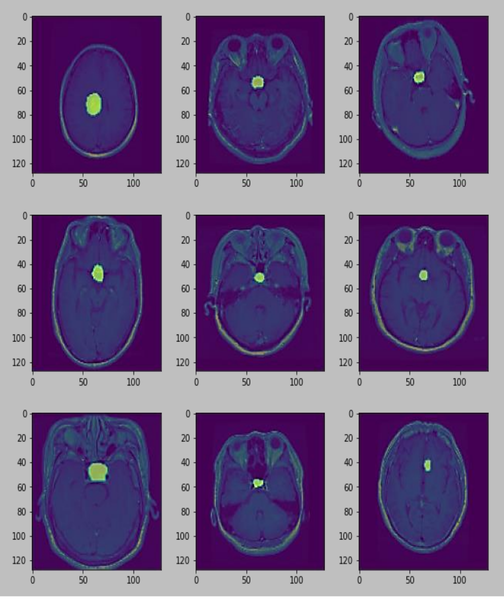
- 3064 T1 – weighted contrast enhanced images .
- 233 patients with three types of tumors .

1. Meningioma (708 slices).
2. Glioma (1426 slices) .
3. Pituitary tumor (930 slices) .

MOTIVATION

- We will be able to do implement we have studied in the course.
- Use transfer learning for training neural networks.

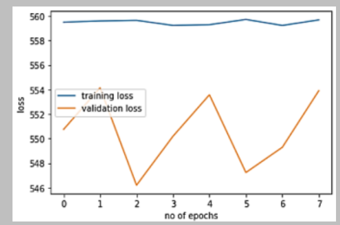
VISUALISING DATA WITH TUMOR MASK



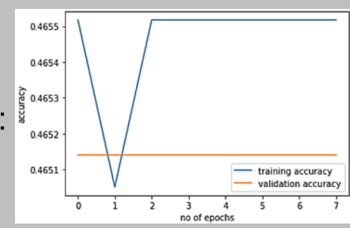
BASE MODEL

BASE MODEL 1 : FULLY CONNECTED NEURAL NETWORK

Plotting training and validation loss:

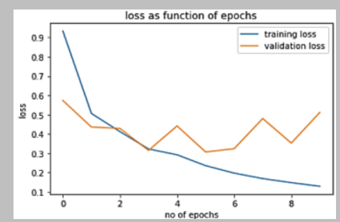


Plotting training and validation accuracy:

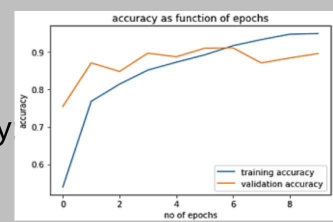


BASE MODEL 2 : CONVOLUTIONAL NEURAL NETWORK

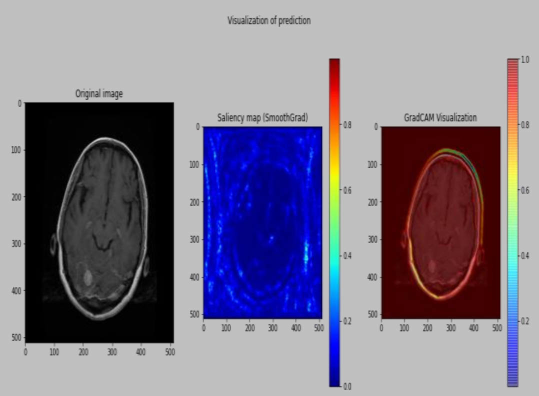
Plotting training and validation loss:



Plotting training and validation accuracy:



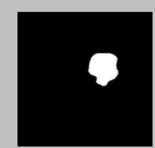
USING SALIENCY MAPS:



LOSSES UTILIZED:

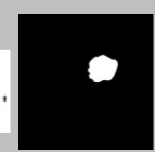
Dice loss

$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$



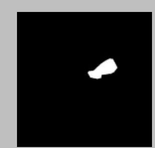
Focal loss

$$\mathrm{FL}(p_t) = -\alpha_t (1 - p_t)^{\gamma} \log(p_t).$$



IOU metric loss

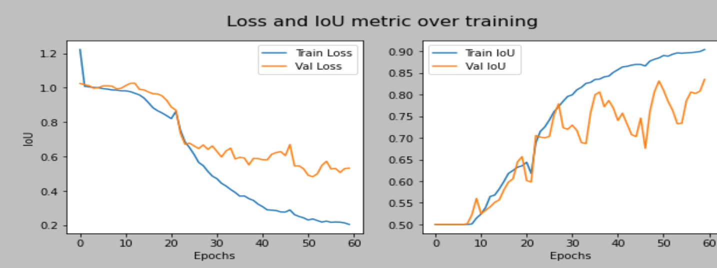
$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

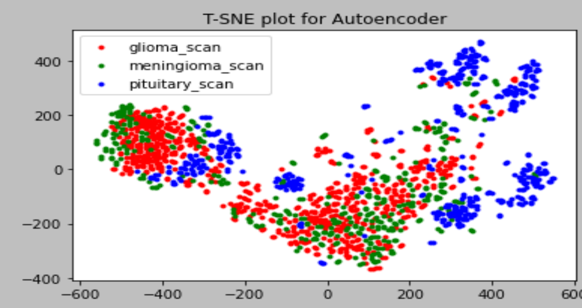


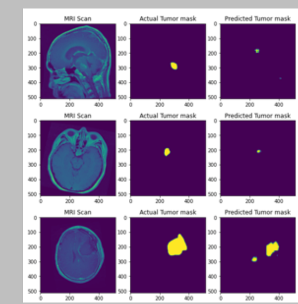
MODELS SEGMENTATION AND CLASSIFICATION

1. SEGMENTATION : BASE AUTO ENCODER

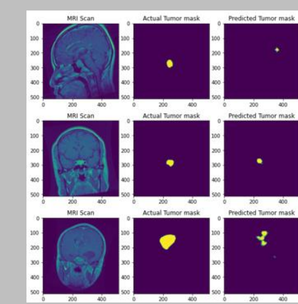
Loss and IOU metric over training





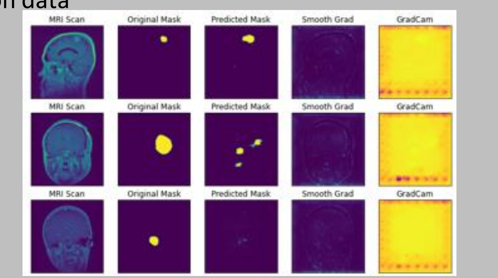


Visualising prediction from Validation data



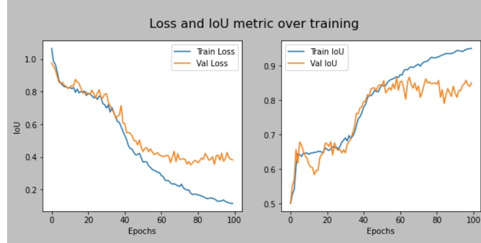
Visualising prediction from test data

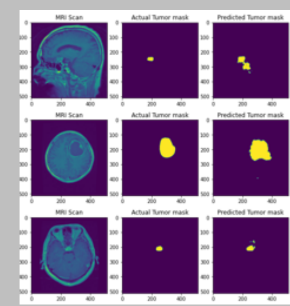
Using Saliency map



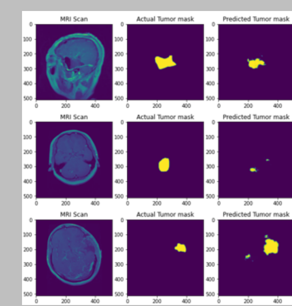
2. SEGMENTATION: SIMPLE VERSION OF UNET

Loss and IOU metric over training

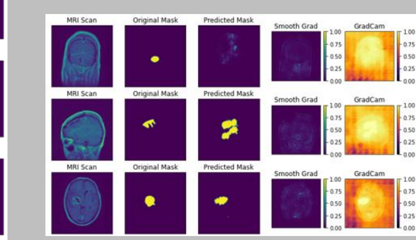




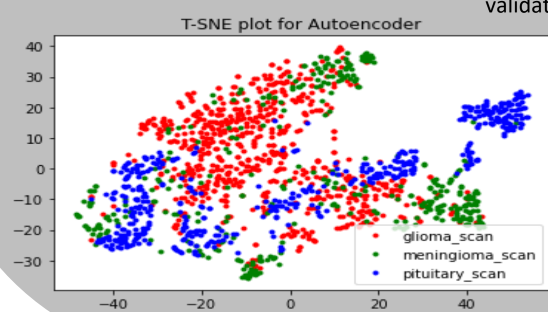
Visualising prediction from validation data

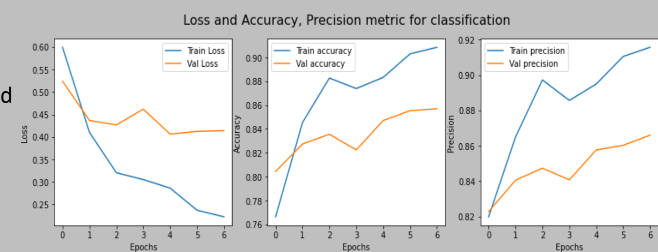


Visualising prediction on test data



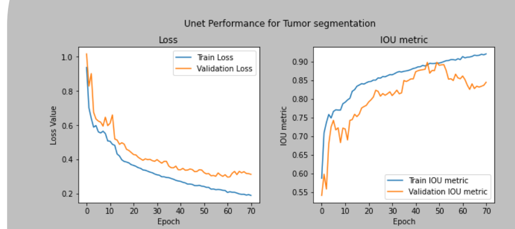
Using Saliency map

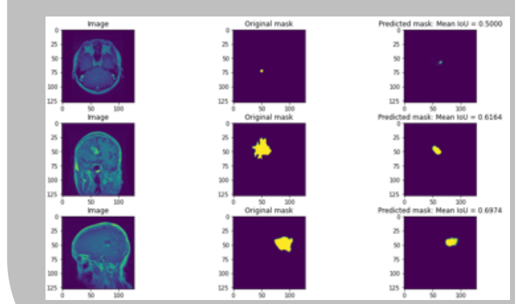




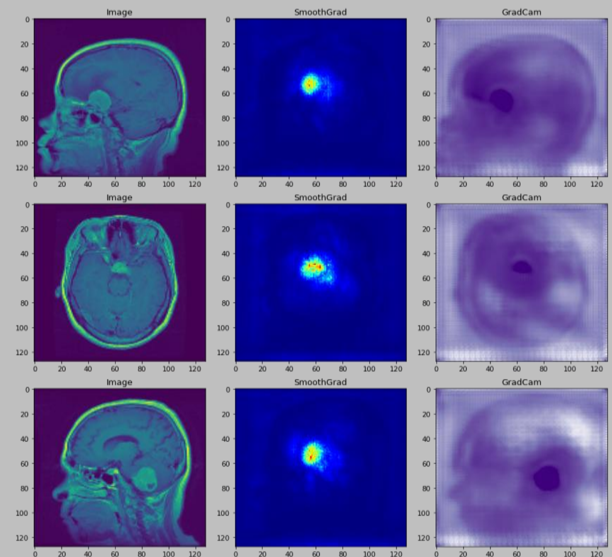
Plot for loss, accuracy and precision for classification

3. FULL UNET IMPLEMENTATION WITH DATA AUGMENTATION AND REGULARIZATION IN UNET

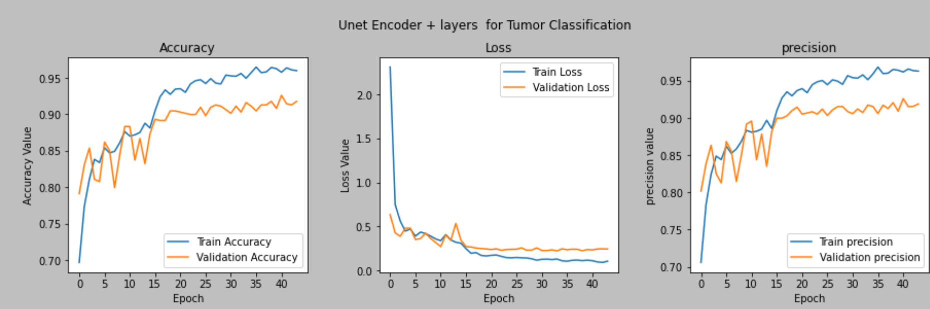




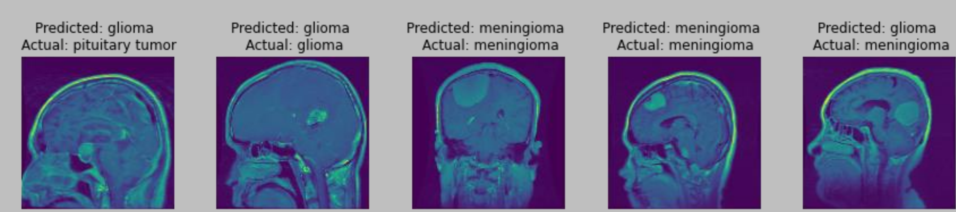
Observing mean IOU



Using Saliency map

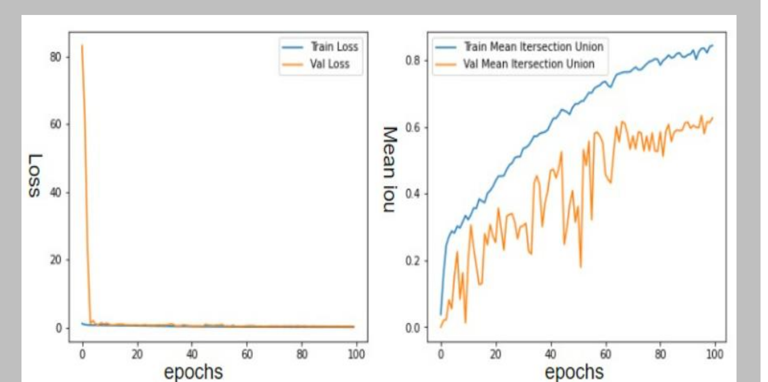


Plot for loss, accuracy and precision for UNET classification



Visualising predictions

4. TRANSFER LEARNING :



Plot for loss and Mean Intersection Union for Train and Validation data

REFERENCES

1. U-Net: Convolutional Networks for Biomedical Image Segmentation (Olaf Ronneberger, Philipp Fischer, Thomas Brox)(https://doi.org/10.48550/arXiv.1505.04597)
2. https://blog.paperspace.com/unet-architecture-image-segmentation/
3. Loss Functions: https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-021-01431-y

CONCLUSIONS AND IWORNFERENCES :

•Classification based on simple models doesn't give good results
•Using basic **AutoEncoder** we couldn't achieve the good Saliency map but we got good saliency map from UNET architectures because of the skip connections they use to focus the region of interest i.e., tumor.
•We have used **Mean IOU** metric for segmentation because the tumor and non-tumor pixels are unbalanced.
•Addition of **three losses** (Binary cross-entropy, Focul loss, Dice Loss) gave much better result compared to using individual loss for segmentation.
•The model, **UNET with batch norm** and data augmentation gave the best result for the data.
•We used almost everything we have studied in this course for this project and we learned alot of field specific things.

IMPROVEMENTS AND FUTURE PLANS:

•**Improve the Classification:**
We can try improving the classification part by analysing the incorrect labeled images and working on the classification fine tuning more since we focused on the segmentation more here
•**Improve the shape preservation**:
We can improve the segmentation part by trying to preserve that shape of the tumor more since we observed that in some images the shape of the image is not preserved much since it preserves the location of the tumor more
•**Transfer learning:**
We can improve the transfer learning using the UNET from keras by training it for more epochs since the graph keeps improving
•**Data augmentation:**
We can try to use more new data and try to use more data augmentation so that we can use it for the real images by fine tuning this models