CS736: Course Project

Brain MRI Segmentation using CNNs

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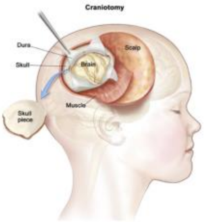
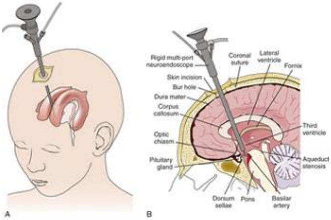
Introduction

Brain tumor segmentation is widely used for applications:-

1. Surgical planning and simulation
2. Treatment planning for radiation therapy
3. Therapy evaluation
4. Image Neurosurgery



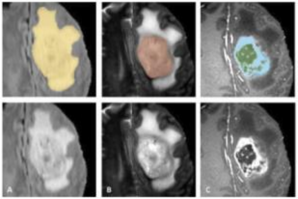


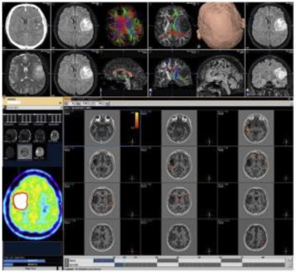
https://www.parashospitals.com/press-releases/paras-hospitals-gurgaon-uses-the-neuronavigation-technique-to-remove-brain-tumor-from-7-year-old-kashmiri-girl
https://www.goutamneurocare.com/neuro-endoscopy-treatment-hyderabad.html

Introduction

Challenges in this domain:-

1. Manual labelling is a highly skill intensive and laborious task.
2. The diagnosis is qualitative so accurate, quantitative thresholds are not determined.
3. The datasets are limited because of the nature of the domain.
4. The datasets are diverse in terms of location, shapes and sizes.



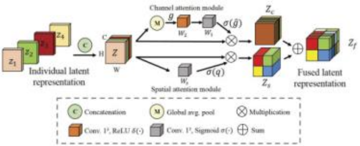


https://healthcare-in-europe.com/en/news/challenges-in-brain-tumour-segmentation.html
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3357627/figure/fig4/

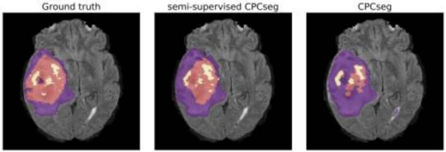
Related Works

Deep Learning based Brain Segmentation:-

1. Designing Effective Segmentation Network
2. Dealing with Imbalance Condition
3. Learning from Multi Modalities



Fusion of multi-modal inputs like T1C, T2-weighted, FLAIR using attention based modules.
Tongxue Zhou, Su Ruan, Yu Guo, Stephane Canu



Multi-task learning methods, to increase the learning of features for better segmentation.
Adel Kermi, Issam Mahmoudi, Mohamed Tarek Khadir

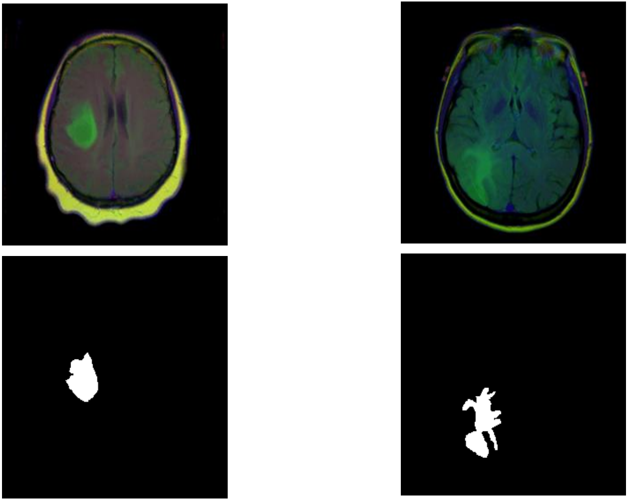
https://arxiv.org/pdf/2007.09479.pdf
https://link.springer.com/content/pdf/10.1007/978-3-030-11726-9_4.pdf

DataSet Used

1. We use the pre-processed version of the The Cancer Imaging Archive (TCIA) Dataset available on kaggle_3m. They correspond to 110 patients included in The Cancer Genome Atlas (TCGA) lower-grade glioma collection
2. Each patient has a different number of slices per volume, ranging from 20 to 88
3. Each slice is a 3 channeled image of size 256x256x3 and correspond to it we have a binary segmentation mask where 1's represent the tumour area in the MRI
4. Total number of slices available in the dataset is 3929 and we do a train-validation split of 70% and 30% after performing a random shuffle.

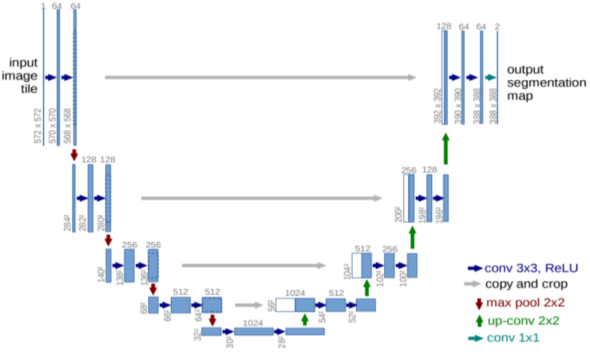
DataSet Used

Sample images and their segmentation masks/labels from the dataset:



Methodology - Model Architecture

We use the popular U-Net architecture for bio-medical segmentation purpose. The following figure illustrates a U-Net Architecture:



The number of channels is denoted on top of the box

Methodology - Training Algorithm

1. For a batch of size 8 in training set, do
2. Pre-process each image by the application of percentile stretching
3. y_pred = U_Net_model(batch)
4. Dice_loss = Dice_loss(y_pred,y_true)

1. Calculate gradients and update parameters of the U_Net_model using Adam optimizer with lr=1e-4 and MultiStep learning rate scheduler

1. Keep track of training and validation losses
2. Repeat steps 1 to 6 for n=150 epochs

Methodology - Loss Function

For medical image segmentation, the extreme scarcity of foreground examples in an image will force the network to have a strong bias to the background. The above problem exists in the cross-entropy loss function.

Hence, **Dice Loss** (softer version) is proposed to balance the foreground and the background, which is formulated as follows:

$$\text{Dice loss} = 1 - \frac{2\sum_{i=1}^{n} p_i g_i}{\sum_{i=1}^{n} p_i + \sum_{i=1}^{n} g_i}$$

Here, p_i is the predicted probability of the i^{th} pixel/voxel and g_i is the ground truth label of the i^{th} pixel/voxel in the MRI image

Methodology - Loss Function

Relation between Dice Loss (Harder version) and IoU:

First, let

$$a = TP, \quad b = TP + FP + TN$$

Then, we have

$$IoU = \frac{TP}{TP + FP + TN} = \frac{a}{b}$$

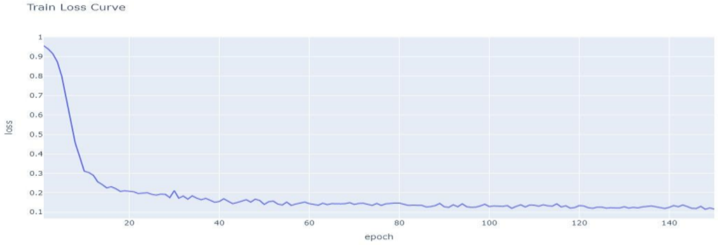
$$Dice = \frac{TP + TP}{TP + TP + FP + TN} = \frac{2a}{a + b}$$

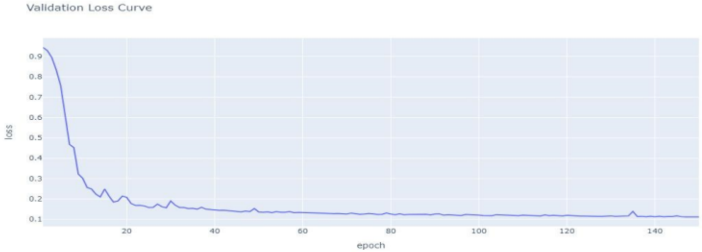
Hence,

$$Dice = \frac{\frac{2a}{b}}{\frac{a+b}{b}} = \frac{2 \cdot \frac{a}{b}}{\frac{a}{b} + 1} = \frac{2 \cdot IoU}{IoU + 1}$$

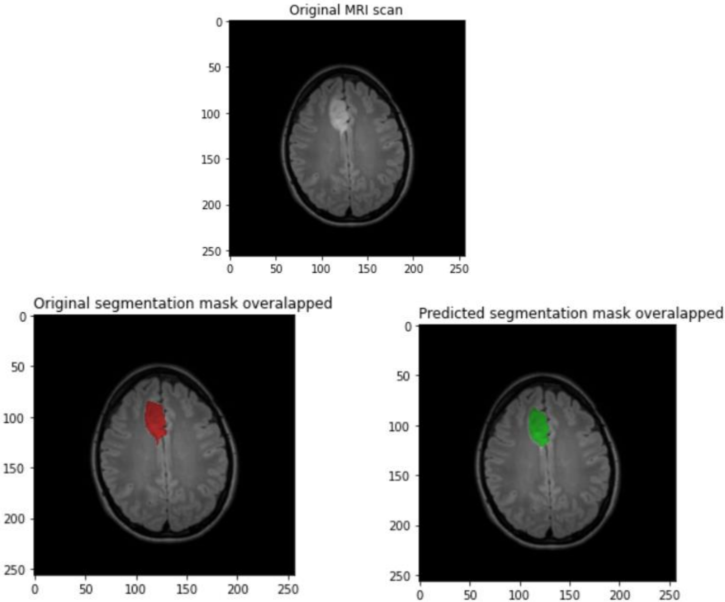
Dice Loss = 1 - Dice = 1 - [2.IoU/(IoU+1)]
Hence, Dice Loss (hard) is monotonically decreasing function of IoU in the range [0,1]

Training and Validation Loss Curves



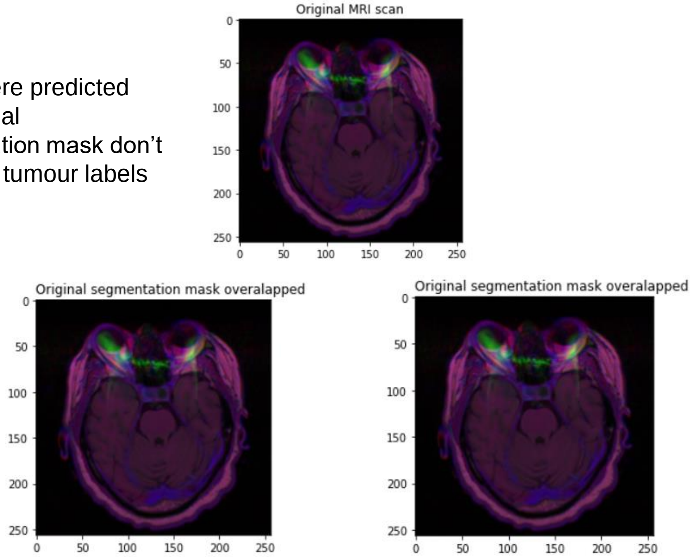


Performance Evaluation

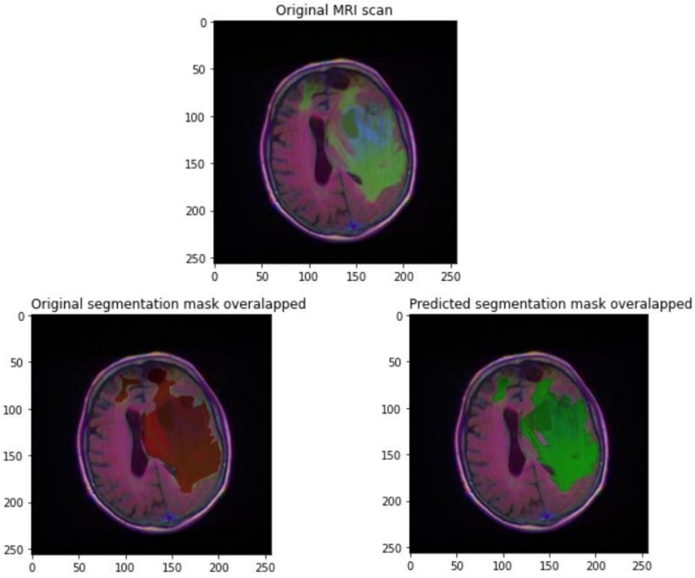


Performance Evaluation

Case where predicted and original segmentation mask don't show any tumour labels



Performance Evaluation



Performance Evaluation

Accuracy of classification of tumour presence:

```
100%|██████████| 2750/2750 [00:29<00:00, 94.78it/s]
 Classification Accuracy of training data = 97.70909090909092
```

```
100%|██████████| 1179/1179 [00:12<00:00, 94.48it/s]
 Classification Accuracy of validation data = 96.77692960135708
```

Conclusion

1. The U-net architecture achieves very good performance on biomedical segmentation applications.
2. Evaluating the performance of the model from classification point of view achieves a very good accuracy of about 96.7% on Validation data
3. From the training and validation loss curves, we conclude that we achieve a high IoU between predicted and original segmentation mask as the Dice loss is inversely proportional to the IoU.

References

[1] [Ronneberger, Fischer, & Brox, 2015] "U-net: Convolutional networks for biomedical image segmentation". *International Conference on Medical image computing and computer-assisted intervention*.

[2] [Milletari, Navab, & Ahmadi, 2016] "V-net: Fully convolutional neural networks for volumetric medical image segmentation". *International Conference on 3D Vision*.