Optimizing Brain Tumor Segmentation using Transfer Learning

Team members:
Aadithya Kandeth 6980-2791
Sai Nikhil Dondapati 2228-6439
Shaanya Singh 3476-2752

Why Brain Tumor Segmentation

- To assist in Medical diagnosis, early detection and treatment
- Clearly differentiate between different tumors
- Leverage Deep Learning applications in Medical Imaging
- Offer quantitative analysis
- Manual segmentation is time consuming
- Need for automated segmentation
- Standardize MRI based segmentation
- Extend to different forms of imaging
- Survival prediction
- Risk factor identification

Challenges in Brain Tumor Segmentation

- Heterogenous shapes and sizes of brain MRIs
- Difference in methodologies of capturing MRIs
- Different forms of imaging
- Different stages of tumor progression
- Different types of tumor cells
- Different shapes and sizes of tumor cells
- Irregular boundaries of tumor cells
- Huge imbalance in the dataset
- Developing custom evaluation metrics
- Generalization for different forms of data

Objectives

- Conduct Literature Review
- Use state of the art methods for Brain Tumor Segmentation
- Optimize the training process by applying transfer learning
- Compare performance of different models
- Compare and contrast different transfer learning models
- Explore 2D modeling along with 3D modeling
- Explore evaluation methods for handling class imbalance
- Evaluate training times of different architectures and methods
- Train, test, and validate different models
- Identify the scope for future work

Literature Review

- Emerging trend is to use Deep Learning for Medical Imaging
- CNNs have been proven to work well for segmentation tasks
- Transfer learning has been an effective method
- Lack of generalized Brain Tumor Segmentation models
- Privacy concerns and variance in imaging methodology
- Limited availability of pretrained 3D models
- Even scarce when it comes to tumor segmentation pretrained models
- U-net has been the winning architecture in recent BrATS challenges
- Other architectures include VGG-16 and Resnet-50
- Literature for understanding different evaluation metrics

Dataset preparation

- We extensively use BraTS challenge datasets publicly available
- Extract patches of 128*128*128 from Brain MRI volumes
- t1ce, t2, and flair images are used, therefore we have 3 input channels
- Input dimension is therefore 128*128*128*3
- GD-enhancing tumor: Label 3
- Peritumoral edema: Label 2
- Necrotic and non-enhancing tumor core (NCR/NET): Label 1
- Normal/Non-tumor: Label 0
- Output dimension is therefore 128*128*128*4
- Our model essentially classifies each pixel as one of the 4 labels

3D Modeling

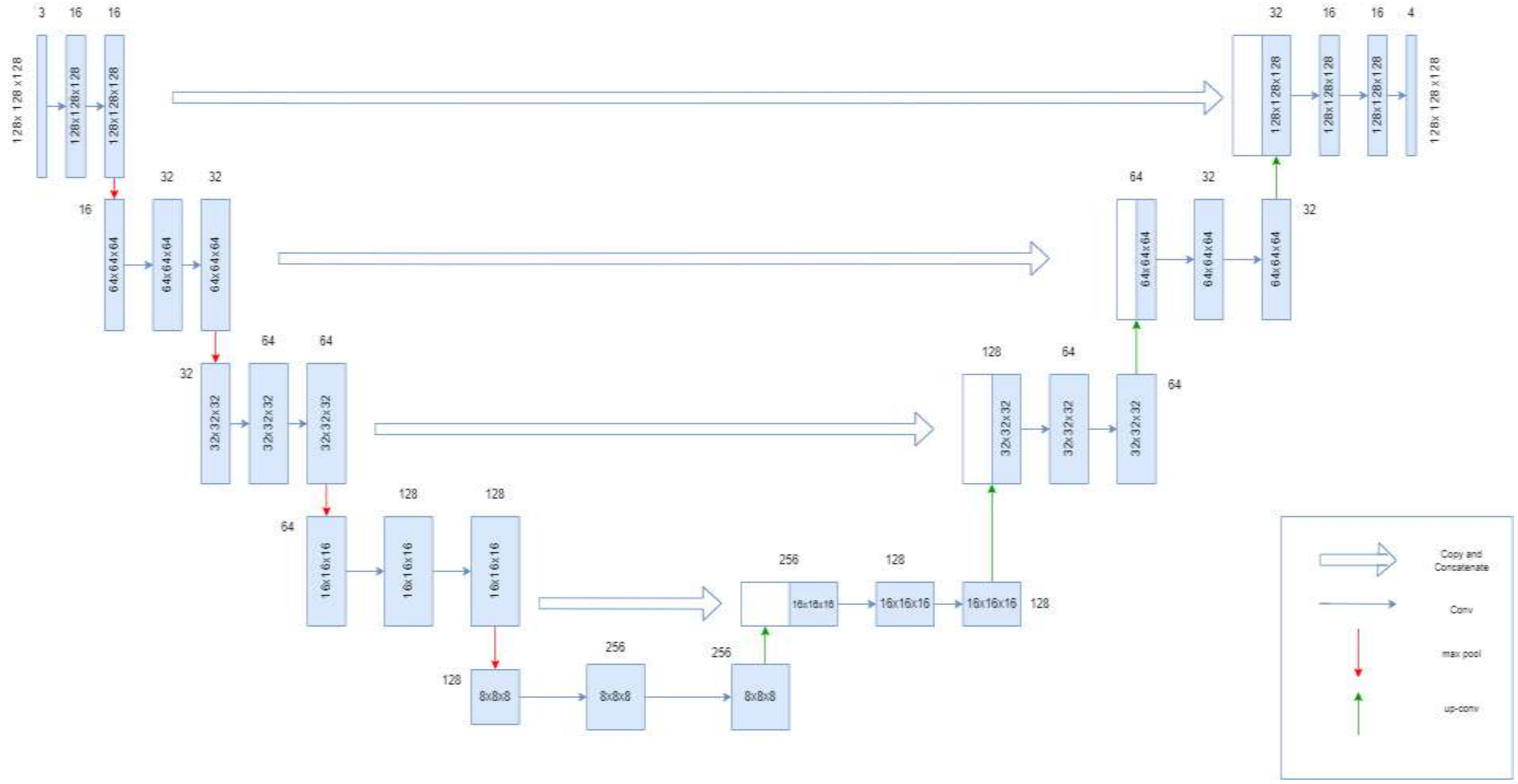
Without transfer learning

- Baseline CNN 3D model (architecture from Project 2)
- U-net architecture for 3D modeling
- VGG-16 based architecture for 3D modeling

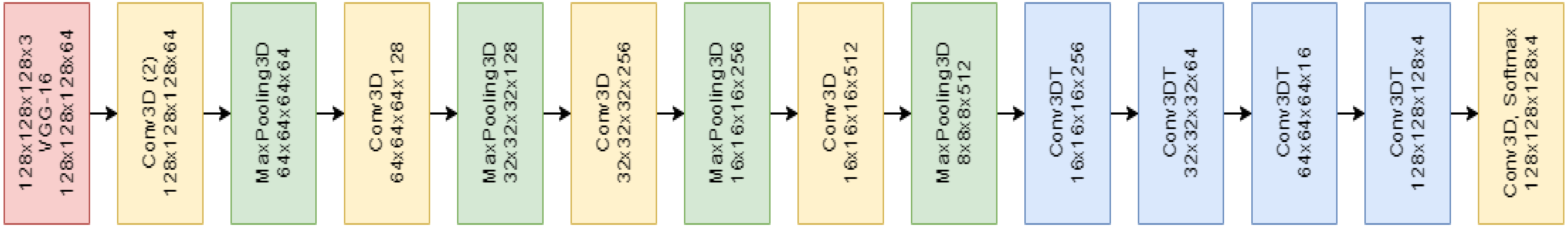
With transfer learning

- VGG-16 based architecture for 3D modeling with transfer learning
- Resnet-50 based architecture for 3D modeling with transfer learning
- Pretrained and imagenet weights used in both cases

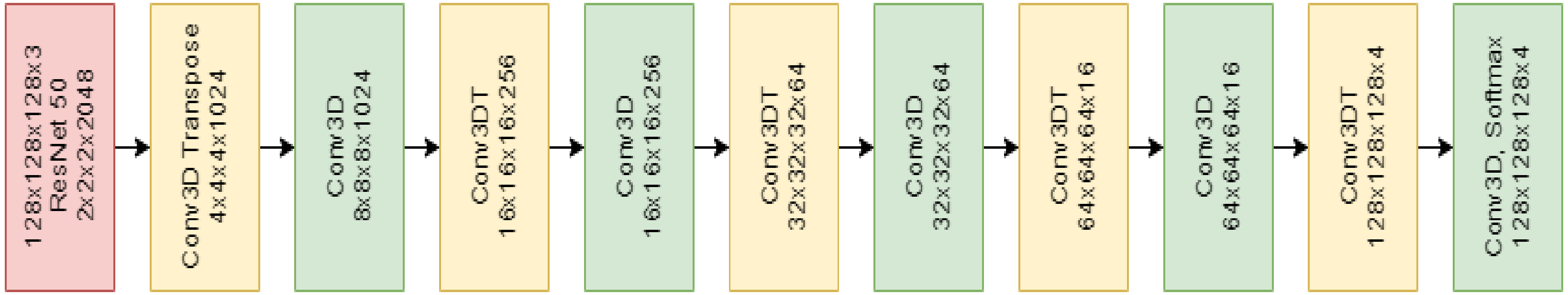
U-net architecture for Brain Tumor segmentation



VGG-16 architecture for Brain Tumor segmentation



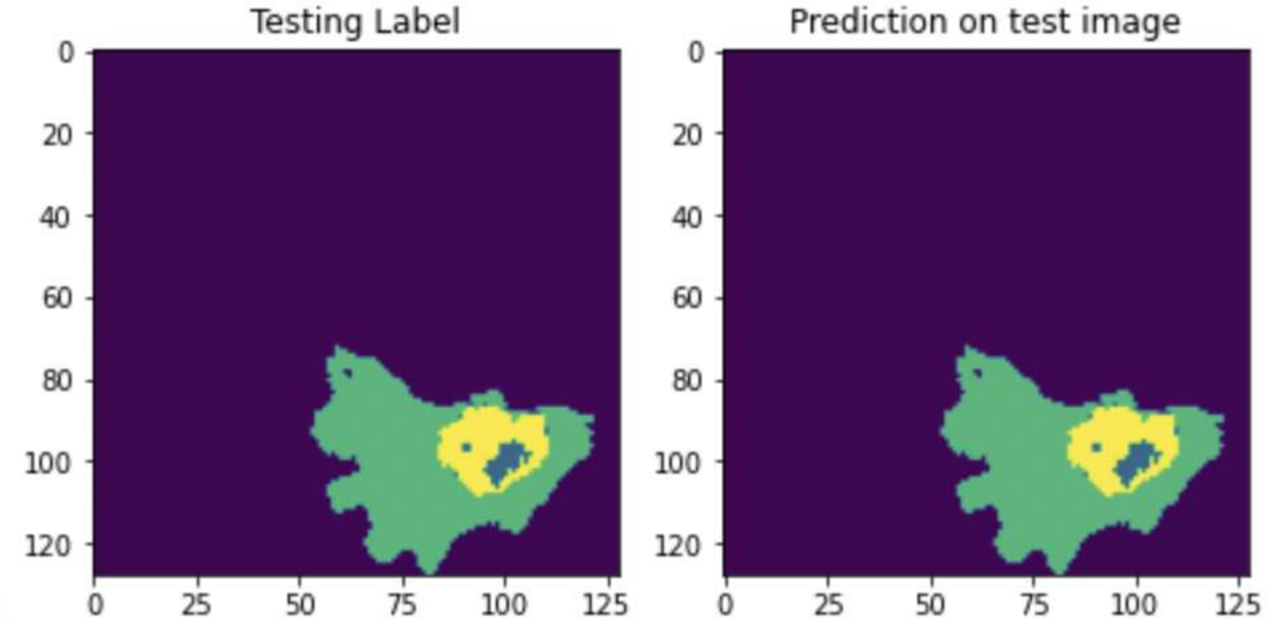
Resnet-50 architecture for Brain tumor segmentation



Evaluation metrics

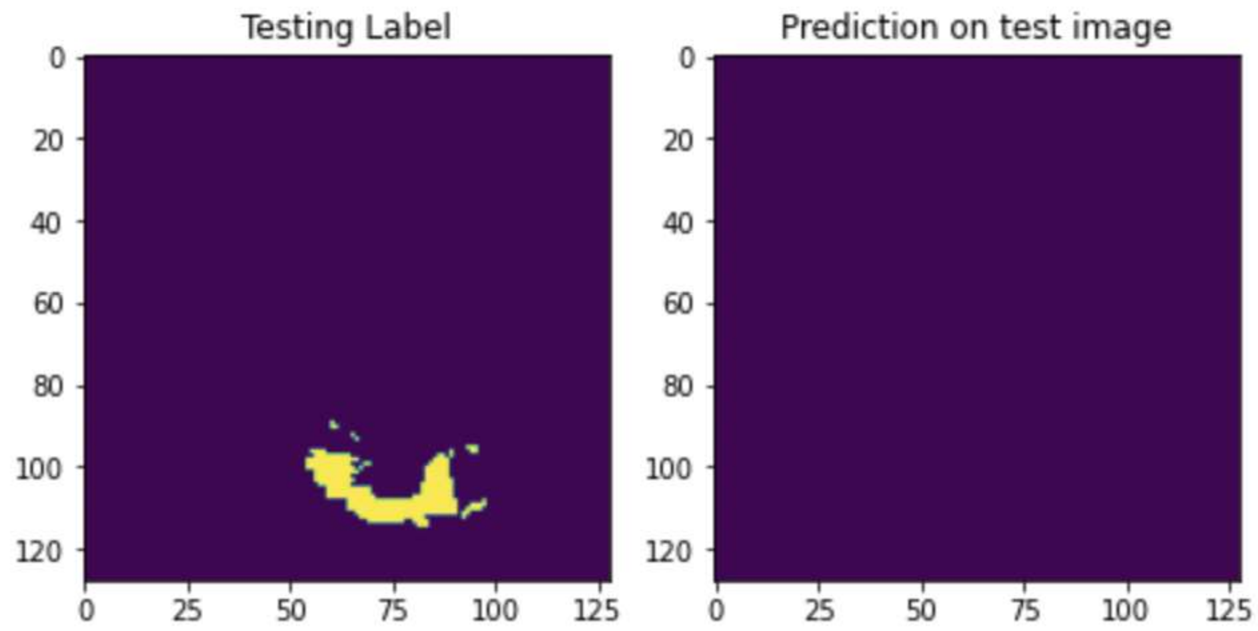
- We cannot rely on accuracy alone because of the huge class imbalance
- Easy to achieve more than 90% accuracy by classifying every pixel as non-tumorous
- Based on literature review and class lectures, we use the following metrics and loss functions:
  - IOU score (Intersection over Union)
  - Dice Loss (Extensively used for segmentation tasks)
  - Categorical Focal Loss
  - Categorical Cross Entropy Loss
- Metrics in our models are IOU score and accuracy
- Total loss as sum of dice loss, categorical focal loss, and cross entropy loss

Results



U-net predictions when there are a lot of tumor cells

Results



U-net failing when there aren’t a lot of tumor cells

Results

Model	Approach	Accuracy	Mean IOU
U-net	No transfer learning	0.97	0.83
VGG-16	No transfer learning	0.94	0.74
VGG-16	Transfer learning	0.94	0.63
Resnet-50	Transfer learning	0.95	0.67
Baseline CNN	No transfer learning	0.75	0.24

Models trained on 258 training MRI images and validated on 86 MRI images

Training time

Model	Approach	Training time per epoch
U-net	No transfer learning	1hr 35 mins
VGG-16	No transfer learning	1hr 45 mins
VGG-16	Transfer learning	16 mins
Resnet-50	Transfer learning	13 mins
Baseline CNN	No transfer learning	23 mins

Models trained on 258 training MRI images and validated on 86 MRI images

Challenges

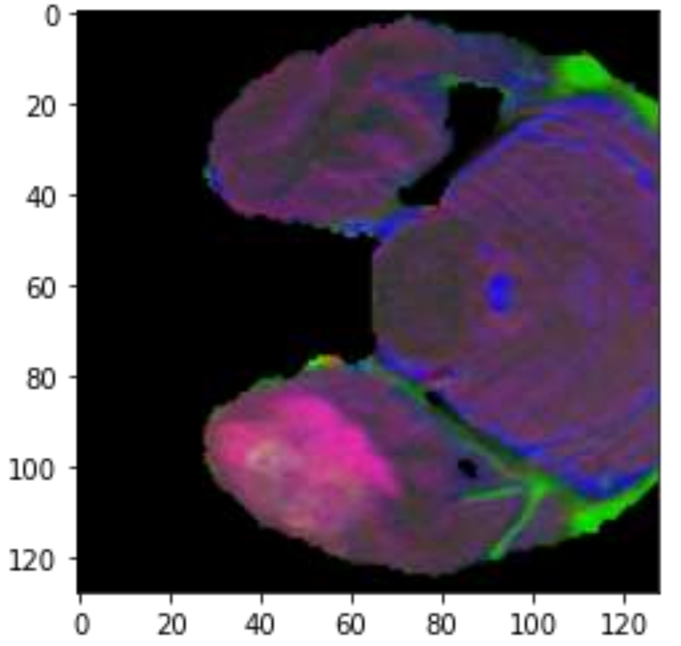
- Very long training time for each model when transfer learning methodology is not used
- When the tumor cells are only a small fraction, the models fail
- Improving generalization is a tough task
- Very limited 3D pretrained models

Proposed Solution

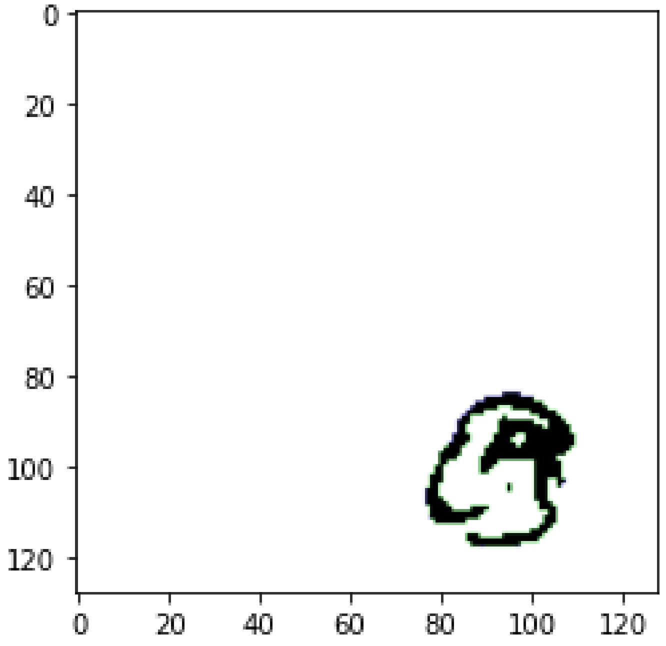
- Extract 2D images from the MRI volumes and build models on 2D images
- Several pretrained 2D models readily available
- Rapid training process
- Reconstruct 3D mask by post-processing
- Compare results of 2D and 3D modeling

2D image extraction

- We extract 2d images from MRI volumes by slicing the data
- We customize 2D pretrained models for solving the task at hand



One slice of MRI image is 128*128*3



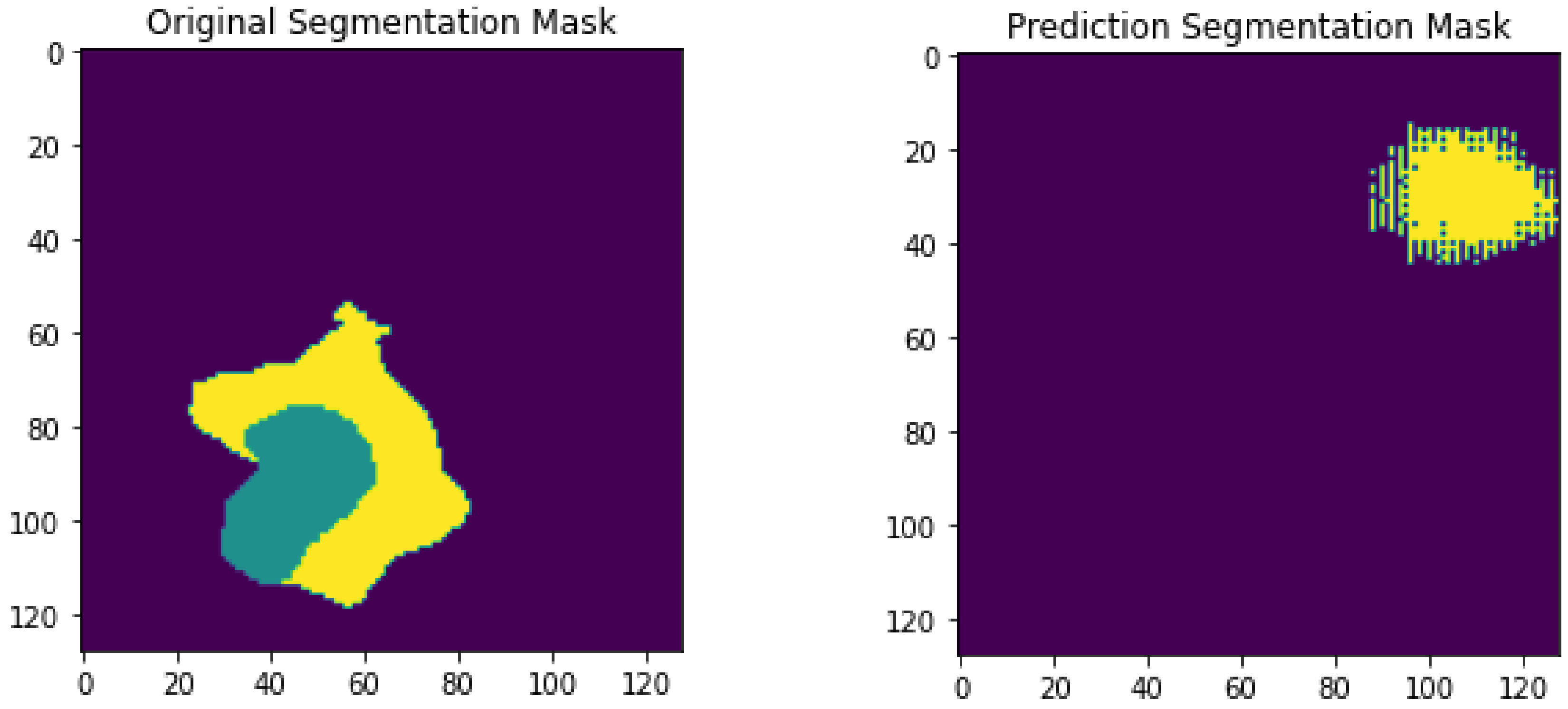
The same slice of tumor mask

2D Modeling with transfer learning

- Inception net V2
- Inception resnet
- VGG-16
- Resnet-50

- We use the same evaluation metrics discussed earlier
- We make use of pretrained models trained on imagenet
- Training process is much quicker
- Reconstruct 3D mask from predicted 2D masks

Results



Best results obtained with 2D Inception resnet model

Results

Model	Approach	Accuracy	Mean IOU
Inception resnet	Transfer learning	0.87	0.53
Inception net	Transfer learning	0.76	0.61
Resnet-50	Transfer learning	0.51	0.25
VGG-16	Transfer learning	0.61	0.32

Models trained on 33024 (258*128) training 2D images and validated on 11008 (86*128) 2D images

Training time

Model	Approach	Training time per epoch
Inception resnet	Transfer learning	9 mins
Inception resnet	No transfer learning	25 mins
VGG-16	Transfer learning	11 mins
VGG-16	No Transfer learning	43 mins
Renet-50	Transfer learning	10 mins
Resnet-50	No transfer learning	13 mins
Inception net V2	Transfer learning	12 mins
Inception net V2	No transfer learning	27 mins

Models trained on 33024 training 2D images and validated on 11008 2D images

Summary & Conclusion

- 3D models clearly outperform 2D models
- Pretrained models are easy to train, and they offer better generalization
- The concatenation layers in U-net model help boost the IOU score
- Necessity for training the models on lot more data
- Inter domain knowledge transfer is challenging
- Importance of selecting good evaluation metrics
- Handling sparse data is a challenging

Future work

- Train the models on large datasets collected from multiple sources
- Develop repositories of pretrained 3D Medical Imaging models
- Experiment with GANs for Segmentation challenges
- Automatic Brain Tumor Segmentation
- Incorporate synthetic data to overcome privacy issues

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