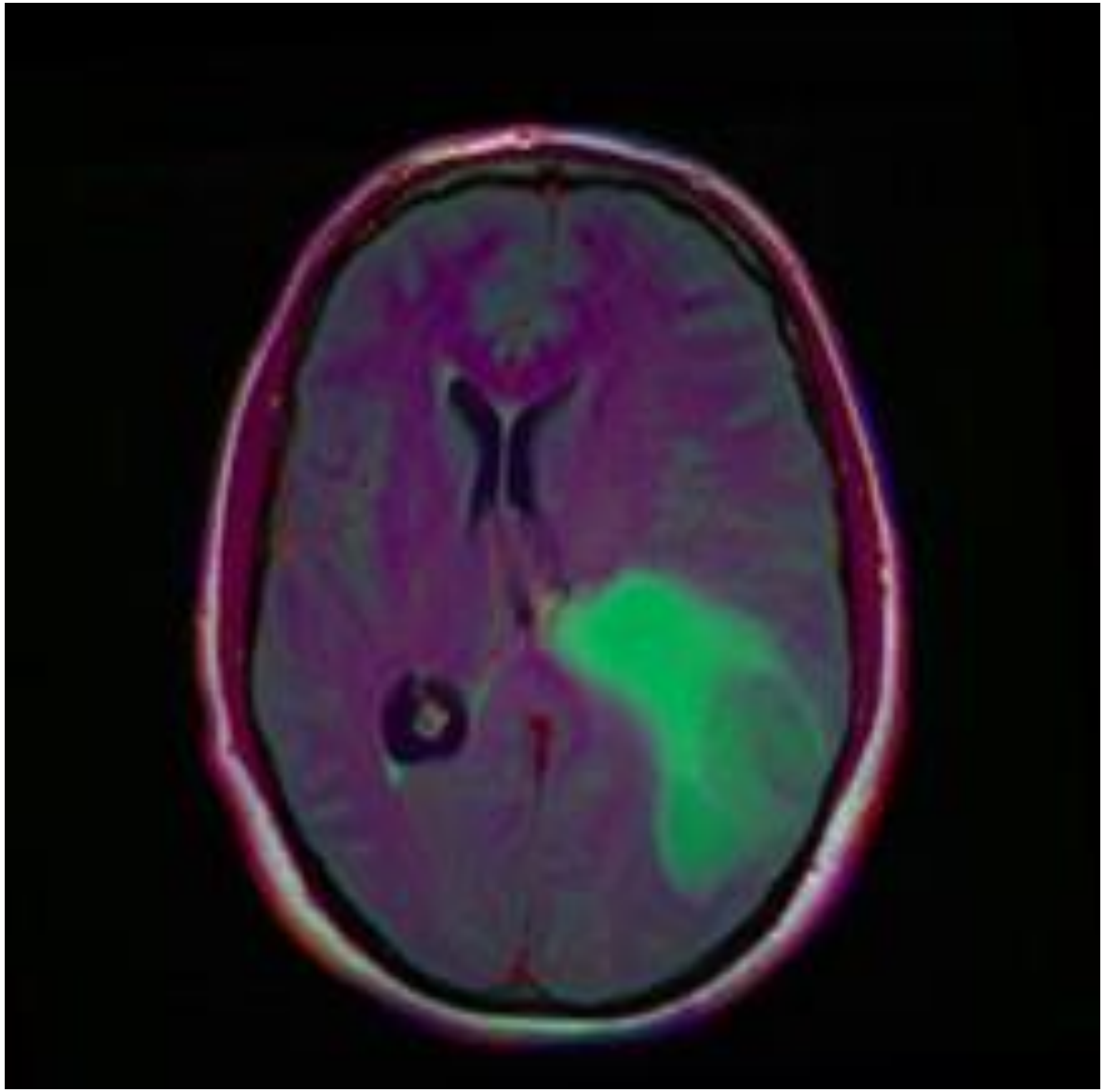
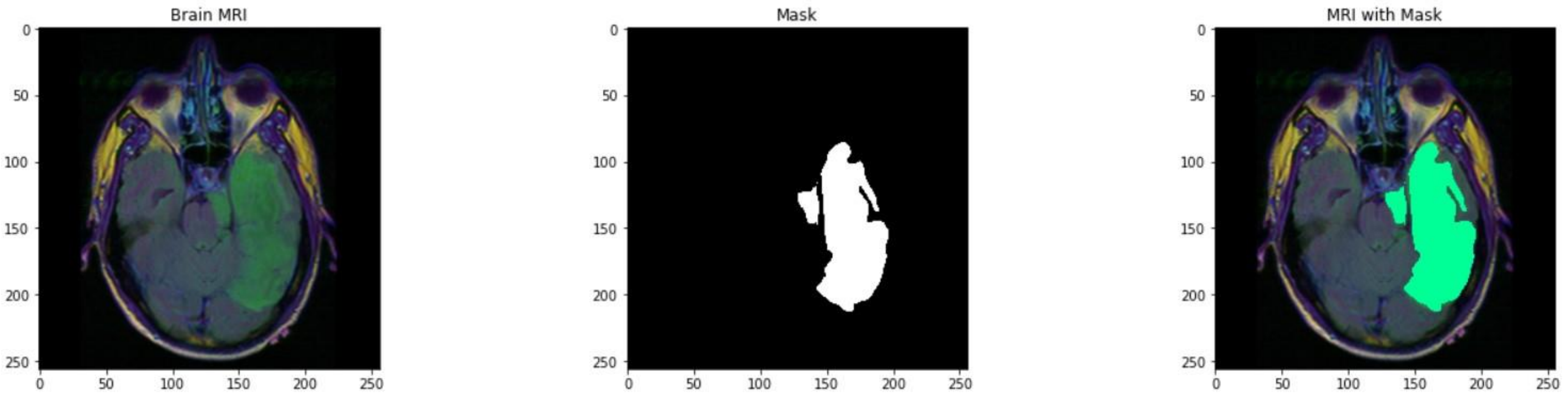
Brain Tumor Classification Using Deep Learning



Executive Summary

- Convolutional neural networks (CNN) have become the driving force behind developments in computer vision in recent years
- The aim of this project is to compare 2 of the well-known CNN architectures against one another for the purpose of classifying and segmenting brain tumors
- Both algorithms performed exceptionally well with the ResNet having the best results for both classification, segmentation and runtime



Problem Statement

- Brain tumors are a fatal disease that can be extremely challenging to diagnose with high accuracy.
- My hope for this project is to aid in the clinical outcomes of patients who may have a brain tumor
- Use two state-of-the-art CNN models to classify and segment brain tumors on MRI images

VGG16 - Structural Details

#	Input Image			output			Layer	Stride	Kernel		in	out	Param
1	224	224	3	224	224	64	conv3-64	1	3	3	3	64	1792
2	224	224	64	224	224	64	conv3064	1	3	3	64	64	36928
	224	224	64	112	112	64	maxpool	2	2	2	64	64	0
3	112	112	64	112	112	128	conv3-128	1	3	3	64	128	73856
4	112	112	128	112	112	128	conv3-128	1	3	3	128	128	147584
	112	112	128	56	56	128	maxpool	2	2	2	128	128	65664
5	56	56	128	56	56	256	conv3-256	1	3	3	128	256	295168
6	56	56	256	56	56	256	conv3-256	1	3	3	256	256	590080
7	56	56	256	56	56	256	conv3-256	1	3	3	256	256	590080
	56	56	256	28	28	256	maxpool	2	2	2	256	256	0
8	28	28	256	28	28	512	conv3-512	1	3	3	256	512	1180160
9	28	28	512	28	28	512	conv3-512	1	3	3	512	512	2359808
10	28	28	512	28	28	512	conv3-512	1	3	3	512	512	2359808
	28	28	512	14	14	512	maxpool	2	2	2	512	512	0
11	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
12	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
13	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
	14	14	512	7	7	512	maxpool	2	2	2	512	512	0
14	1	1	25088	1	1	4096	fc		1	1	25088	4096	102764544
15	1	1	4096	1	1	4096	fc		1	1	4096	4096	16781312
16	1	1	4096	1	1	1000	fc		1	1	4096	1000	4097000
							Total						138,423,208

VGGNet

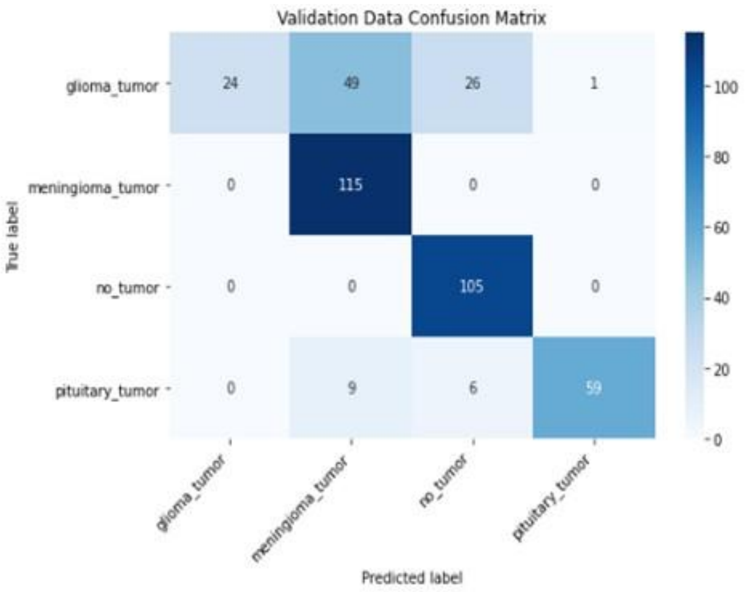
ResNet18 - Structural Details

#	Input Image			output			Layer	Stride	Pad	Kernel		in	out	Param
1	227	227	3	112	112	64	conv1	2	1	7	7	3	64	9472
	112	112	64	56	56	64	maxpool	2	0.5	3	3	64	64	0
2	56	56	64	56	56	64	conv2-1	1	1	3	3	64	64	36928
3	56	56	64	56	56	64	conv2-2	1	1	3	3	64	64	36928
4	56	56	64	56	56	64	conv2-3	1	1	3	3	64	64	36928
5	56	56	64	56	56	64	conv2-4	1	1	3	3	64	64	36928
6	56	56	64	28	28	128	conv3-1	2	0.5	3	3	64	128	73856
7	28	28	128	28	28	128	conv3-2	1	1	3	3	128	128	147584
8	28	28	128	28	28	128	conv3-3	1	1	3	3	128	128	147584
9	28	28	128	28	28	128	conv3-4	1	1	3	3	128	128	147584
10	28	28	128	14	14	256	conv4-1	2	0.5	3	3	128	256	295168
11	14	14	256	14	14	256	conv4-2	1	1	3	3	256	256	590080
12	14	14	256	14	14	256	conv4-3	1	1	3	3	256	256	590080
13	14	14	256	14	14	256	conv4-4	1	1	3	3	256	256	590080
14	14	14	256	7	7	512	conv5-1	2	0.5	3	3	256	512	1180160
15	7	7	512	7	7	512	conv5-2	1	1	3	3	512	512	2359808
16	7	7	512	7	7	512	conv5-3	1	1	3	3	512	512	2359808
17	7	7	512	7	7	512	conv5-4	1	1	3	3	512	512	2359808
	7	7	512	1	1	512	avg pool	7	0	7	7	512	512	0
18	1	1	512	1	1	1000	fc					512	1000	513000
							Total							11,511,784

ResNet

Related Work

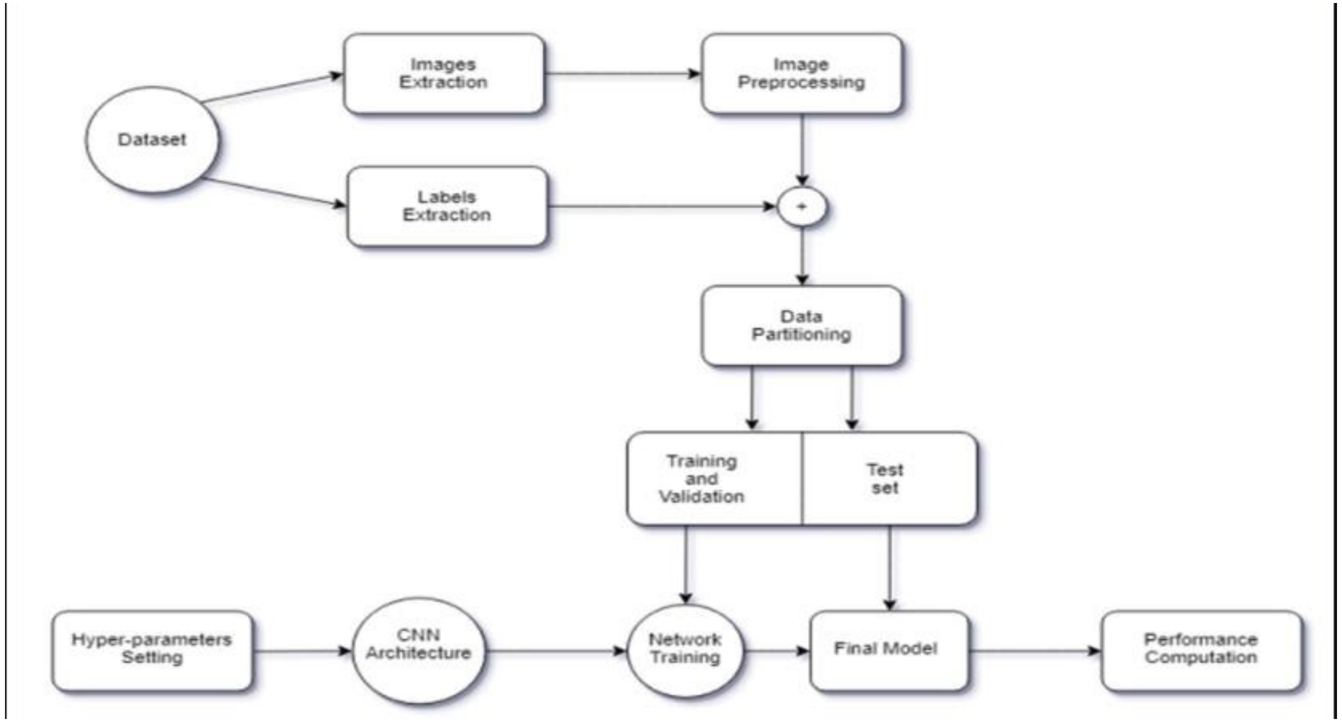
- To this point the most common CNN architecture used for medical imaging classification has been the ResNet model.
- Little work has been done on other models relating to brain tumor classification



Confusion matrix from prior work

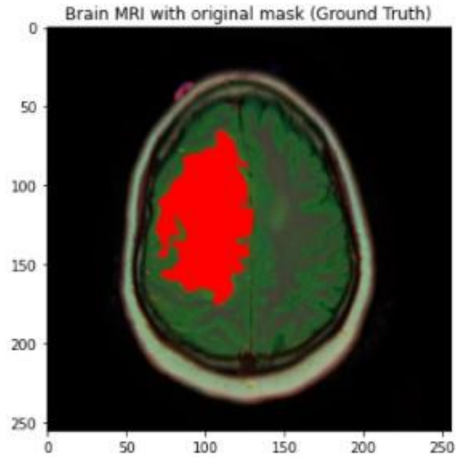
Proposed work

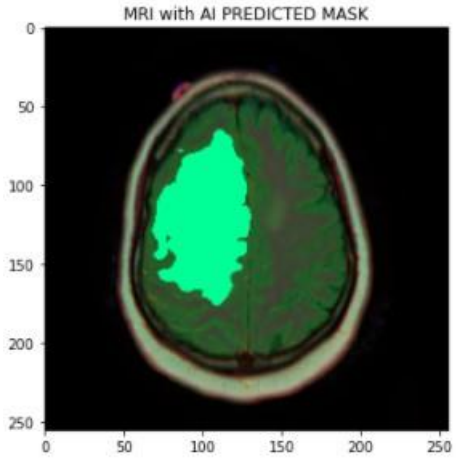
- The general workflow is presented below
- The workflow shows from dataset acquisition to final model



Proposed Work Cont.

- The end goal is to have a two-part model for each algorithm
- The first section will consist of classification of the images into either having a tumor or not having a tumor
- We will use 90% certainty as our baseline for whether the MRI has a tumor
- If it is identified as having one, then it will be run through the segmentation model which will identify and highlight which part of the brain contains the tumor





Evaluation

- The goal is to compare both CNNs based on 7 evaluation metrics. Those being precision, recall, F-1 Score, Tversky score, overall accuracy, and run time.

	Precision	Recall	F-1 Score	Support
Glioma Tumor	0.99	1.00	0.99	826
Meningioma Tumor	1.00	1.00	1.00	822
No Tumor	1.00	1.00	1.00	395
Pituitary Tumor	1.00	1.00	1.00	827
Accuracy			1.00	2870

Table 1: Training Evaluation Report

	Precision	Recall	F-1 Score	Support
Glioma Tumor	0.24	1.00	0.38	100
Meningioma Tumor	1.00	0.70	0.82	115
No Tumor	1.00	0.80	0.88	105
Pituitary Tumor	0.79	0.98	0.87	74
Accuracy			0.78	394

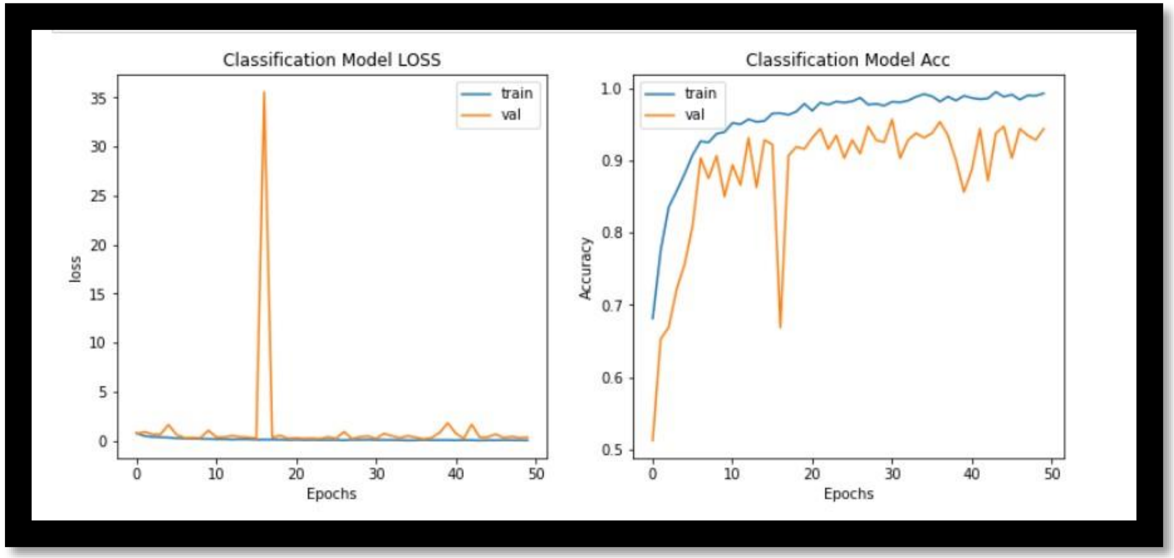
Table 2: Validation Evaluation Report

Example of evaluation metrics

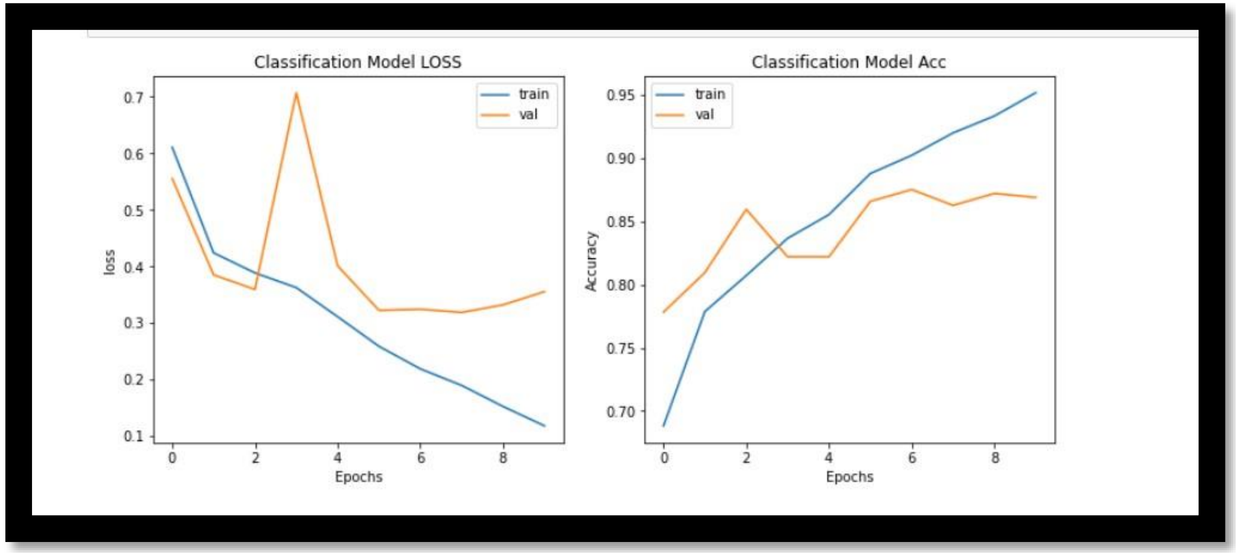
Evaluation Results

- The results for both algorithms fared decently well given all things considered, but in the end one model was clearly better than the other. That model being the ResNet.
- When looking at the two models, it was initially assumed that the VGGNet would perform better than the ResNet, because it was training on more parameters. The trade off here would obviously be it took a much longer time to run.
- In the end though, the ResNet not only ran much faster then the VGGNet but it also had a higher overall precision, recall, f-1 score and overall accuracy on the same sized validation set which can be seen from the support number

Evaluation Visualizations Part 1



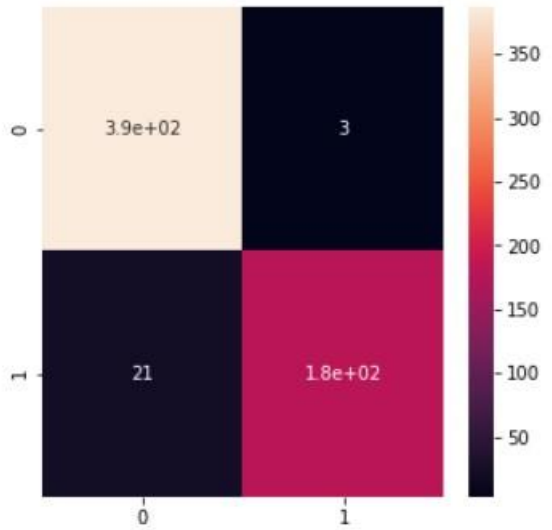
ResNet Loss and Accuracy Metrics



VGGNet Loss and Accuracy Metrics

Evaluation Visualizations Part 2

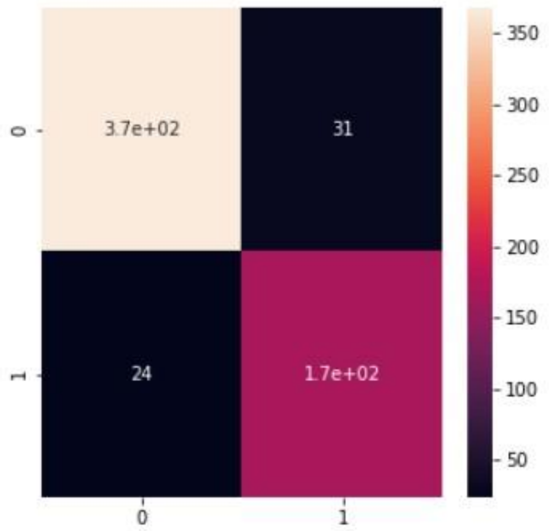
	precision	recall	f1-score	support
0	0.95	0.99	0.97	390
1	0.98	0.90	0.94	200
accuracy			0.96	590
macro avg	0.97	0.94	0.95	590
weighted avg	0.96	0.96	0.96	590



ResNet Classification Metrics

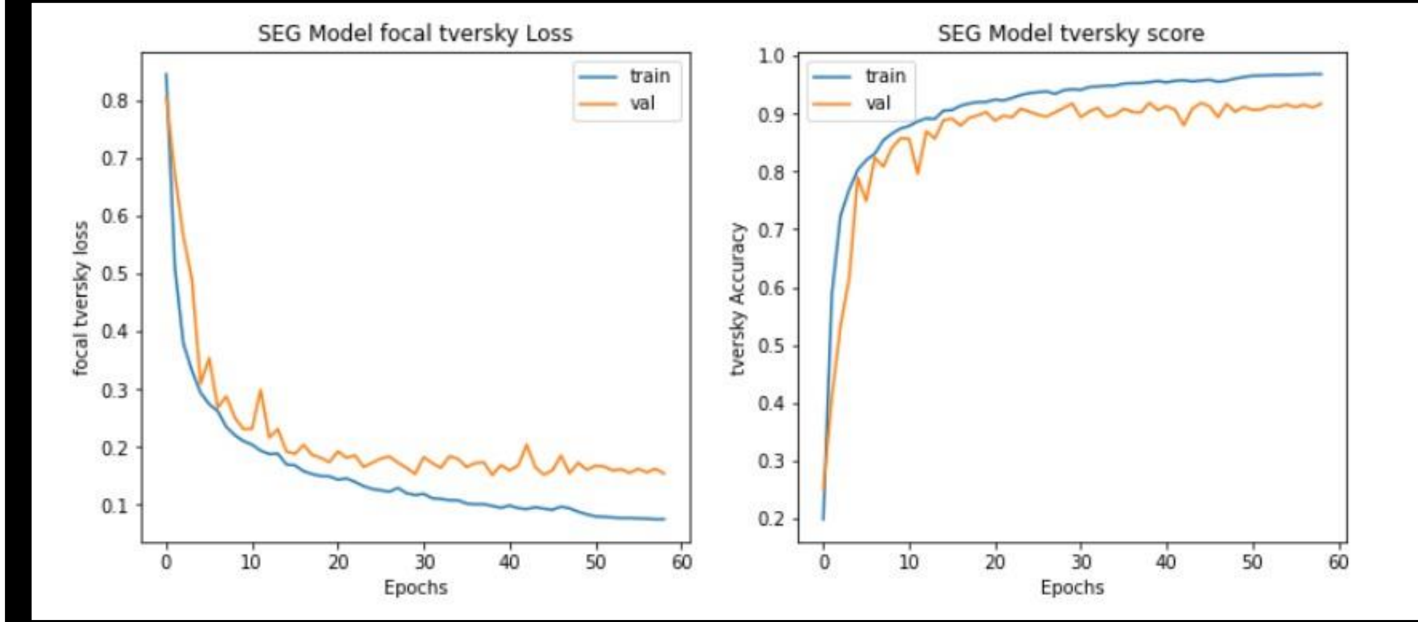
0.9067796610169492

	precision	recall	f1-score	support
0	0.94	0.92	0.93	399
1	0.84	0.87	0.86	191
accuracy			0.91	590
macro avg	0.89	0.90	0.89	590
weighted avg	0.91	0.91	0.91	590

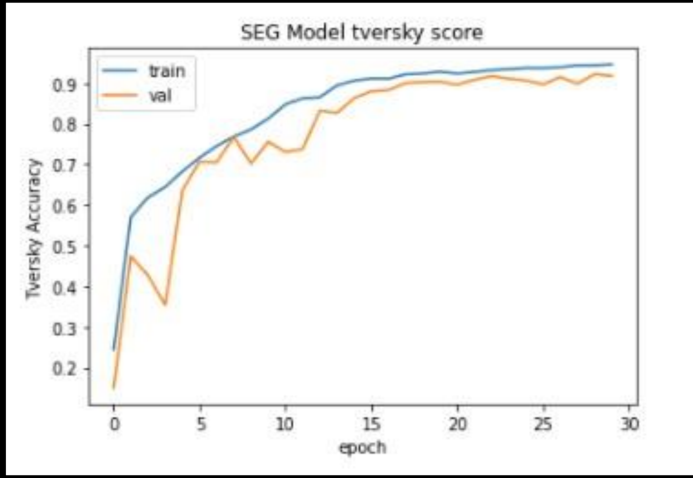


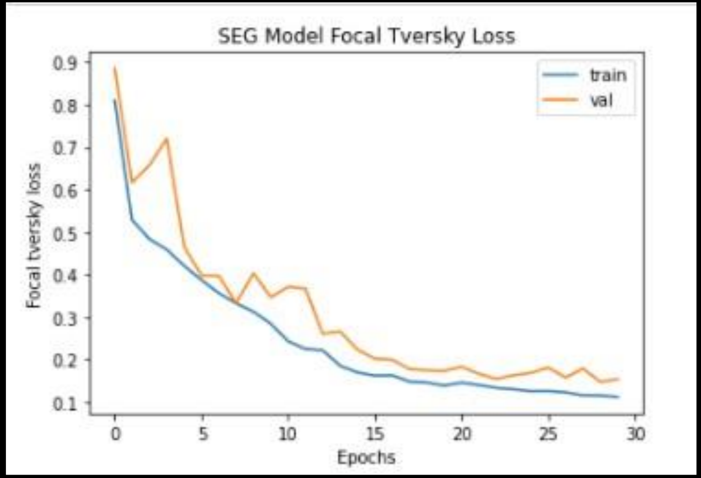
VGGNet Classification Metrics

Evaluation Visualizations Part 3



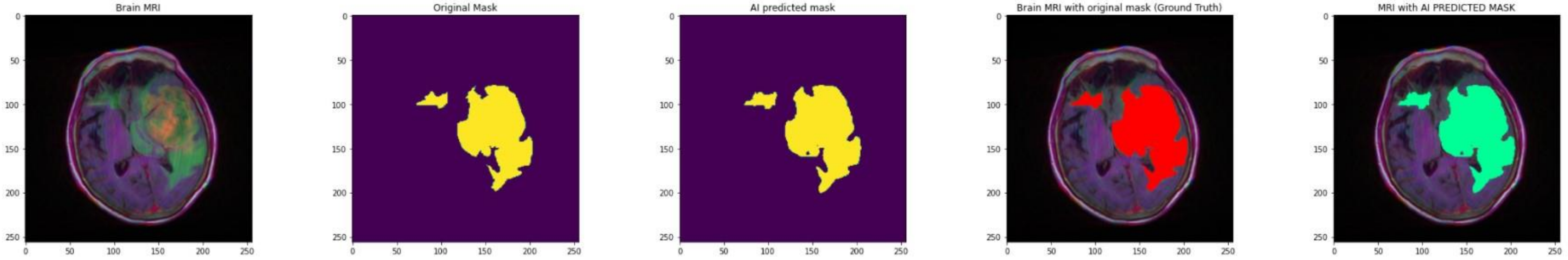
ResNet Tversky Scores



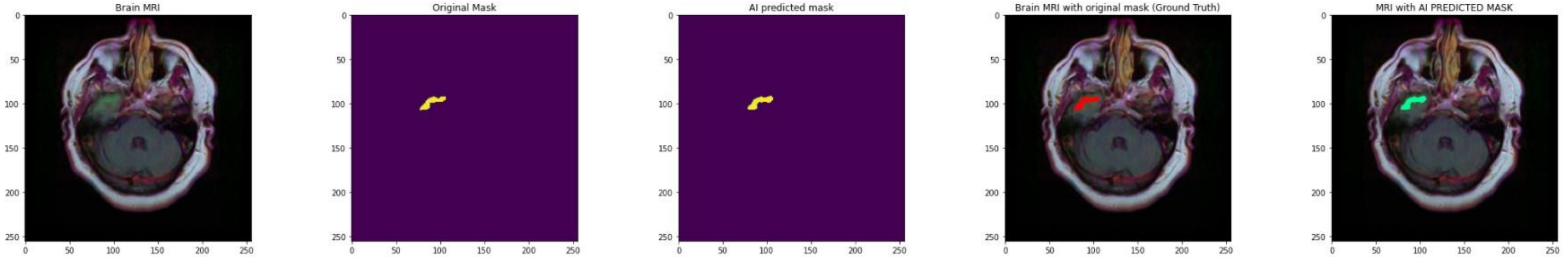


VGGNet Tversky Scores

Segmentation Visualization

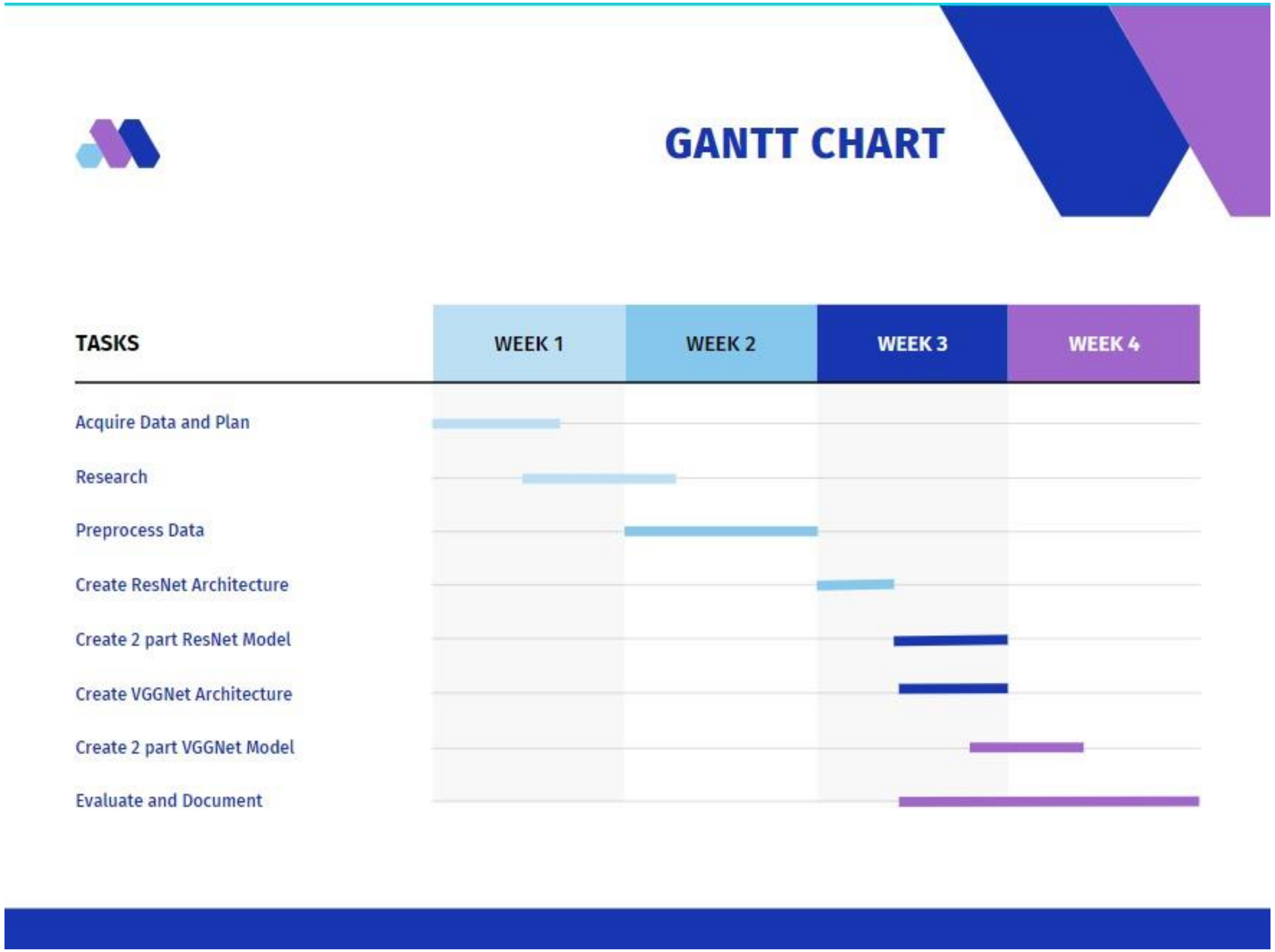


ResNet Segmentation Images



VGGNet Segmentation Images

Timeline


GANTT CHART
TASKS
WEEK 1
WEEK 2
WEEK 3
WEEK 4
Acquire Data and Plan
Research
Preprocess Data
Create ResNet Architecture
Create 2 part ResNet Model
Create VGGNet Architecture
Create 2 part VGGNet Model
Evaluate and Document

Conclusion

- Applying machine learning methodologies to medical classification has the potential to save lives. Brain tumors are a fatal disease that can be extremely challenging to diagnose with high accuracy
- This project proved past research to be true in that the ResNet reigned supreme in terms of not only accuracy, but runtime as well
- The ResNet beat the VGGNet by up to 8% in certain metrics and when pairing that with the fact that every sliver of a percent could save a human life, it is pertinent to use what is proven to be the most effective model

Future Work

- In terms of future work, I believe continued experimentation with CNNs is important
- Trying out other CNNs against ResNet could provide potentially valuable insight in increasing performance of image classification
- Focusing on efficient run time will also be of the utmost importance