Machine Learning For Segmentation and Classification of MRI Imaging

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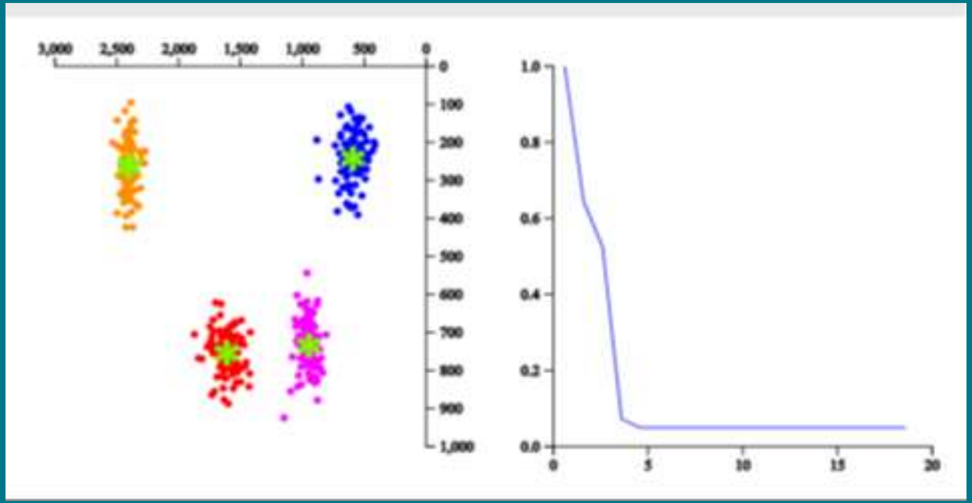
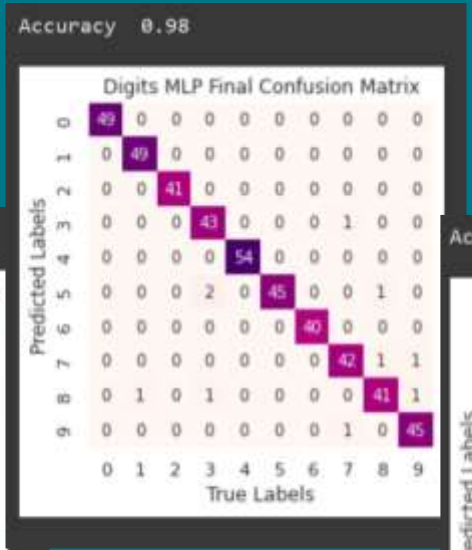
Presentation Agenda

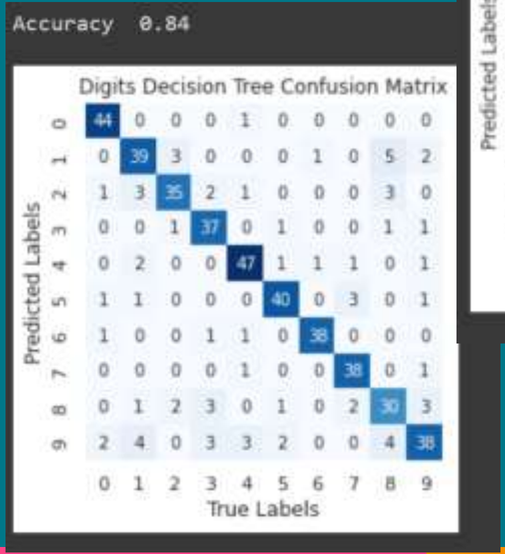
- Pretraining at ASU
- Identification of problem statement
- Literature review/previous works
- Our solution structure
- Results
- Conclusion and next steps
- Reflections/cultural experiences

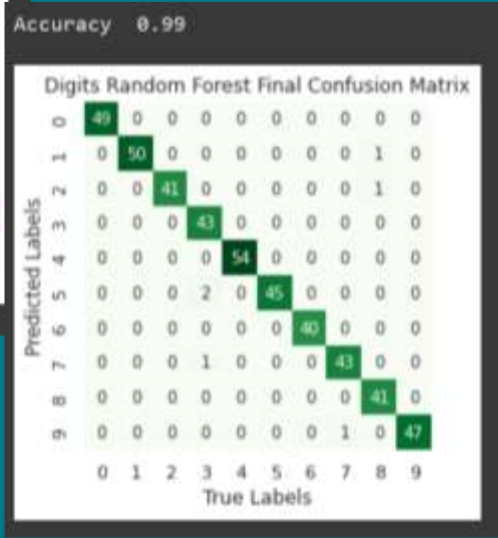
Pretraining at ASU

- Introductory MATLAB and Python modules
- What is Machine Learning?
- Adaptive noise canceling and digit recognition using the Fast Fourier Transform
- Basic Classification and Regression Algorithms
    - SVM, Linear, Kmeans, Clustering
- Decision Trees and Random Forests in Python, intro to Neural Networks (MLP)









Problem Statement/Challenge:

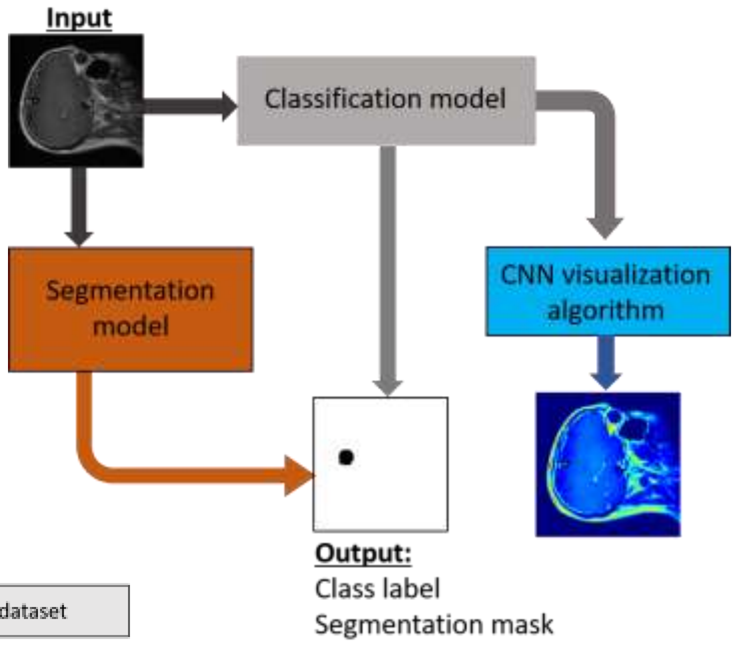
Create an ML deep learning algorithm that can analyze MRI brain scans and classify various tumor types, in addition to correctly segmenting the tumor.

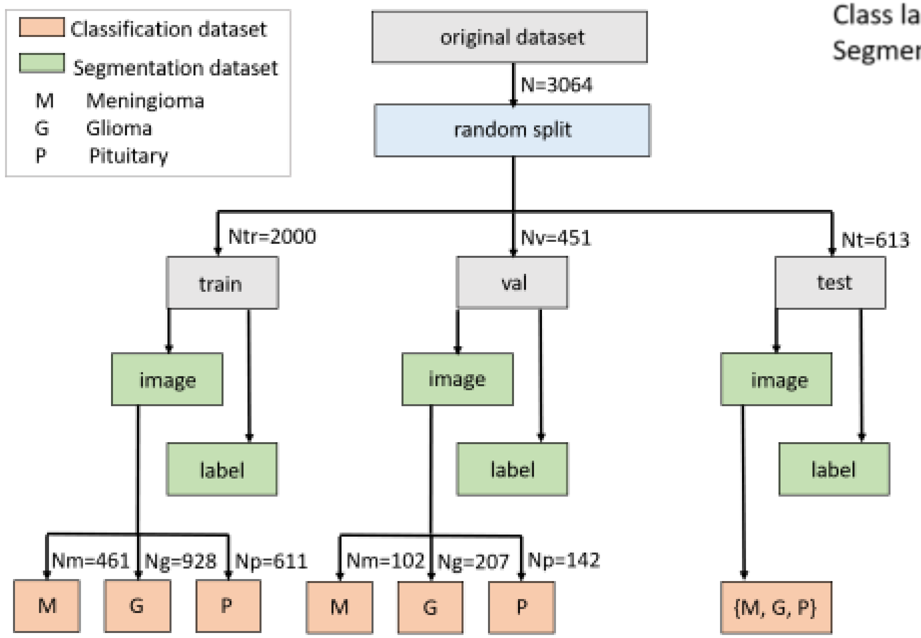
Literature Review

- Krizhevsky et. al; used deep CNNs to classify images and created a new algorithm for classification called AlexNet[1]
- Reinhold et. al; evaluated the impact of intensity normalization and skull stripping on MRI imaging segmentation[2]
- Cheng et. al; the original paper which used a T1-weighted MRI image dataset for classification, achieved 91.28% accuracy[3]
- Deepak et. al; used the MRI dataset from Cheng and improved classification accuracy to 92.3% using CNN and min-max intensity normalization[4]
- Ronneberger et. al; created a novel method of image segmentation for medical applications called UNET (decoder-encoder with skip connections to increase location specificity after upsampling) [5]

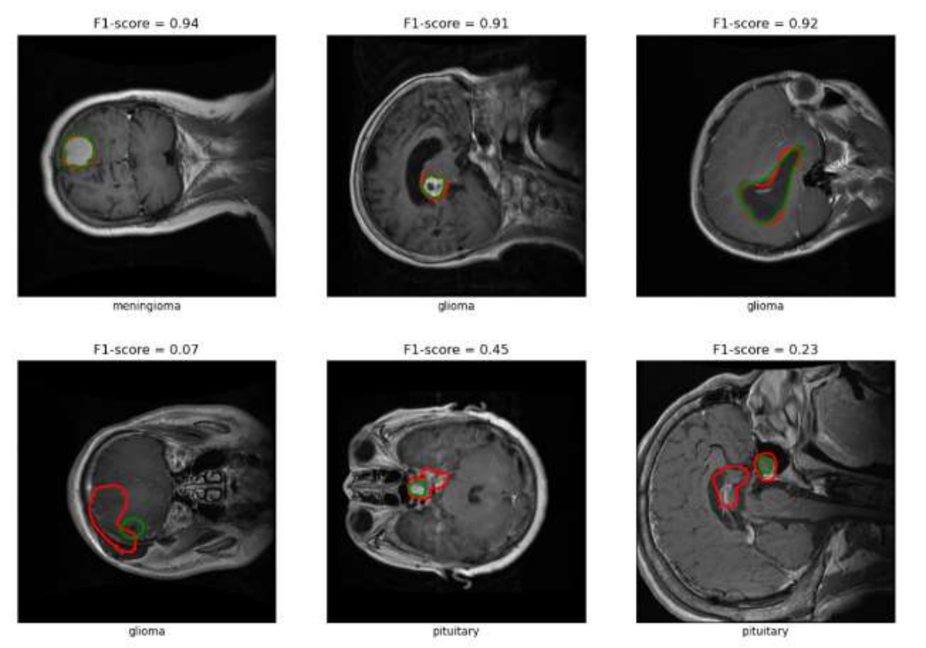
Our Solution Structure

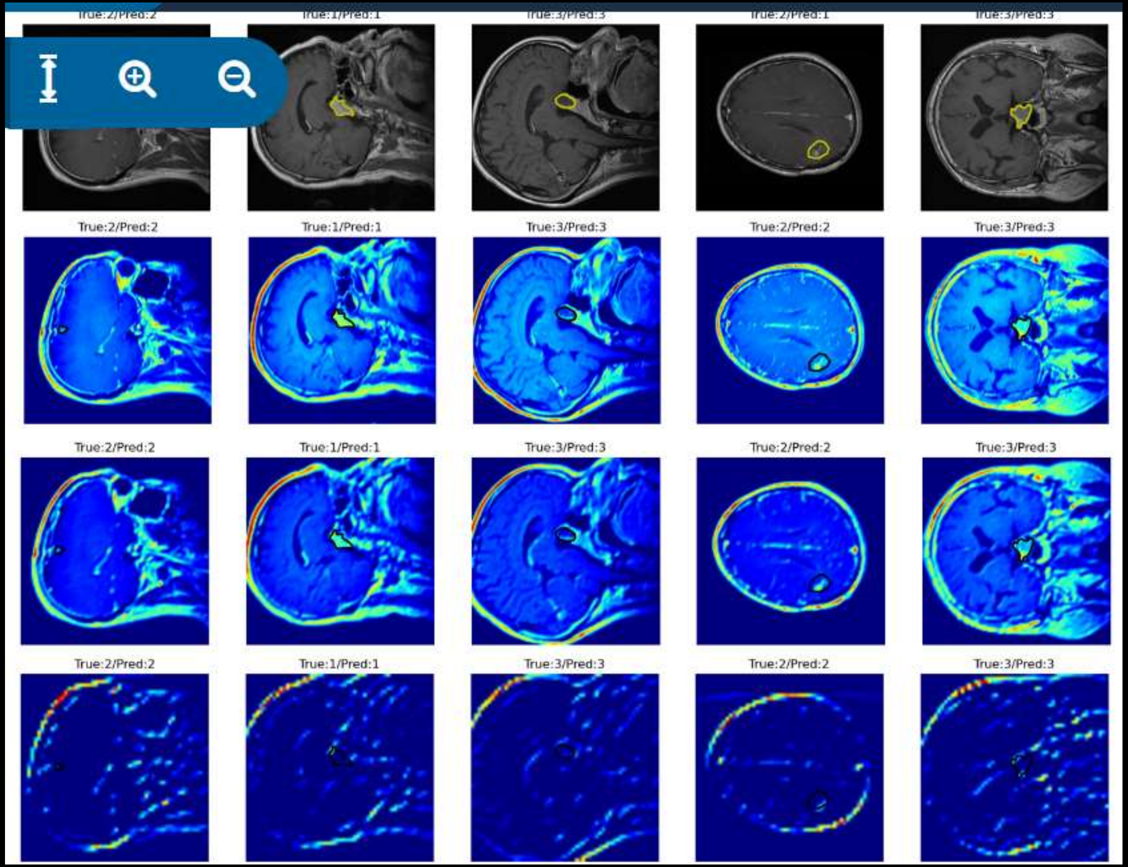
- Python environment utilizing Keras and TensorFlow in conjunction with NumPy, cuDNN (deep neural networks), and Scikit-Learn
- Data preprocessing (train/test/validation splits, class weights, color intensity normalization, augmentation)
- Classification using modified AlexNet
- Segmentation of tumors into Glioma, Meningioma, and Pituitary using modified UNET
- Refine results by integrating attention blocks into AlexNet/UNET





Results with Classification:





Classifier	# epochs	Optimizer	Maxpool Size	Learning Rate	Loss Function	Accuracy
AlexNet	50	Adam	4x4,2x2,2x2	0.01	Sparse categorical crossentropy	**95.1%**
VGG16	50	Adam	4x4,2x2,2x2	0.01	Sparse categorical crossentropy	93.8%

Score-CAM results after training VGG16 with four convolutional blocks for 50 epochs. The top row shows the ground truth tumors.

Results with Segmentation:

Tumor Category	Train	Validation	Test	Class Weights
Meningioma	510	65	...	1.45
Glioma	988	140	...	0.72
Pituitary	647	101	...	1.09
Total	2145	306	613	

Loss Function	Dropout?	# Epochs	Optimizer	Positive Weight	F1 Score	Accuracy	Precision	Jaccard Coefficient	Recall
Binary Crossentropy	No	50	Adam	--	0.739	99.14%	73.3%	0.64	80.0%
Binary Crossentropy	Yes	50	Adam	--	0.658	97.92%	57.4%	0.545	91.2%
Weighted bce	No	300	Adam	5	**0.800**	**99.36%**	**83.9%**	**0.707**	80.9%
Weighted bce	No	300	Adam	20	0.797	99.33%	82.4%	0.705	81.8%
Keras Focal Loss	No	300	Adam	--	--	97.84%	--	--	--
Focal_Loss	No	300	Adam	--	0.720	97.19%	68.6%	0.635	**91.8%**

Conclusion

For classification of tumors, our modified version of AlexNet proved to be the most accurate algorithm for the T1-weighted CE-MRI images.

For segmentation, we achieved a high degree of accuracy across the board with U-NET, but the best performance occurred with a weighted binary crossentropy loss function and a positive weight of 5.

Next Steps/Reflection

- Addition of attention networks, such as in the case of Attention U-Net[6] could help to improve accuracy of segmentation and classification in the future
- CAMs (Score-CAM, Grad-CAM) could be used to improve interpretability/saliency of results
- Preprocessing images using image intensity normalization would likely improve results
- Future research: add custom attention blocks to AlexNet and combine segmentation and classification into a joint pipeline to work simultaneously

References

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3. J. Cheng *et al.*, "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition," *PLoS ONE*, vol. 10, no. 10, p. e0140381, Oct. 2015, doi: 10.1371/journal.pone.0140381.
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Questions & answers