Brain Image Analysis Using Deep Learning

Sarwan Ali

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Introduction

Introduction

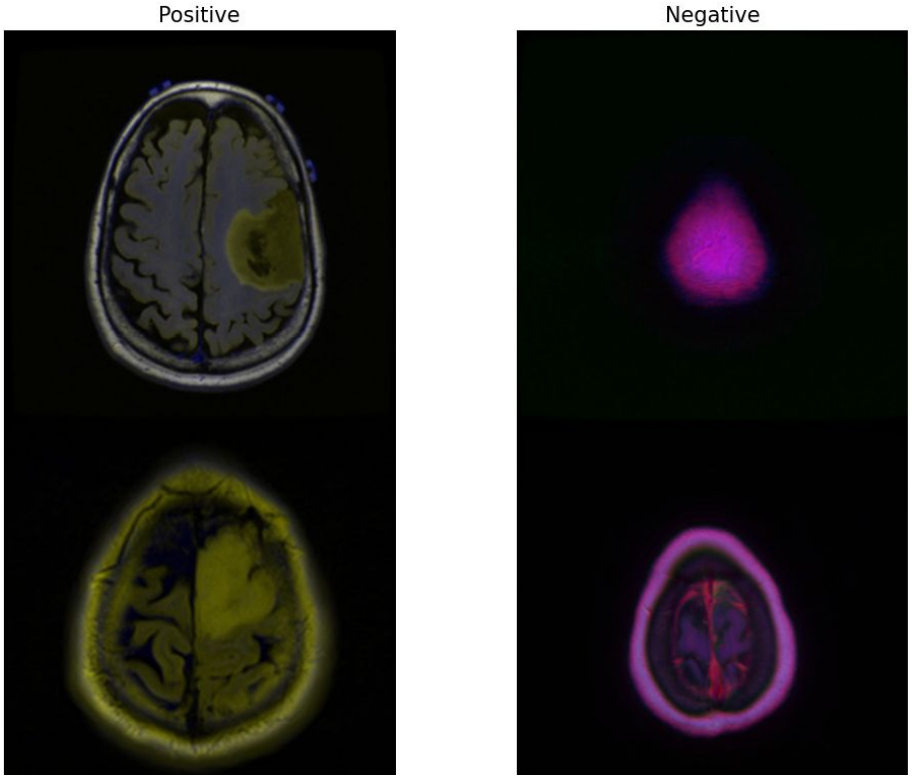
Background and Motivation

- Functional Magnetic Resonance Imaging (fMRI) is a widely used imaging technique to study brain function
- fMRI data can be used to **identify and understand brain regions** involved in various cognitive processes
- Image **classification** and **segmentation** techniques can help automate the analysis of fMRI data and improve the accuracy and efficiency of brain mapping
- **Application:**
    - Brain Tumor Detection, Brain Activity Classification, Brain Region Segmentation, Brain Connectivity Analysis
- **Challenges:**
    - fMRI data analysis is a complex and challenging task due to the high dimensionality, noise, and variability of the data
- **Solution:**
    - Developing novel and effective methods for fMRI image classification and segmentation is crucial for advancing our understanding of brain function and improving the diagnosis and treatment of neurological disorders
- **Aim of this project:**
    - Explore and compare different machine learning and deep learning techniques for fMRI image classification and segmentation, and evaluate their performance on real-world fMRI dataset

Introduction

Research Question

- Given 3D brain images of people
    - Classify them for having tumor or not
    - Image segmentation to locally identify tumor



Introduction

Methodology

- Classification
  - Embedding methods
    - 3-Layer CNN
    - 4-Layer CNN
  - Image Classification Methods
    - 3-Layer CNN
    - 4-Layer CNN
    - RESNET50 (Pre-Trained Model)
    - VGG-19 (Pre-Trained Model)
- Segmentation
  - Feature Pyramid Network
  - Unet
  - Modified Unet (my contribution)

Literature Review

Literature Review

Brief Background

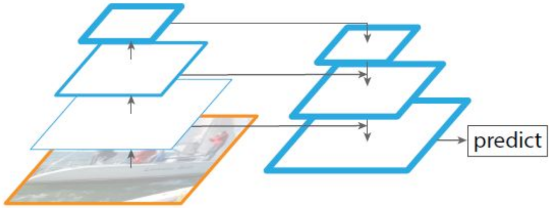


Fig. FPN Architecture*

- Feature Pyramid Network [1]
    - It build a pyramid of feature maps with different spatial resolutions, where each level of the pyramid corresponds to a different scale of the image
    - At each level, features from the previous level are combined with features from higher resolution levels through a process called feature fusion (combining the multi-scale feature maps)
    - This allows the network to capture both high-level semantic information and low-level spatial details
- Unet [2]
    - A fully convolutional neural network with the U-Net architecture
    - It consists of a *contracting path* (comprised of a series of convolutional and pooling layers) that encodes the input image and a symmetric *expanding path* that produces the segmentation map
    - It also includes skip connections that concatenate feature maps from the contracting path with the corresponding feature maps in the expanding path. This allows the network to recover spatial information lost during the downsampling process
    - The expanding path consists of a series of upsampling and convolutional layers that gradually increase the spatial resolution of the feature maps
- Deep Neural Network (DNN) [3]
    - A modified CNN architecture for image segmentation that uses both local features as well as more global contextual features simultaneously. Also, they propose 2-phase training procedure, where output from one CNN model is used as additional input to the other CNN model

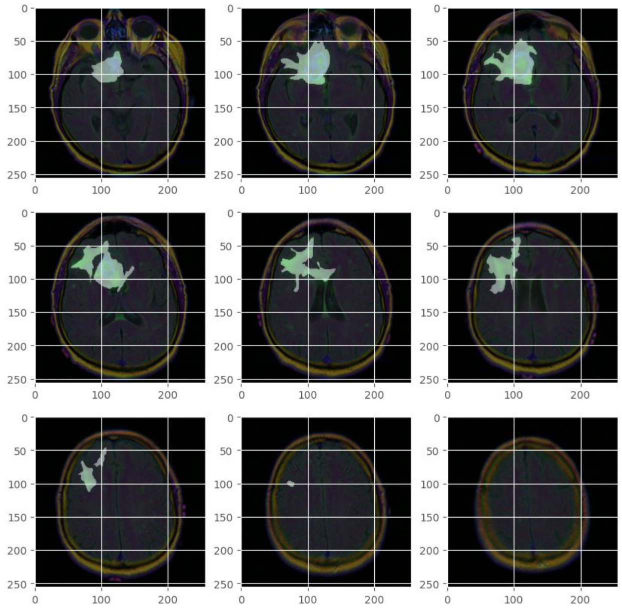
*https://towardsdatascience.com/review-fpn-feature-pyramid-network-object-detection-262fc7482610

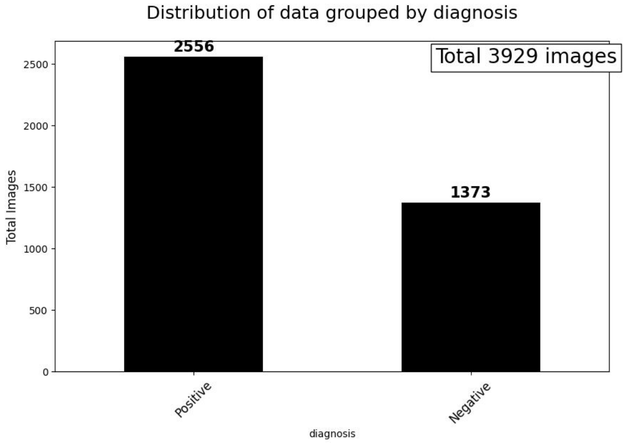
Dataset Statistics

Dataset Statistics

Data Source and Statistics

- Brain images from TCIA LGG collection with segmentation masks approved by a board-certified radiologist at Duke University [4,5]
- 110 patients data included in The Cancer Genome Atlas (TCGA)
- Total Images: 3929
    - Training: 2828
    - Validation: 708
    - Test: 393





Research Tasks

Research Tasks

Classification

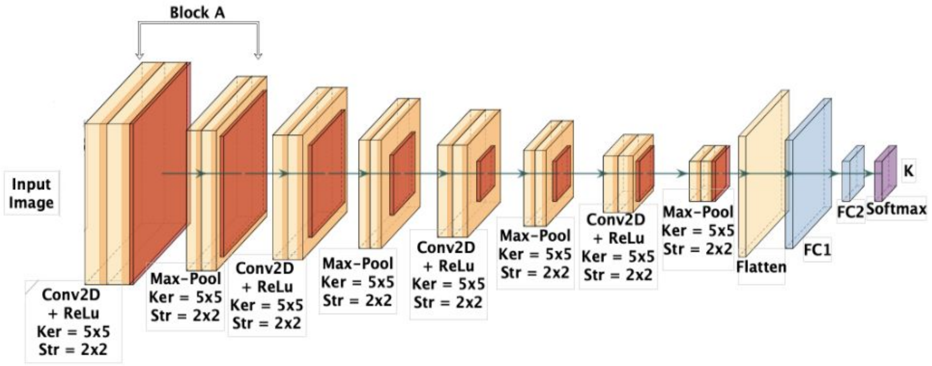
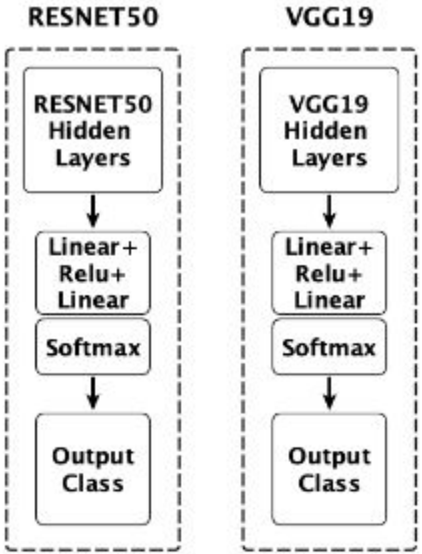


Fig. The architectures of the 4-layer CNN model, which is used to classify 'K' classes. Here ker represents kernel and str represents stride filter size



- ResNet50 has 50 layers and uses residual connections to allow deeper networks to be trained more effectively
- VGG19 has 19 layers and is characterized by its use of 3x3 convolutional filters and pooling layers
- Both models were trained on the ImageNet dataset, which contains over a million images across 1000 different classes.

Research Tasks

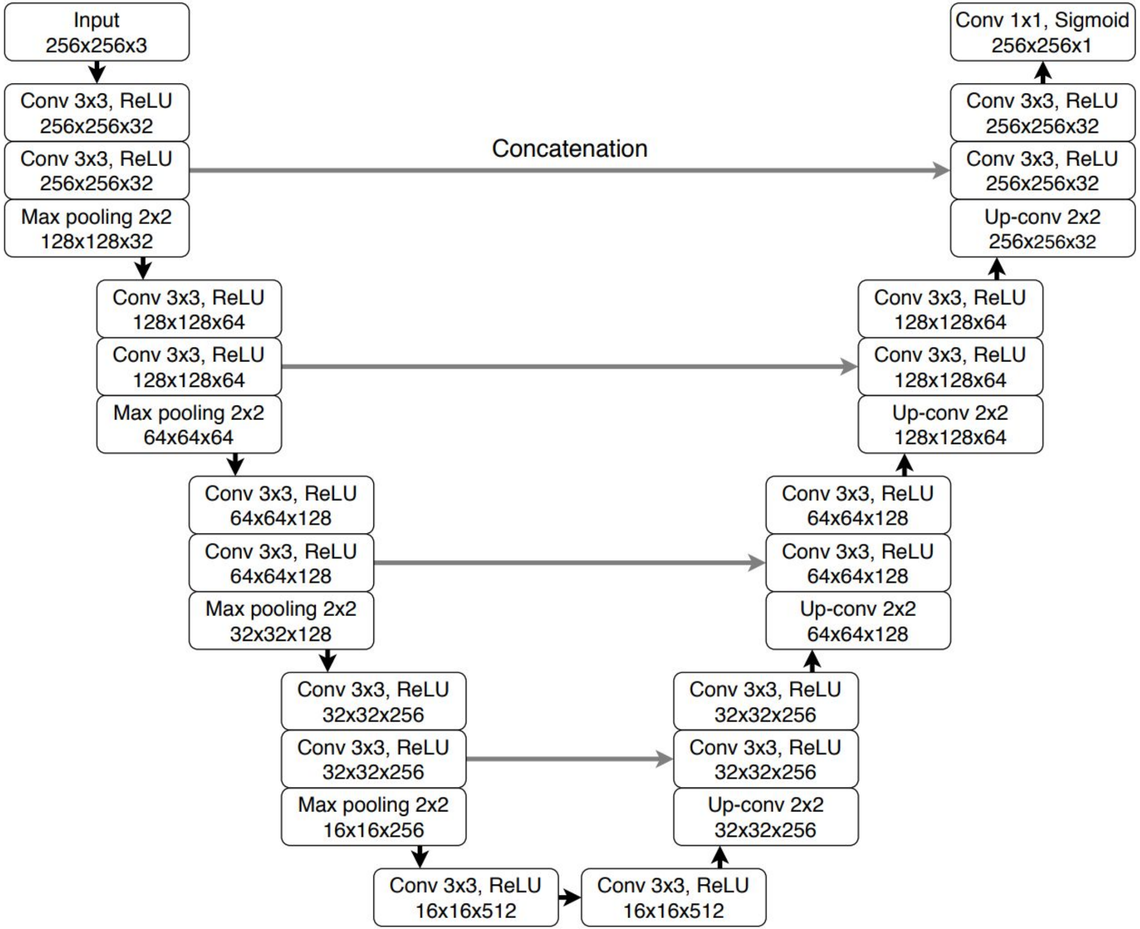
Segmentation

- Feature Pyramid Network [1]
  - It is an extension of the popular convolutional neural network (CNN) model, called ResNet
  - FPN addresses the problem of detecting objects at different scales in an image. It does this by building a pyramid of feature maps with different scales, and then merging these feature maps together to create a multi-scale representation of the image

Research Tasks

Segmentation

- Unet



Research Tasks

- Modified Unet

1. One potential problem with the U-Net architecture is that it may not be able to capture enough contextual information.
    a. This can result in the model not being able to accurately segment complex structures in the fMRI images
    b. Solution:
        i. Incorporate (self) attention mechanisms into the U-Net architecture
        ii. Spatial attention module learns to weigh the feature maps of each channel based on their importance to the target feature, while the channel attention module learns to weigh the importance of each channel based on their correlation with other channels
        iii. The attention mechanism is incorporated into the bottleneck layer, which is the last convolutional layer before the upsampling path
2. Another potential problem is the vanishing gradient problem (gradient become too small, hence weights are updated very slowly or not at all
    a. This can occur when the gradients become too small during backpropagation, which can result in the model not being able to learn effectively. Gradient measure of how much the cost function changes with respect to small changes in the model's parameters
    b. Solution:
        i. Use residual connections, which can help mitigate the vanishing gradient problem by allowing gradients to bypass layers.
3. Another potential problem is overfitting, especially when working with limited data.
    a. Solution:
        i. Use regularization techniques, such as dropout, L1 (lasso) regularization, and early stopping
        ii. Can be applied to the convolutional layers in the encoder and decoder sections to prevent overfitting
        iii. Early stopping can also be applied during the training process to stop the training when the validation loss no longer decreases

Research Tasks

Evaluation Metrics (Segmentation)

- Loss
  - Indicates how well the model is performing (lower value is better). It measures pixel-wise difference between the predicted segmentation mask and the ground truth mask
- Intersection Over Union (IOU)
  - Measures how well the predicted mask overlaps with the ground truth mask (higher value is better). Value range is between 0-1
- Dice Coefficient
  - Defined as twice the intersection of the predicted and ground truth masks divided by the sum of the areas of the two masks (higher value is better). Value range is between 0-1

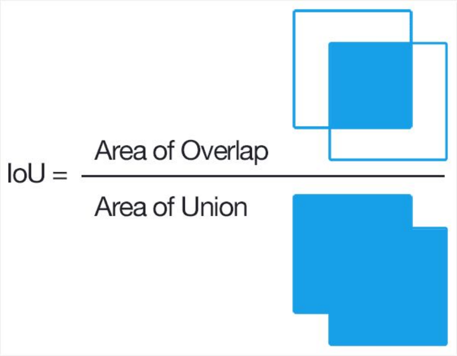


Fig. Example of IOU*

*https://www.semanticscholar.org/paper/Comparison-of-Jaccard%2C-Dice%2C-Cosine-Similarity-To-Thada-Jaglan/8575e8beef47bd2880c92f54a749f933db983e56

Research Tasks

Evaluation Metrics (Classification)

- Accuracy
  - Proportion of true results (both true positives and true negatives) among the total number of cases examined
  - (TP + TN) / (TP + FP + TN + FN)
- Precision
  - Measures the proportion of true positives among the predicted positive cases
  - TP / (TP + FP)
- Recall
  - Measures the proportion of true positives among the actual positive cases
  - TP / (TP + FN)
- F1 Weighted
  - Harmonic mean of precision and recall, weighted by the number of instances in each class
  - F1 = (2 * Precision * Recall) / (Precision + Recall)
  - F1 Weighted = (sum(w_i * F1_i)) / sum(w_i)
  - F1_i is the F1 score for class i, and w_i is the weight for class i, which is the number of samples in that class divided by the total number of samples
- F1 Macro
  - Unweighted average of the F1 scores for each class.
  - (F1_1 + F1_2 + ... + F1_n) / n
  - where F1_i is the F1 score for class i and n is the total number of classes
- ROC-AUC
  - Calculated as the area under the ROC curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different threshold values
  - TPR = TP / (TP + FN)
  - FPR = FP / (FP + TN)

Results and Conclusion

Results and Conclusion

Classification

Method	DL Model	Accuracy	Precision	Recall	F1 Weighted	F1 Macro	ROC-AUC
Feature Embedding	**3-Layer CNN**	0.635	0.485	0.635	0.513	0.243	0.599
	4-Layer CNN	0.676	0.525	0.676	0.584	0.235	0.641
Image Classification	**3-Layer CNN**	0.750	0.713	0.750	0.714	0.731	0.841
	4-Layer CNN	**0.755**	**0.731**	**0.755**	**0.735**	**0.745**	**0.849**
	RESNET50	0.679	0.592	0.679	0.615	0.517	0.746
	VGG19	0.484	0.221	0.484	0.299	0.0495	0.512

Results and Conclusion

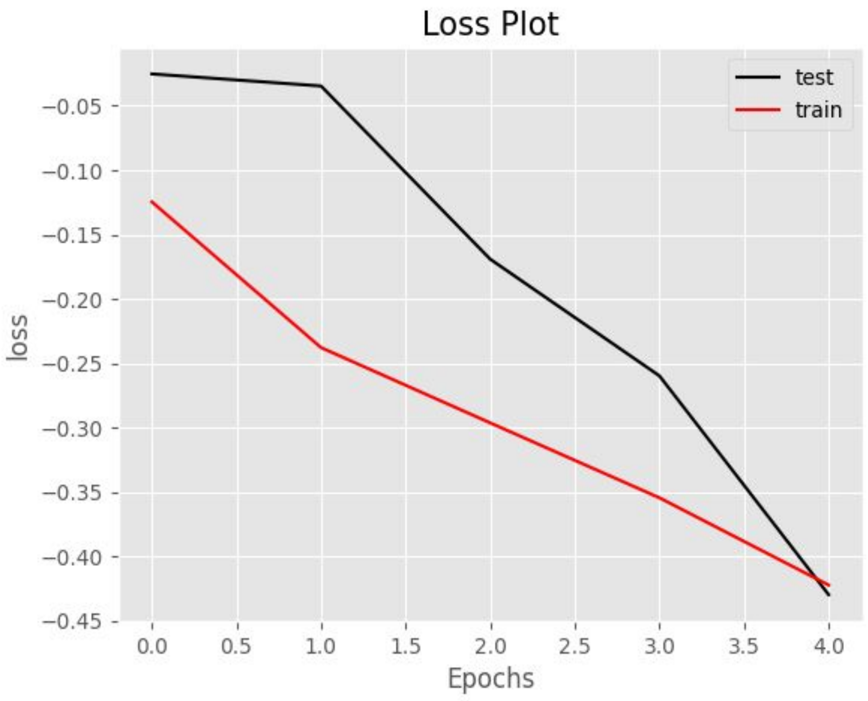
Segmentation

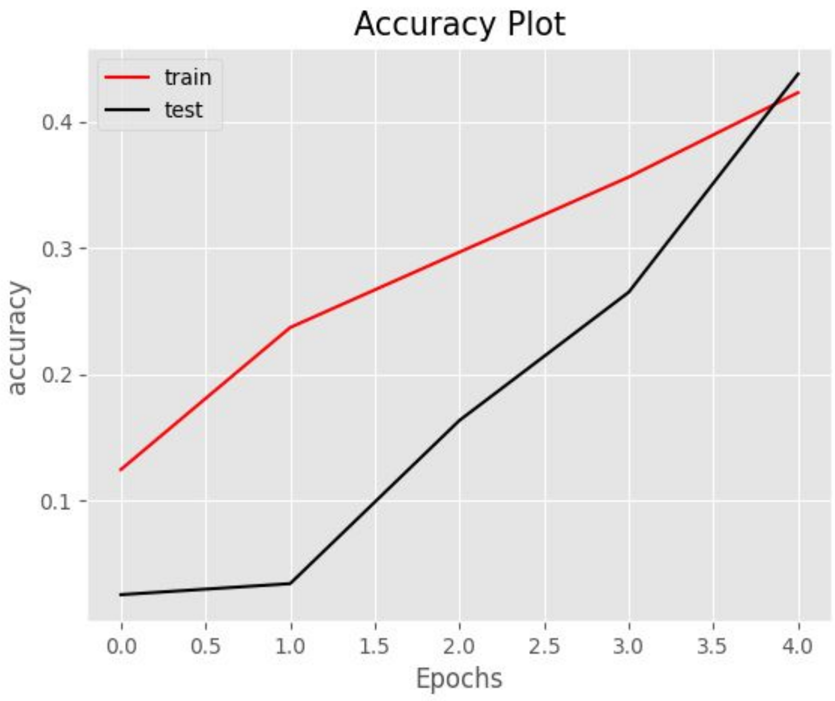
Method	Loss	IOU	Dice Coefficient
FPN	-0.16782	0.965248	0.82734
Unet	-0.91796	0.998135	0.84774
Modified Unet	**-0.95531**	**0.999654**	**0.86542**

- Results for 5 Epochs
- Negative Loss indicates that the model is performing better than expected

Results and Conclusion

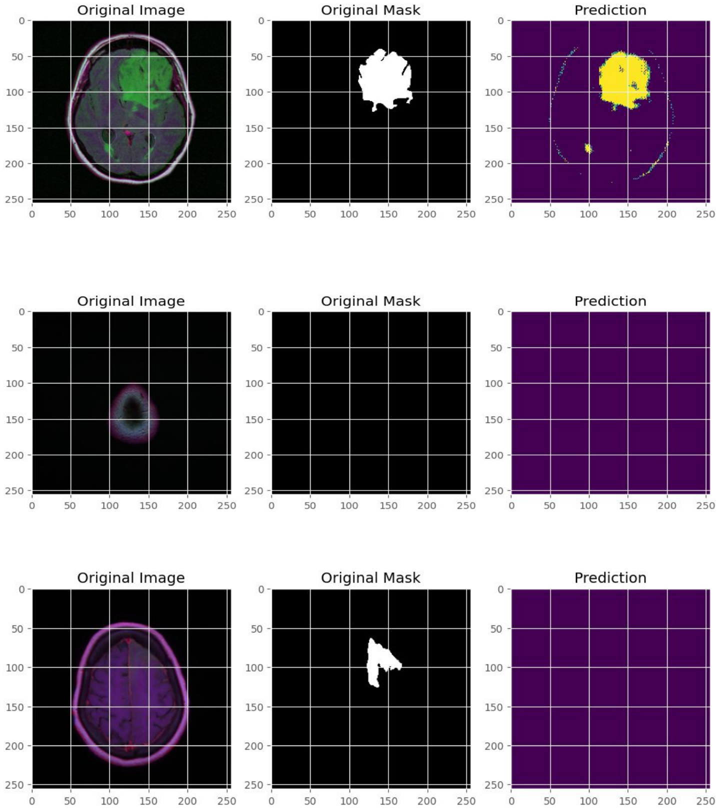
Segmentation (Model Plots)





Results and Conclusion

Segmentation (Visualization)



Questions!!!

References

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3. Havaei, Mohammad, et al. "Brain tumor segmentation with deep neural networks." Medical image analysis 35 (2017): 18-31.
4. Mateusz Buda, Ashirbani Saha, Maciej A. Mazurowski "Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm." Computers in Biology and Medicine, 2019
5. Maciej A. Mazurowski, Kal Clark, Nicholas M. Czarnek, Parisa Shamsesfandabadi, Katherine B. Peters, Ashirbani Saha "Radiogenomics of lower-grade glioma: algorithmically-assessed tumor shape is associated with tumor genomic subtypes and patient outcomes in a multi-institutional study with The Cancer Genome Atlas data." Journal of Neuro-Oncology, 2017.