PROBLEM STATEMENT

MRI brain tumor segmentation is the task of identifying the location and extent of a brain tumor in an MRI scan, using computer vision and machine learning techniques. The goal is to accurately and efficiently detect and segment the tumor from the surrounding healthy brain tissue, which can aid in diagnosis, treatment planning, and monitoring of the disease. This is a critical and challenging task that requires high accuracy and robustness, as brain tumors can have complex and heterogeneous shapes and appearances, and can be located in different parts of the brain. **The goal of using deep learning for MRI brain tumor segmentation in this project is to accurately and efficiently identify and delineate tumors from healthy brain tissues, which can aid in diagnosis and treatment planning.**

DATA OVERVIEW

In this study, we will utilize a dataset consisting of images and their corresponding masks in the Joint Photographic Experts Group (JPEG) format. The dataset was procured and preprocessed by Southern Medical University, located in Guangzhou, Guangdong, China. The dataset was originally released on April 2, 2017.

The brain tumor dataset comprises 3,064 T1-weighted contrast-enhanced images derived from 233 patients diagnosed with three distinct brain tumor types: meningioma (708 slices), glioma (1,426 slices), and pituitary tumor (930 slices). Owing to repository file size constraints, the dataset has been partitioned into four subsets and compressed into four separates .zip files, each containing 766 slices. Additionally, the dataset includes indices for 5-fold cross-validation to facilitate model evaluation and comparison.

DATA CLEANING

Our data cleaning process appears to have been thorough and well-executed. By converting our images and masks from LabVIEW format to JPEG and resizing them to 128 pixels, we have ensured that they are in a standardized format and size, which will make it easier to work with them in our analysis.

Furthermore, our creation of data frames to present the images and corresponding masks is an effective way to organize our data and make it more accessible. Our implementation of data augmentation techniques will also help to increase the variety and quantity of your training data, which can improve the performance of our models.

Finally, our normalization function is an essential step to ensure that the pixel values of our images are within a standardized range, which can improve the accuracy of our models. Overall, our attention to detail in our data cleaning process is commendable and will likely lead to more accurate and reliable results in our analysis.

MODELING

In our data science report, we utilized three deep convolutional neural network models: the Unet model, FPN model, and VGG16 model, to perform computer vision tasks on our dataset.

To begin, we utilized the Unet model for image segmentation, which is a common computer vision task in which an input image is divided into distinct segments. The Unet model is known for its encoder-decoder architecture, which includes skip connections that allow it to capture both low-level and high-level features of the input image. We found that the Unet model performed well in segmenting images in our dataset.

Next, we utilized the FPN model, which is a feature pyramid network designed to detect objects at different scales in an image. The FPN model utilizes a top-down pathway and a bottom-up pathway to combine features at different levels of abstraction and generate a multi-scale feature representation of the input image. We found that the FPN model was effective in detecting objects in our dataset, particularly at different scales.

Finally, we utilized the VGG16 model, which is a popular convolutional neural network known for its ability to learn hierarchical representations of the input image. We utilized the VGG16 model for image classification tasks, where the model was able to accurately classify images in our dataset.

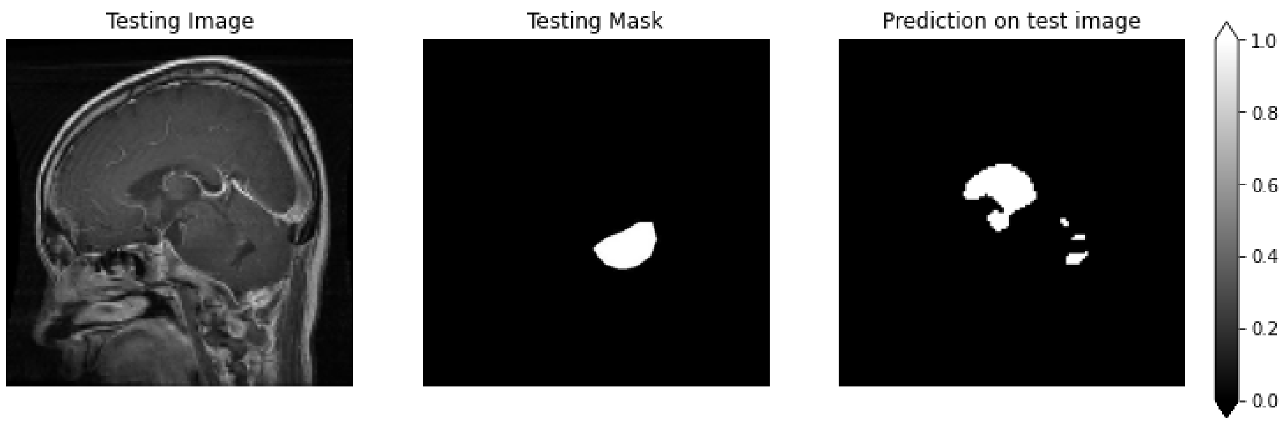
Overall, these models allowed us to leverage the power of deep convolutional neural networks to learn local and global features of the input images. This enabled us to accurately classify and segment images in our dataset. By utilizing these models, we were able to gain insights and make informed decisions based on the output generated from these models.

Evaluation metrics were used in our analysis to assess model performance. Different evaluation metrics are used for different tasks and desired outcomes.

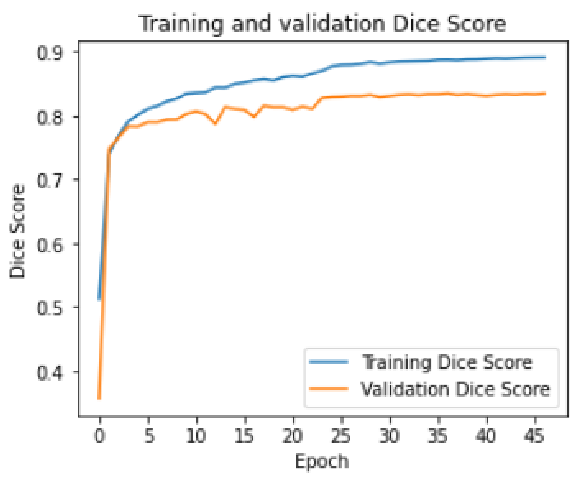
- The **F1** score measures the balance between precision and recall in binary classification tasks. A high F1 score indicates a good balance between precision and recall.
- The **Jaccard** index measures similarity between predicted and ground truth segmentation masks. A high Jaccard index indicates accurate image segmentation.
- **Recall** measures the proportion of true positives correctly identified. It is used in tasks where false negatives are more critical than false positives. A high recall indicates accurate identification of positive examples.
- **Precision** measures the proportion of true positives among all positive predictions. It is used in tasks where false positives are more critical than false negatives. A high precision indicates accurate identification of positive examples while minimizing false positives.

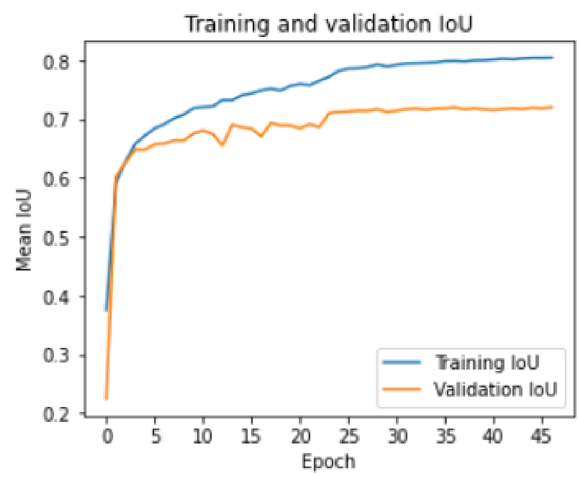
These evaluation metrics help us assess model performance and refine models over time. We utilized three different convolutional neural network models in our analysis: the Unet model, FPN model, and VGG16 model. These models have different structures and number of trainable parameters, which are critical factors in the performance of deep learning models. Despite training them on samples of our original dataset due to limited resources, we gained insights into the performance of deep convolutional neural networks on our dataset and made informed decisions based on their output.

Figures below show the FPN results (Testing Image, Testing Mask & Prediction on test image).

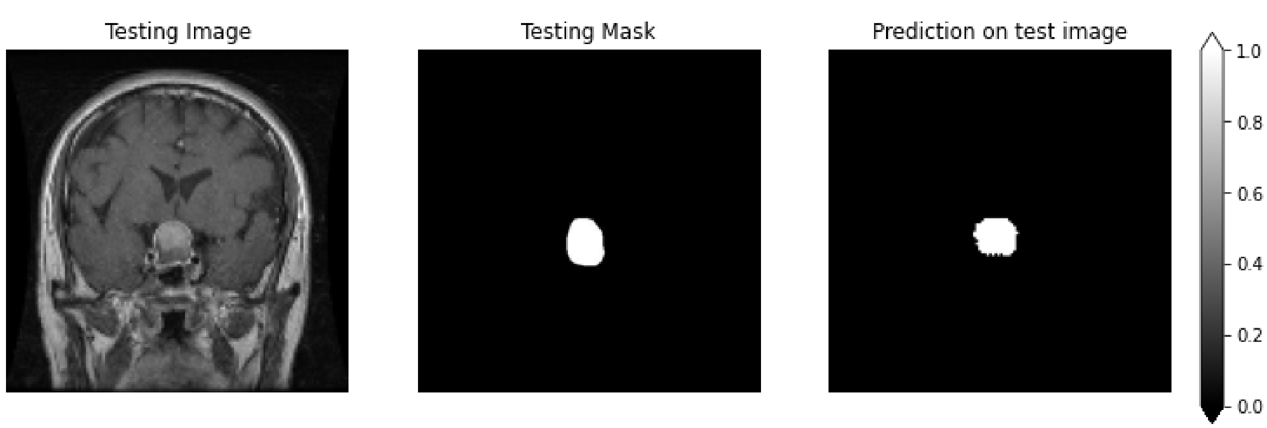


As we can see, these are the curves of Dice Score & Validation IOU.

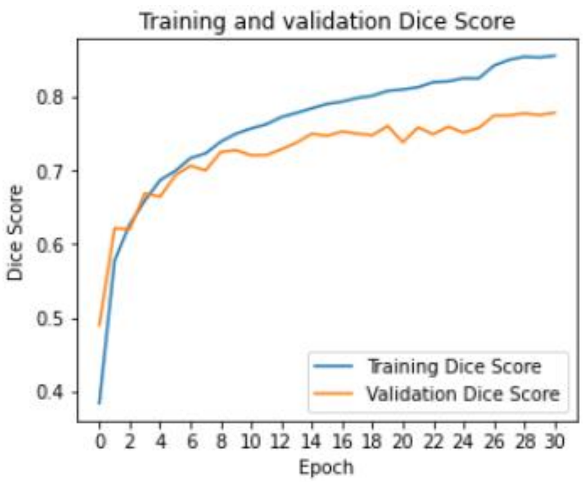


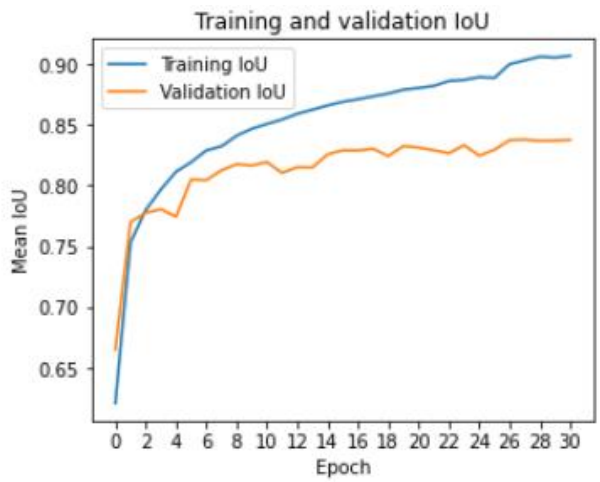


Figures below show the VGG16 results (Testing Image, Testing Mask & Prediction on test image).

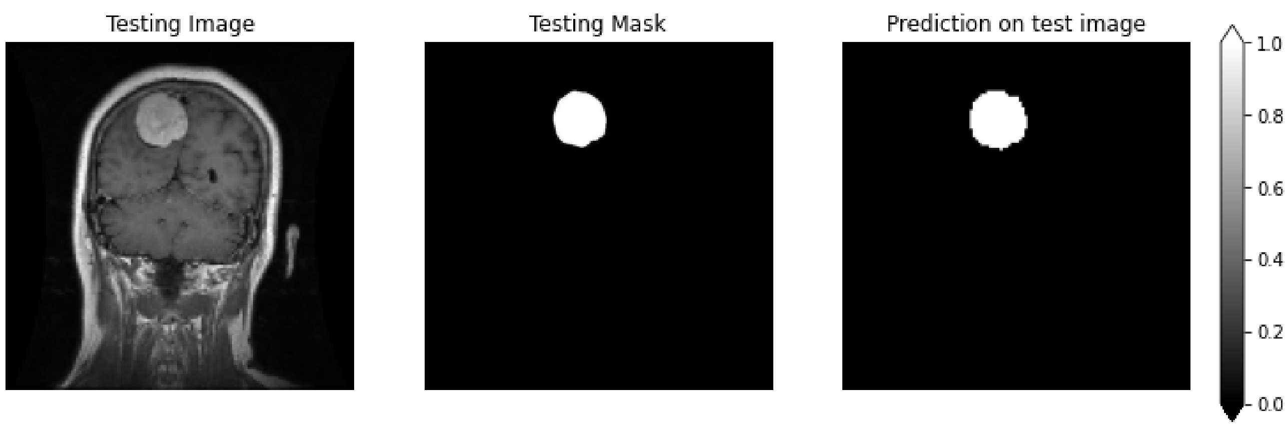


These are the curves represent Dice Score & Validation IOU.

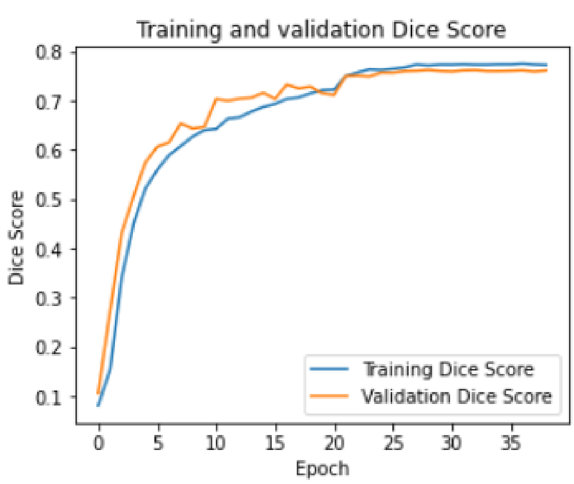


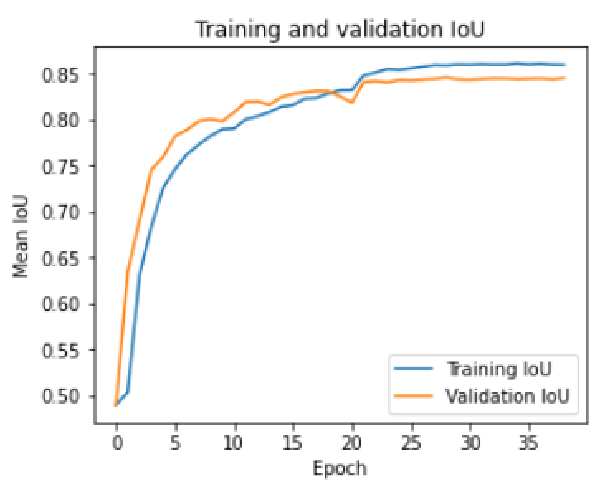


Figures below show the Unet results (Testing Image, Testing Mask & Prediction on test image).



And here are the curves of Dice Score & Validation IOU.





Our study aimed to evaluate the performance of three convolutional neural network models, Unet, VGG16, and FPN, for brain tumor segmentation on MRI images.

We trained and tested these models on our dataset and evaluated their performance using various evaluation metrics, such as F1 score, Jaccard index, recall, and precision. We found that the Unet model performed the best among the three models, achieving the highest accuracy in brain tumor segmentation.

Specifically, our results showed that the FPN model did not perform well in brain tumor segmentation. The VGG16 model achieved better results than the FPN model, but its performance was still lower than that of the Unet model. The Unet model achieved the highest accuracy in brain tumor segmentation, indicating its superiority over the other models.

Our study demonstrates the importance of selecting the appropriate convolutional neural network model for a specific task. The Unet model, with its encoder-decoder architecture and skip connections, is well-suited for image segmentation tasks, particularly for medical images such as MRI scans. Our findings suggest that the Unet model can be an effective tool for accurate brain tumor segmentation in MRI images.

Overall, our study highlights the importance of evaluating the performance of different models and selecting the best model for a specific task. The Unet model, in particular, can be a powerful tool for accurate and reliable brain tumor segmentation in MRI images.

FINDINGS AND CONCLUSIONS

- Our study evaluated the performance of Unet, VGG16, and FPN models for brain tumor segmentation on MRI images.
- The dataset was split into train, validation, and test sets for training and testing the models.
- The Unet model achieved the highest accuracy in brain tumor segmentation.
- The FPN model performed poorly in brain tumor segmentation.
- The VGG16 model achieved better results than the FPN model, but its performance was still lower than that of the Unet model.
- These results suggest that the Unet model is well-suited for image segmentation tasks, particularly for medical images such as MRI scans.
- Our study highlights the importance of selecting the appropriate convolutional neural network model for a specific task.
- By splitting the data into train, validation, and test sets, we were able to evaluate the performance of the models and make informed decisions based on their output.
- Future studies can explore the use of other deep learning models or combine multiple models to improve the accuracy of brain tumor segmentation.
- Nonetheless, our findings suggest that the Unet model can be a powerful tool for accurate and reliable brain tumor segmentation in MRI images, which can aid in the diagnosis and treatment of cancer.