Multi-modal MRI Image Segmentation of Brain Tumors for Multi-class Segmentation

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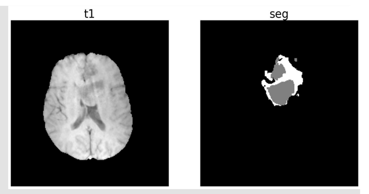
Introduction

- MRI is extensively used in clinical and experimental applications; however, radiologists face challenges in distinguishing specific areas and making accurate judgments based on images.
- Deep learning-based segmentation methods have the potential to enhance diagnostic accuracy and enable more precise treatment and research.
- The proposed approach employs multi-model MRI imaging (T1/T1CE/T2/FLAIR) and a CNN UNET algorithm for multi-class segmentation.
- This method surpasses existing techniques in terms of loss value and Dice score, indicating improved performance in brain tumor segmentation.

Brain Tumor



- Brain tumors are abnormal growths of cells in the brain, which can be benign (noncancerous) or malignant (cancerous).
- MRI scan images enable the non-invasive detection and diagnosis of brain tumors by providing high-resolution, detailed visualization of soft tissues, allowing for the precise identification and analysis of abnormal growths.

Semantic Segmentation

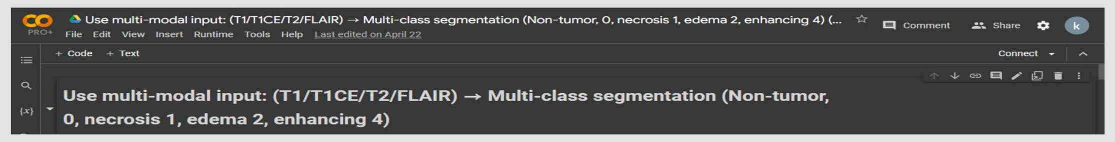
- Semantic segmentation in medical imaging assigns labels to pixels representing different body parts, tissues, or organs, providing accurate boundaries and shapes.
- Deep learning techniques, such as Convolutional Neural Networks (CNNs), are commonly used for highly accurate semantic segmentation.
- In medical imaging, semantic segmentation classifies each pixel into categories, such as Non-tumor (0), Necrosis (1), Edema (2), and Enhancing (4), for precise identification and analysis of different tissue types.

UNET

- U-Net's architecture consists of an encoder-decoder structure with skip connections, enabling it to learn efficiently and provide precise localization in medical images.
- The encoder captures context by successively downscaling the image using convolutional and pooling layers, while the decoder restores spatial resolution through upscaling and concatenating feature maps, making U-Net highly effective for complex brain tumor segmentation.

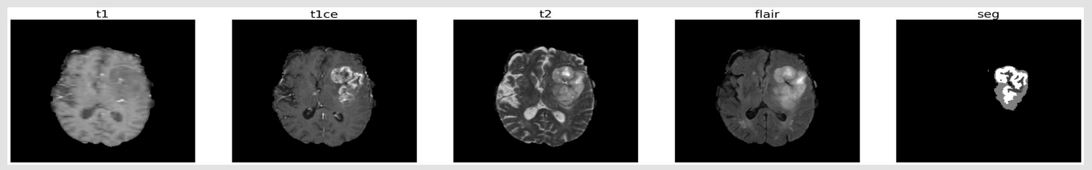
Methodology: Data

1. Colab



- Leveraged the Colab platform for deep learning, utilizing TensorFlow and Keras libraries for an efficient workflow.
- Employed the Nibabel library to effectively read and process medical image data.
- Optimized analysis of large image datasets by taking advantage of GPU and high-performance RAM support in Colab.

2. Data preparation

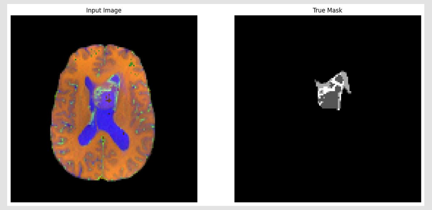


- The BraTS2020 dataset (Brain Tumor Segmentation) was used for this study.
- The dataset includes T1, T1CE, T2, and FLAIR MRI images, as well as corresponding segmentation images for predicting tumor location.
- All images were preprocessed and loaded into the model for segmentation analysis.

Methodology: Computational Tools

3. Image preprocessing

1. The four MRI images (T1, T1CE, T2, and FLAIR) are merged into a single image using normalization.



2. One-hot encoding also enables easy decoding of the output for evaluation purposes.

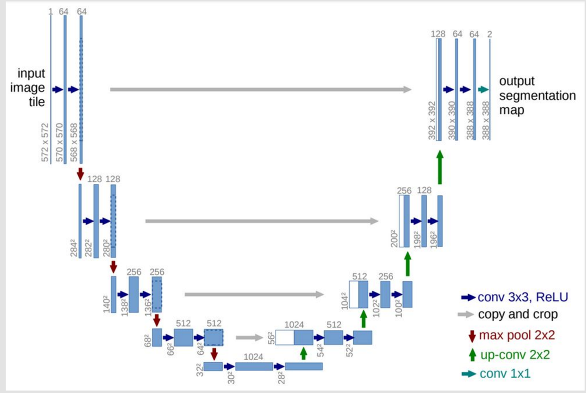
Segmentation
Non-tumor
Necrosis
Edema
Enhancing

Non-tumor	Necrosis	Edema	Enhancing
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

3. The UNet model in Brain Tumor Segmentation multimodal produces a 4-channel mask of the various tissue types in brain scans.

4. The output is one-hot encoded for multi-class classification, which helps to calculate the binary cross-entropy loss function during training.

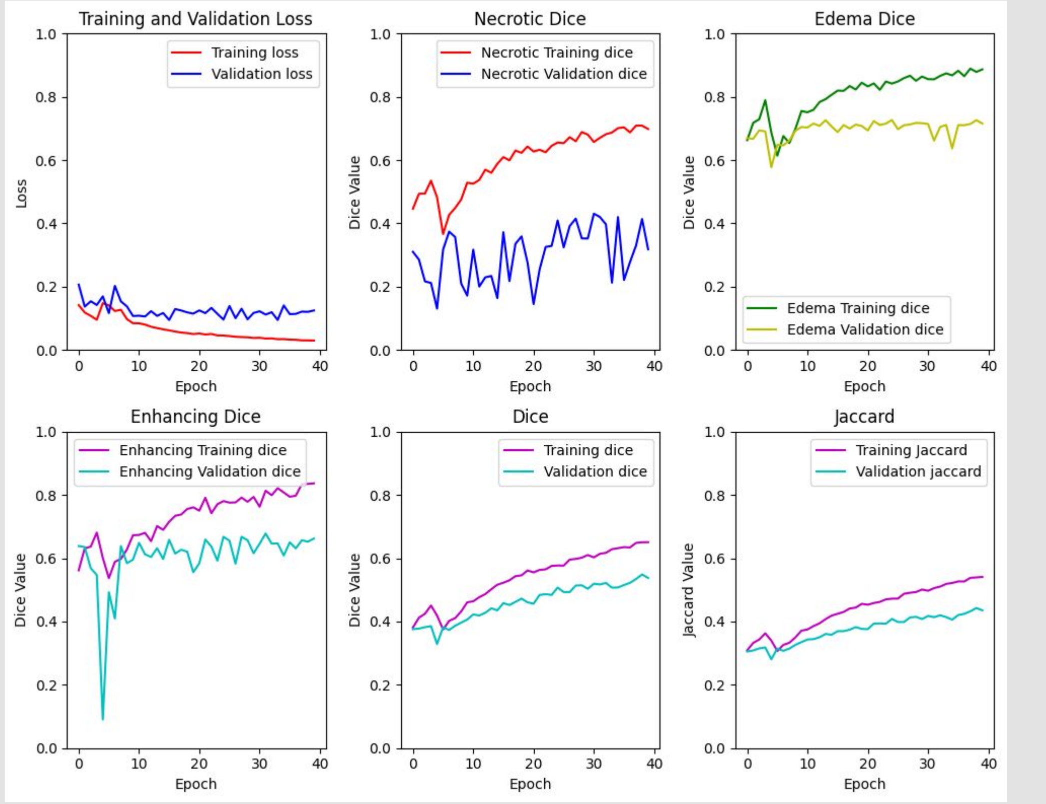
4. Training

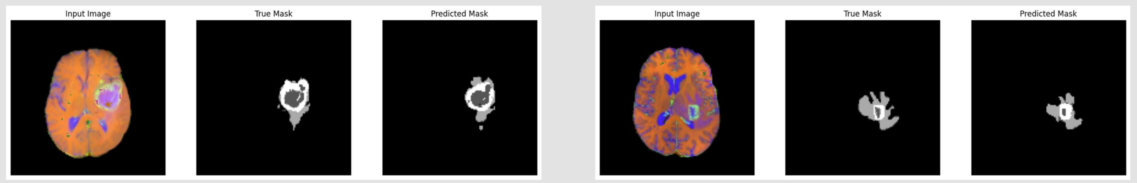


- The training process employs the U-Net model with softmax activation, designed for sophisticated multi-class segmentation.
- Optimization is achieved using the categorical cross-entropy loss function.
- The model is trained to predict masks closely resembling true masks based on input images.

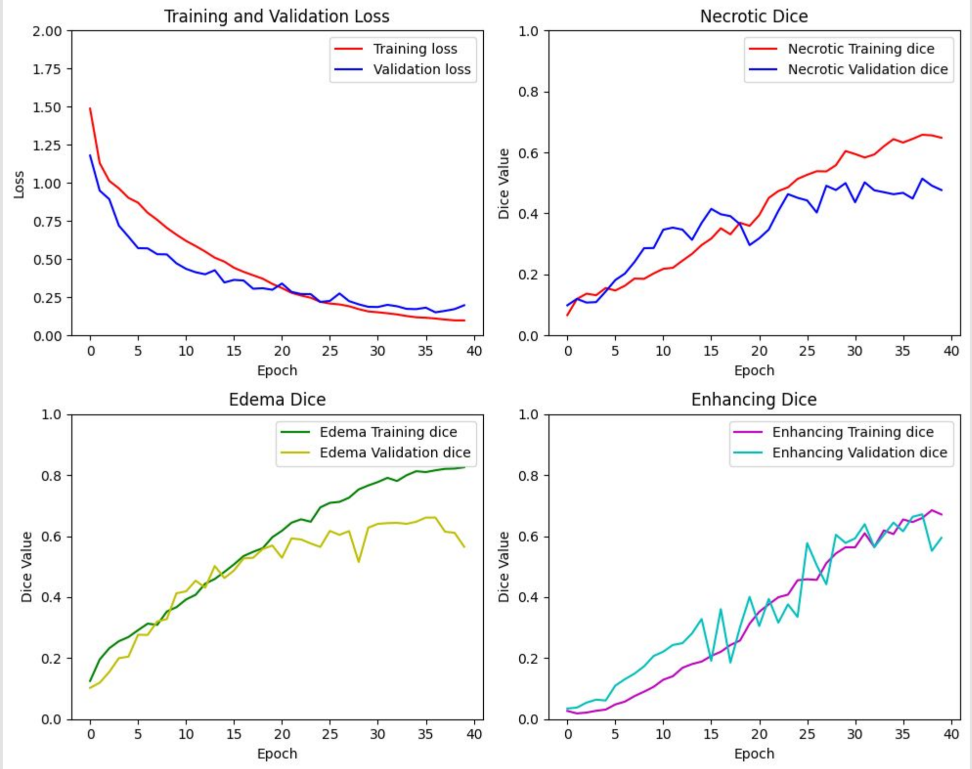
Results

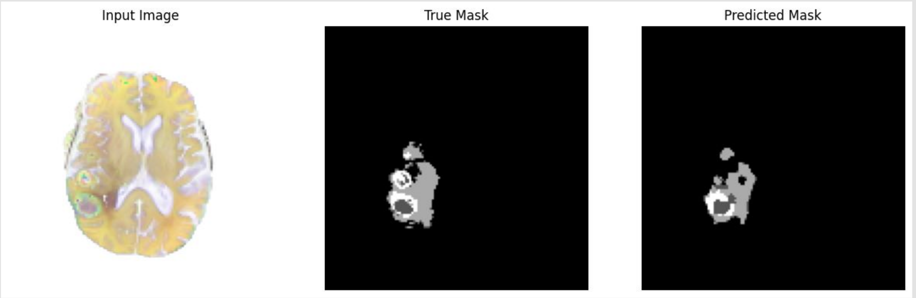
3 Classes: 128x128 pixels, 40 Epochs, Loss Rate of 0.00005





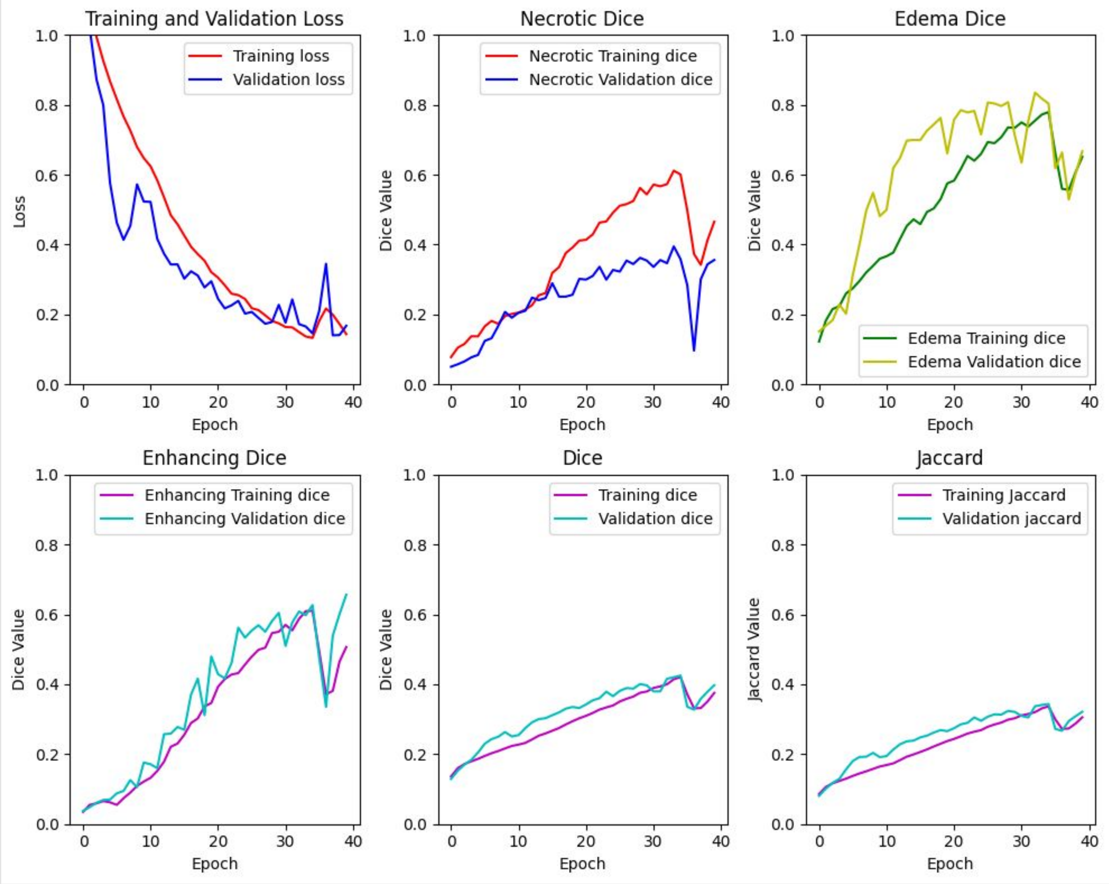
4 Classes: 256x256 pixels, 40 Epochs, Loss Rate of 0.00005

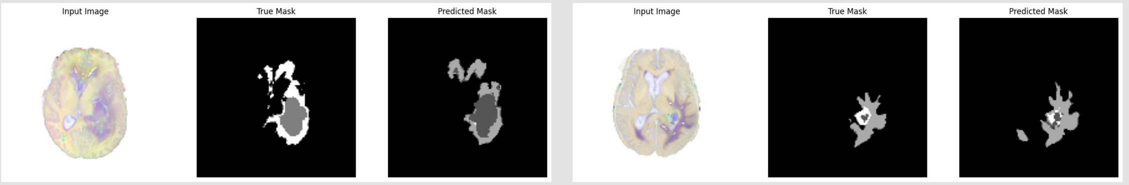




Results

4 Classes: 128x128 pixels, 40 Epochs, Loss Rate of 0.00005





Conclusion

- Preprocessing code prepares MRI scan data for UNet model
- UNet model produces a multiclass mask indicating tumor locations in the brain
- Multiclass segmentation, including one-hot encoding and decoding, supports the process
- Model hyperparameters are fine-tuned based on specific training and testing criteria to achieve optimal results
- The segmented results can be utilized for extracting features and diagnosing tumors.

References

Ronneberger, O., Fischer, P., Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab, N., Hornegger, J., Wells, W., Frangi, A. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer Science(), vol 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28