Mini Project

Brain Tumor Segmentation

B.Tech. VI Semester Department of Information Technology

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Introduction & Motivation

- Brain and nervous system tumors have a high death rate and are the leading cause of cancer death among young males and females. Gliomas have the highest incidence rate among such malignancies.[1]
- Accurate identification of tumors can help doctors achieve better diagnosis and treatment strategies.
- Many deep learning methods have been used for MRI image segmentation but not all produce accurate results.
- This paper uses 3D-UNET with Spatial Attention which outperforms other methods.[3]
- UNET can lose local features during encoding, resulting in reduced accuracy.

  Spatial attention is used to preserve local features during encoding and decoding. The encoding path includes additional modules (min, max pooling) at each level to preserve local features.

Problem Statement

Develop a Brain Tumor Segmentation model to improve Diagnosis and Treatment Planning from MRI scans

Literature Review

Paper title /Year	Method/ approach used	Achieved Performance	Disadvantages	Dataset
SAResU-Net [7]	1.Combines SA blocks and residual modules with 3D U-Net 2.Adds SA blocks to skip connections to capture local spatial and channel information 3.Uses a self-ensemble module to further enhance model performance.	DSC values of 77.74%, 90.40% an 83.58%, 79.17%, 90.02% and 82.00% for the enhancing tumor (ET), the whole tumor (WT), and tumor core(TC) on the BraTS 2019 and 2020 validation dataset	We cant intrepret the modules that are used and also more complex modules, using these can cause overfitting in data.	2019 and 2020 Brats Dataset
MBANet[4]	1. MBANet is a 3D convolutional neural network with 3D multi-branch attention 2. BU module is constructed using optimised shuffle unit 3. BU module uses channel shuffle and group convolution 4. Multi-branch 3D Shuffle Attention (SA) module is used for attention layer in encoder of MBANet.	Experiments on the BraTS 2018 and BraTS 2019 show that the dice of ET, WT and TC reach 80.18%, 89.80%, 85.47% and 78.21%, 89.79%, 83.04%, respectively.	MBANet solely uses publicly available multimodal datasets for its experiments.	BraTS 2018 and BraTS 2019 validation datasets
DPAFNet [8]	1. Consists of 3D feature extraction block and 3D IDCM block 2. Feature extraction block uses Dual-Path and Multi-scale Attention Fusion modules to capture spatial and contextual information and aggregate global and local information 3. 3D IDCM block merges feature maps with different receptive fields for dense pixel-level prediction 4. DPAFNet is expected to improve accuracy and speed of brain tumor segmentation.	results on BraTS2020 training set is DPAFNet 78.1 89.4 83.2 and on BraTS2018 training set is DPAFNet Yes 78.9 89.5 79.9.	The DPAFNet model has some limitations, including: complexity, computational demands, limitations in handling non-uniform tumors, and limitations in handling low contrast tumors.	BraTS2018, BraTS2019 and BraTS2020

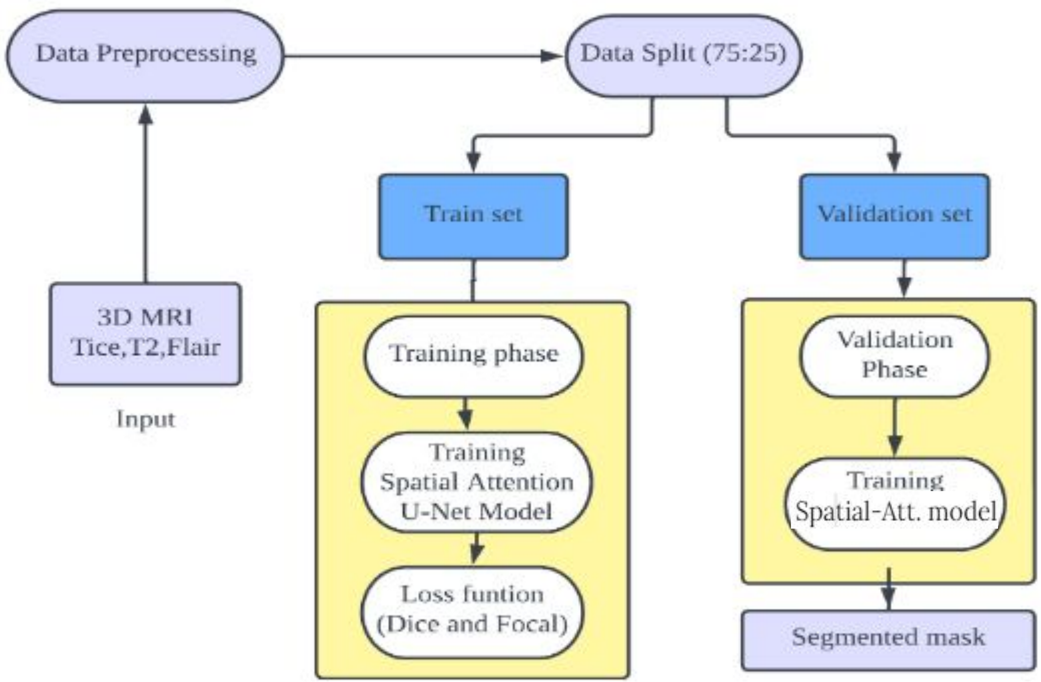
Paper title /Year	Method/ approach used	Achieved Performance	Disadvantages	Dataset
dResU-Net [5]	1. Proposed model is called dResU-Net and is a hybrid of deep residual network and U-Net model 2. Residual network used as encoder and U-Net decoder used to handle vanishing gradient 3. Designed to take advantage of low-level and high-level features simultaneously for prediction 4. Shortcut connections employed between residual network to preserve low-level features at each level.	Dice score for the tumor core (TC) - 0.8357, whole tumor (WT) -0.8660, and enhancing tumor (ET)-0.8004, on the BraTS 2020 dataset	dResU-Net 3D is computationally expensive to train and execute.dResU-Net 3D has shown relatively poor performance in segmenting heterogeneous tumors, which are tumors with varying shapes, sizes, and intensities.	The model was trained and validated on the BraTS 2020 training dataset.
Edge U-Net [10]	1. Edge U-Net is a modified version of U-Net model for brain tumor segmentation in MRI images 2. Incorporates boundary information to improve segmentation accuracy 3. Uses combination of convolutional and deconvolutional layers, skip connections, and edge maps 4. Identifies and segments tumor regions.	The Edge U-Net model achieved a Dice similarity coefficient (DSC) of 0.88 and a Jaccard index (JI) of 0.81 on the BraTS 2018 validation dataset, which outperforms several state-of-the-art methods.	The main disadvantage of the Edge U-Net model is that it requires additional computational resources and time compared to the original U-Net model due to the incorporation of boundary information. Additionally, the model may be sensitive to the quality of the edge maps generated during training.	The Edge U-Net model was evaluated on the BraTS 2018 dataset, which includes multimodal MRI images of brain tumors from multiple institutions. The dataset contains 285 training images and 66 validation images

Methods

Preprocessing:

- Loaded MRI scans and masks.
- Resampled MRI scans and masks to a common resolution of 128mm x 128mm x 128mm.
- Normalized MRI scans intensity values to a range of 0 to 1.
- Stacked three MRI scans into a single 3D image volume.
- Cropped image volume and its corresponding mask to remove empty borders.
- Converted mask to a one-hot encoded representation.
- Saved preprocessed image and mask as NumPy arrays.
- Data is split into training and validation sets with a ratio of 75:25.

Proposed Methodology



The Proposed Methodology General Flow

Dataset

The Dataset selected is Brain Tumor Segmentation(BraTS2020) for training and BraTS 2021 for testing.

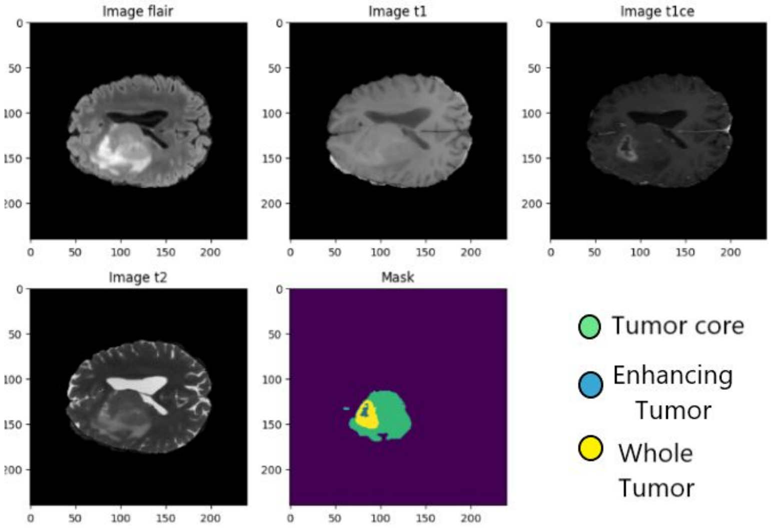
Tools and Libraries used

python 3.7, pytorch 1.6.0

torchvision 0.7.0

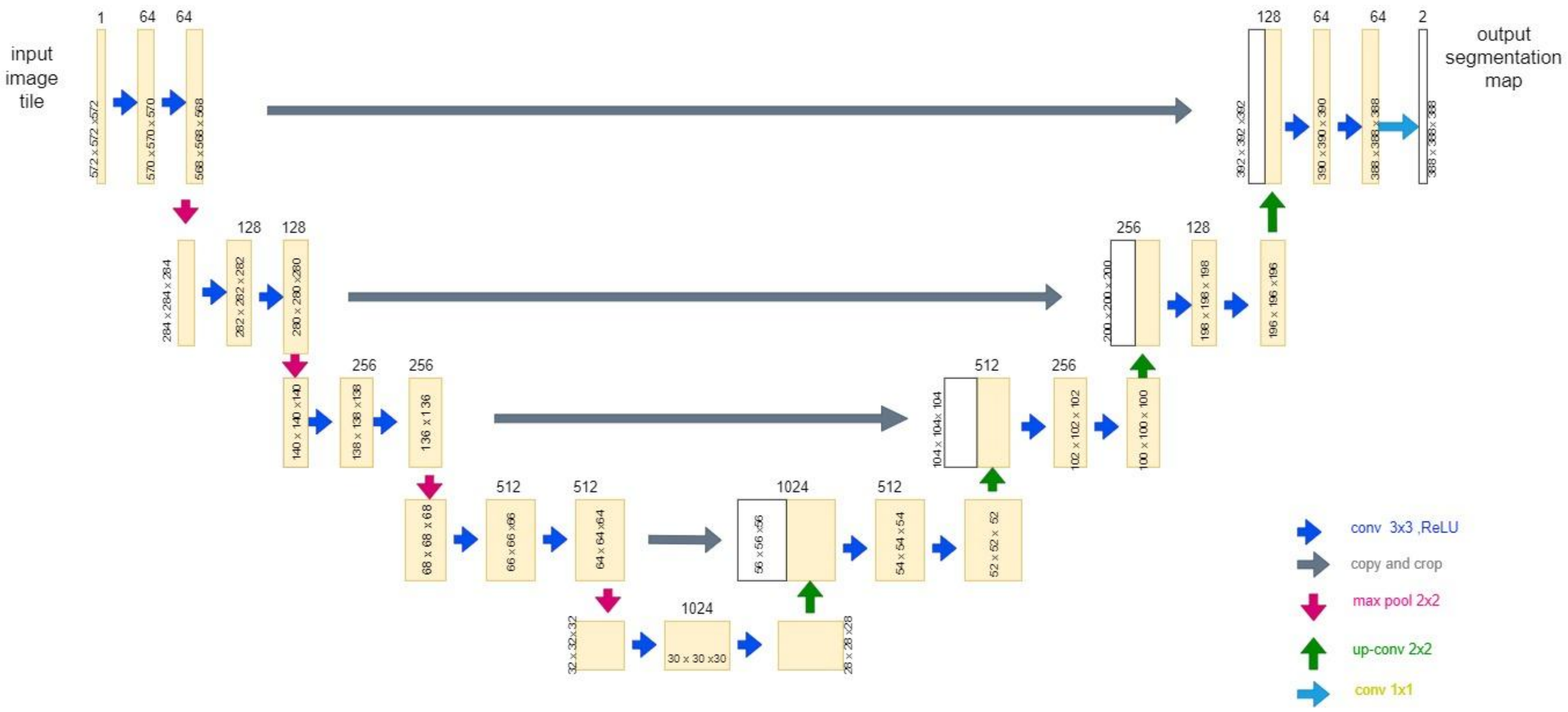
Pickle, Keras, glob

Nibabel, splitfolders

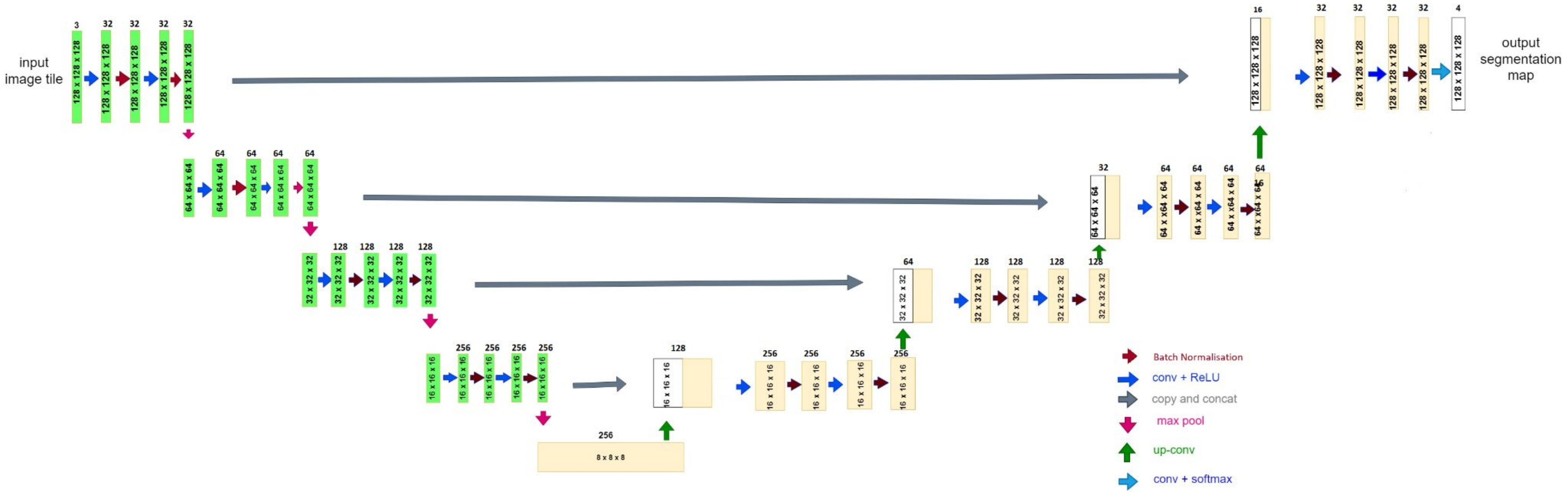


Sample MRI images and their ground truth

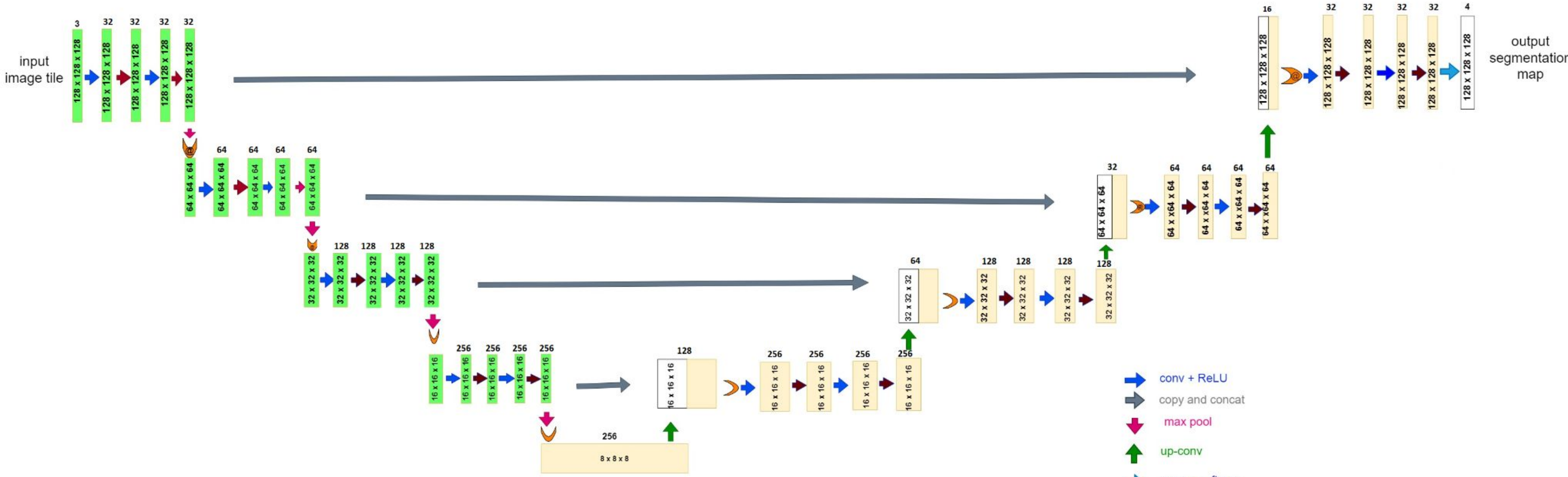
Basic U-Net Model



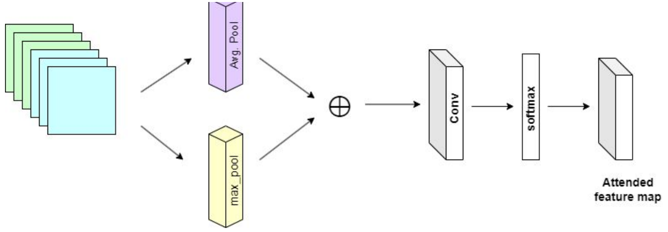
Modified U-Net



Spatial Attention U-Net Model



Spatial Attention Module



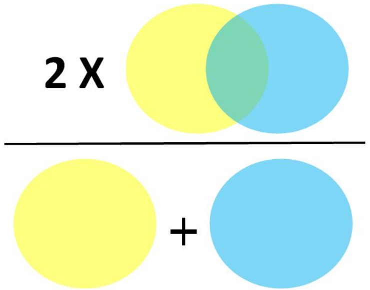
Loss Function, Metrics, and Optimization

Loss Function:

1. **Dice Loss Function:**

   A loss function used in image segmentation tasks to measure the overlap between predicted and ground-truth segmentation masks

   Dice Loss = 1 - (2 * TP) / (2 * TP + FP + FN)



2. **Categorical Focal Loss:**

   A modification of the standard cross-entropy loss function to address the problem of class imbalance in multi-class classification tasks.

   Focal Loss = -α(1 - p)^γ log(p)

Metrics:

Two evaluation metrics are defined - accuracy and IOU (Intersection over Union) Score.

IoU Score = TP / (TP + FP + FN)

Adam Optimiser:

A method used to update the weights of a deep learning model during training, such as Adam Optimizer, which is widely used due to its efficiency and robustness.

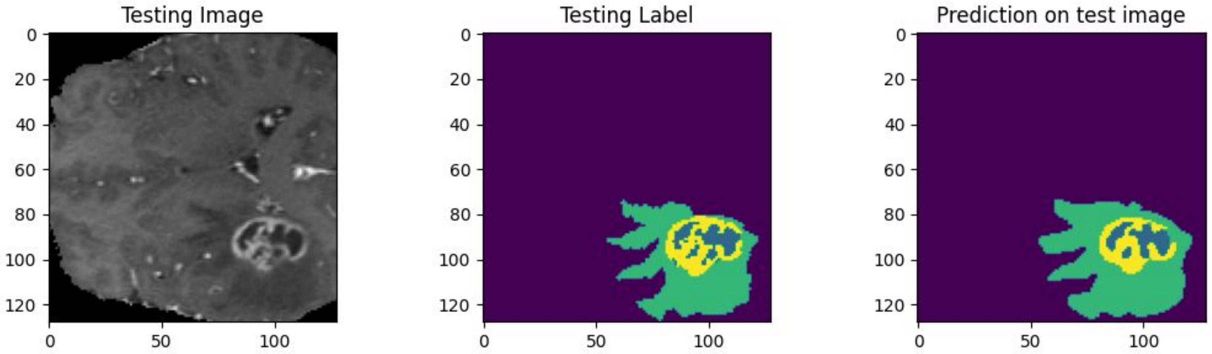
$$w_t = w_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Result Analysis

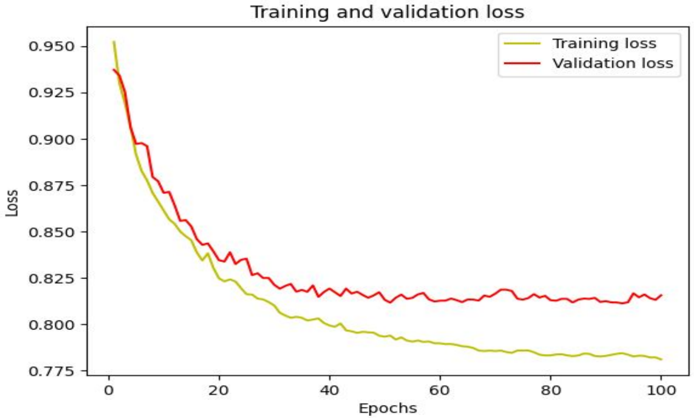
Experimental Setup:

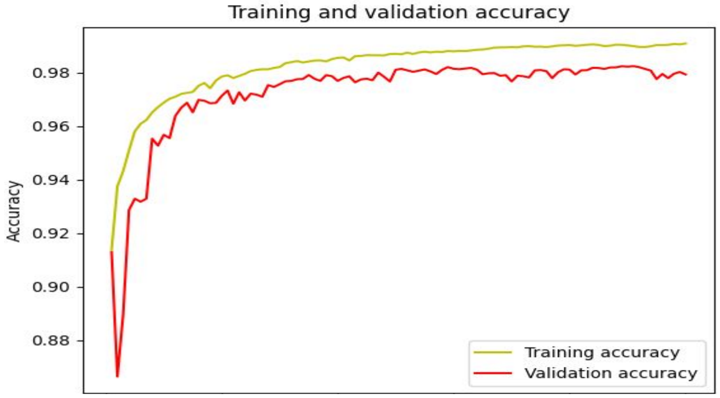
- The proposed model was implemented using Python, Keras library, and TensorFlow as backend.
- ADAM optimizer with a learning rate of 0.0001 was used.
- ReLU activation function with batch normalization was employed for increased stability and normalization.
- The model was trained for 100 epochs with a batch size of 2 due to limited computational resources.
- Experiments were conducted on the BraTS 2020 benchmark dataset with 75% data used for training and 25% for testing.

Simple UNet Architecture Prediction Image

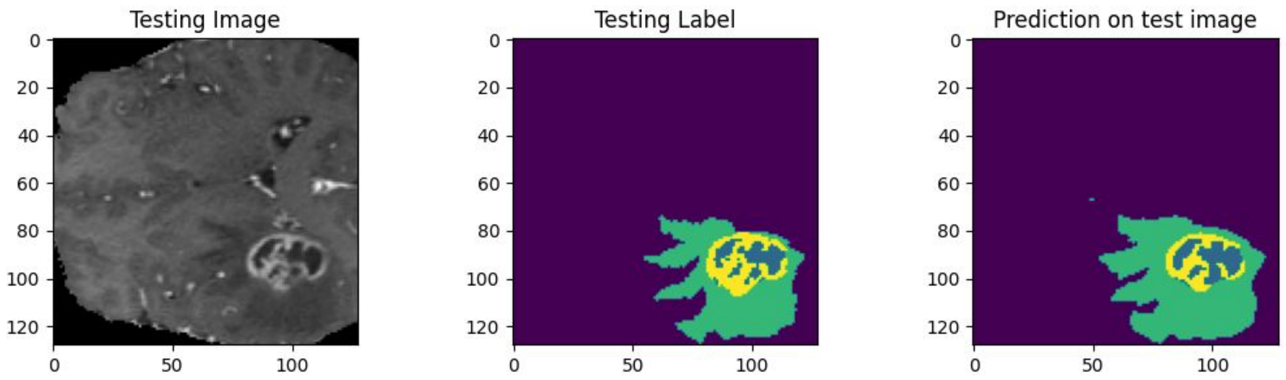


Simple Unet Training And Validation Loss with Training and Validation accuracy

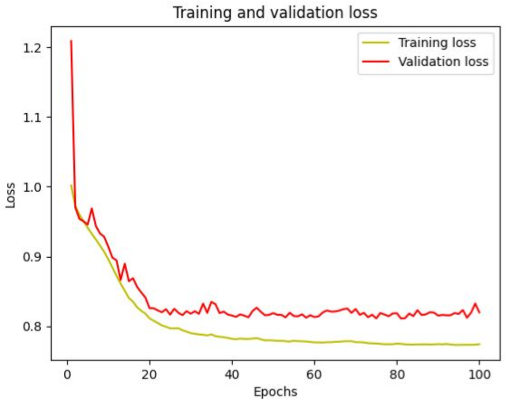


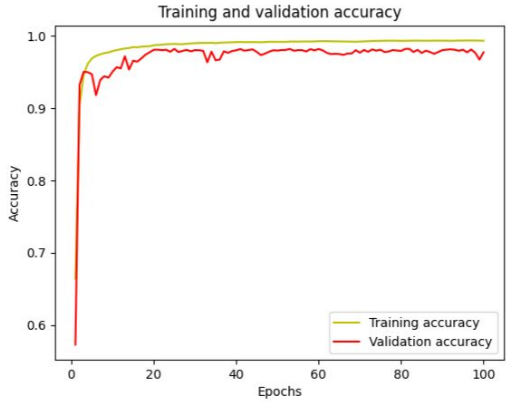


Modified UNet Architecture Prediction Image

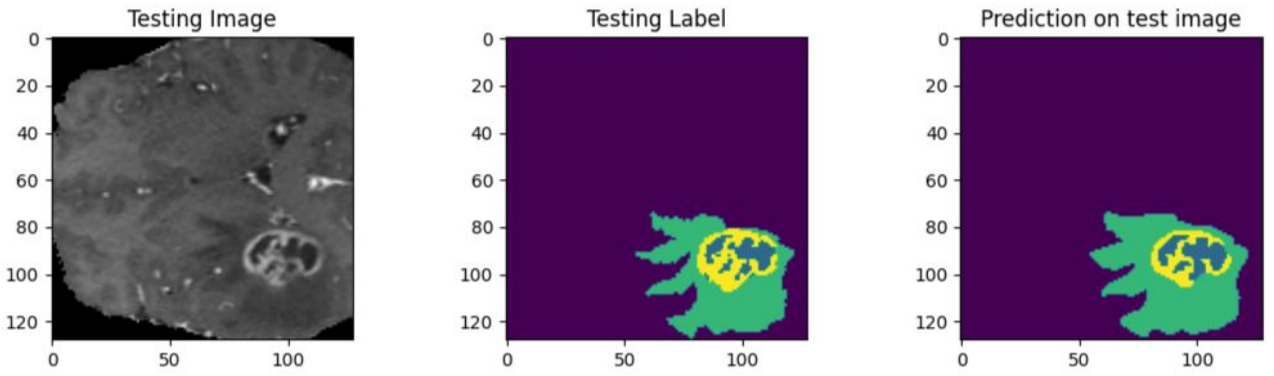


Modified Unet Training And Validation Loss with Training and Validation accuracy

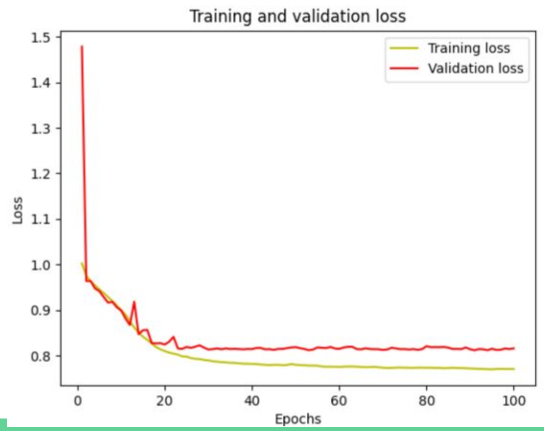


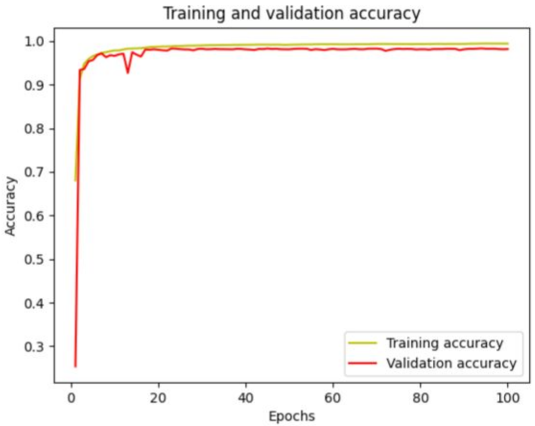


Spatial Attention UNet Architecture Prediction Image



Spatial attention Unet Training And Validation Loss with Training and Validation accuracy





Results

Training (75%) and Validation (25%) - BraTS 2020 Dataset
Testing - BraTS 2021 Dataset

Models	Accuracy		IOU		IOU (Test)
	Train	Validation	Train	Validation	
Simple Unet	0.9908	0.9792	0.8123	0.6753	0.6965
Modified U-Net	0.9932	0.9774	0.8502	0.6675	0.7025
Spatial Attention U-Net	0.9942	0.9818	0.8698	0.6773	0.6962

QUANTITATIVE RESULTS (Dice Score) OF TRAIN AND TEST SET OF THE PROPOSED ARCHITECTURE

Models	Dataset	Tumor Core (TC)	Whole Tumor (WT)	Enhancing Tumor (ET)
Simple UNET	Train 2020	0.8930	0.8684	0.8910
	Test 2021	0.7966	0.7495	0.6857
Modified UNET	Train 2020	0.7331	0.7551	0.8700
	Test 2021	0.8206	0.7682	0.6630
Spatial Attention UNET	Train 2020	0.9027	0.8868	0.9067
	Test 2021	0.8039	0.7640	0.6689

Conclusion

- Spatial U-Net proposed to improve brain tumor segmentation on 3D MRI images.
- Future improvements can be made through data augmentation, exploring other 3D-based architectures, and utilizing post-processing techniques.
- Proposed method can be applied to other segmentation problems in medical imaging.

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