

The background of the slide features a series of thin, flowing lines in shades of light blue and purple. These lines originate from the left side and curve towards the right, creating a sense of movement and depth. The lines are closely spaced in some areas, forming a dense, textured effect, while in other areas, they are more spread out. The overall color palette is soft and modern, with the purple lines adding a touch of vibrancy to the predominantly blue and white composition.

Brain Tumor Segmentation

Introduction:

Problem Definition:

Brain tumor segmentation is a challenging task in the field of medical imaging. The problem involves the identification and delineation of tumor regions within brain Magnetic Resonance Imaging (MRI) scans. Brain tumors can vary greatly in terms of size, shape, location, and intensity, making them difficult to distinguish from healthy brain tissue. Additionally, MRI scans can contain noise and artifacts, further complicating the task.

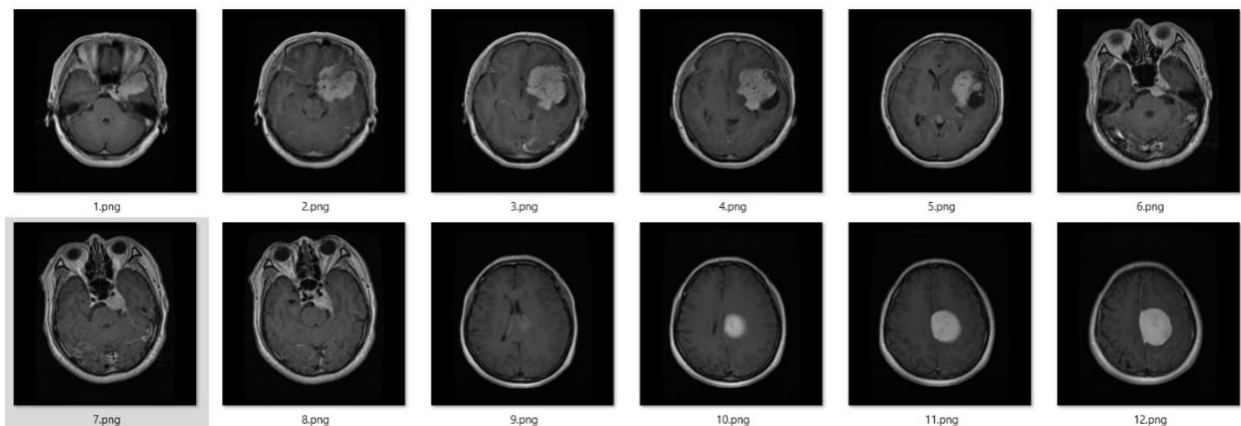
The objective of brain tumor segmentation is to develop a model that can accurately identify and segment tumor regions within MRI scans using different deep learning architectures like 3D U-Net, Inception U-Net, and VGG. . The ultimate goal is to create a tool that can assist radiologists and clinicians, reducing the time and effort required for manual segmentation, and potentially improving patient outcomes.

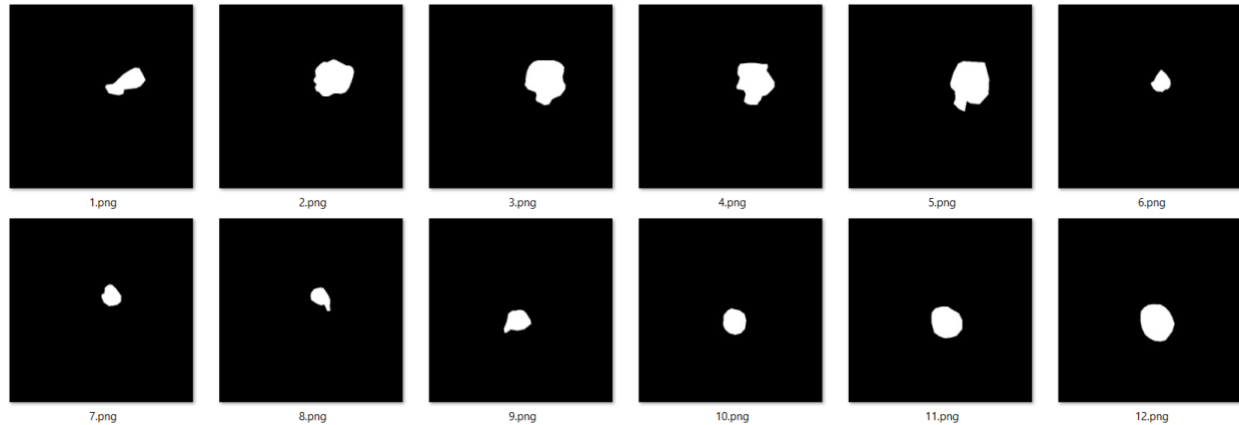
Dataset Description

The dataset utilized for this brain tumor segmentation task comprises two distinct folders (images and masks), each containing 3064 PNG images. The images are grayscale and possess dimensions of 512x512 pixels, portraying MRI scans of the brain.

The Masks images serve as ground truth labels or masks, indicating the specific regions of brain tumors present in the corresponding MRI scans.

Masks are binary, depicting tumor regions in white and background in black, aiding in the segmentation process.





Dataset: <https://www.kaggle.com/datasets/nikhilroxtomar/brain-tumor-segmentation>

Literature Review

1- [Inception Modules Enhance Brain Tumor Segmentation\(paper1\)](#)

The primary objective was to perform precise brain tumor segmentation from MRI data using deep learning models. A novel framework combining the U-Net architecture with Inception modules was introduced. Two distinct learning objectives were explored: segmenting glioma sub-regions and intra-tumoral structures.

Four model variations were created, focusing on different combinations of these objectives and architectures.

1- U-Net with Intra-Tumoral Structures

2- U-Net with Glioma Sub-Regions

3- U-Net with Inception Modules and Intra-Tumoral Structures Objective

4- U-Net with Inception Modules and Glioma Sub-Regions Objective

Results from rigorous evaluation using cross-validation demonstrated significant improvements in tumor segmentation performance when integrating Inception modules into the U-Net architecture. This enhancement was attributed to the ability of Inception modules to capture multi-scale contextual information efficiently during the learning process.

2- [MRI Brain Tumor Segmentation Using U-Net \(paper2\)](#)

The main objective was to develop an automated system to segment brain tumor images with minimal error using the U-Net algorithm. Apply U-Net for image segmentation to precisely identify and localize tumors. Aim for a system with high accuracy and minimal error to assist medical professionals in diagnosis.

The results of the study are successfully developed an automated system using the U-Net algorithm, significantly improving brain tumor segmentation accuracy in medical imaging.

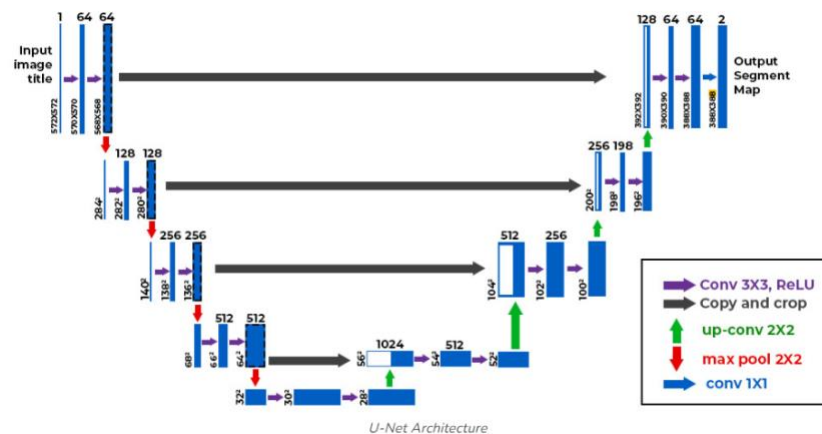
Achieved high accuracy in segmentation (Dice Coefficient: 0.924446) and IOU of 0.862625, indicating successful tumor localization.

Methodology

The methodology employed for brain tumor segmentation involved the utilization of various convolutional neural network (CNN) architectures tailored for semantic segmentation tasks. Three distinct architectures—U-Net and Inception U-Net—were implemented and assessed for their effectiveness in accurately segmenting brain tumor regions from MRI scans.

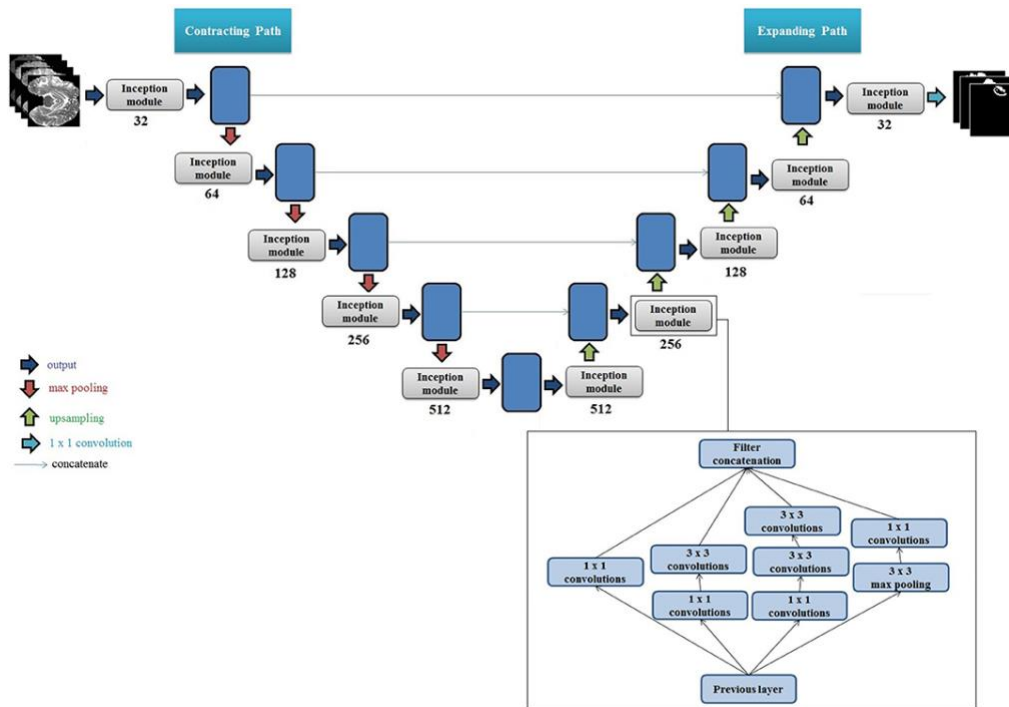
1. U-Net

The U-Net architecture, introduced by Ronneberger et al., is a widely adopted CNN architecture renowned for its success in biomedical image segmentation tasks. Its architecture comprises an encoder-decoder structure, where the encoder extracts features from input images while the decoder reconstructs the spatial information to generate segmentation masks.

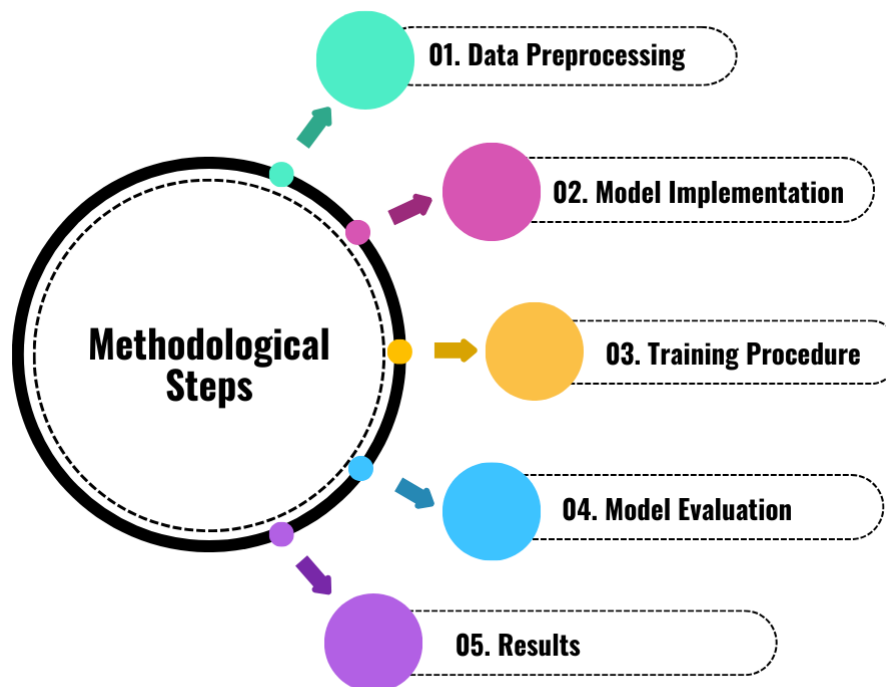


2. Inception U-Net

The Inception U-Net architecture amalgamates the robust feature extraction capabilities of the Inception modules with the U-Net's segmentation prowess. This architecture enhances the feature learning process by integrating Inception blocks within the U-Net's encoder and decoder pathways. The Inception modules, characterized by their inception blocks featuring multiple filter sizes concatenated in parallel, allow the network to capture multi-scale information efficiently, contributing to improved segmentation performance.



Methodological Steps:



- Data Preprocessing:**

The dataset consisting of 3064 MRI images and corresponding masks (each sized at 512x512 pixels) was preprocessed. This involved loading the images, resizing them to a

standard size (256x256 pixels), normalization, and splitting into training, validation, and test sets.

- **Model Implementation and Compilation:**

TensorFlow and Keras libraries were utilized to implement the 3D U-Net, Inception U-Net, and VGG architectures. The models were compiled using appropriate loss functions (such as Dice loss), optimizers (e.g., Adam), and evaluation metrics (Dice coefficient, accuracy).

- **Training Procedure:**

The training process involved 50 epochs for each architecture with a defined batch size and a learning rate of 1e-3.

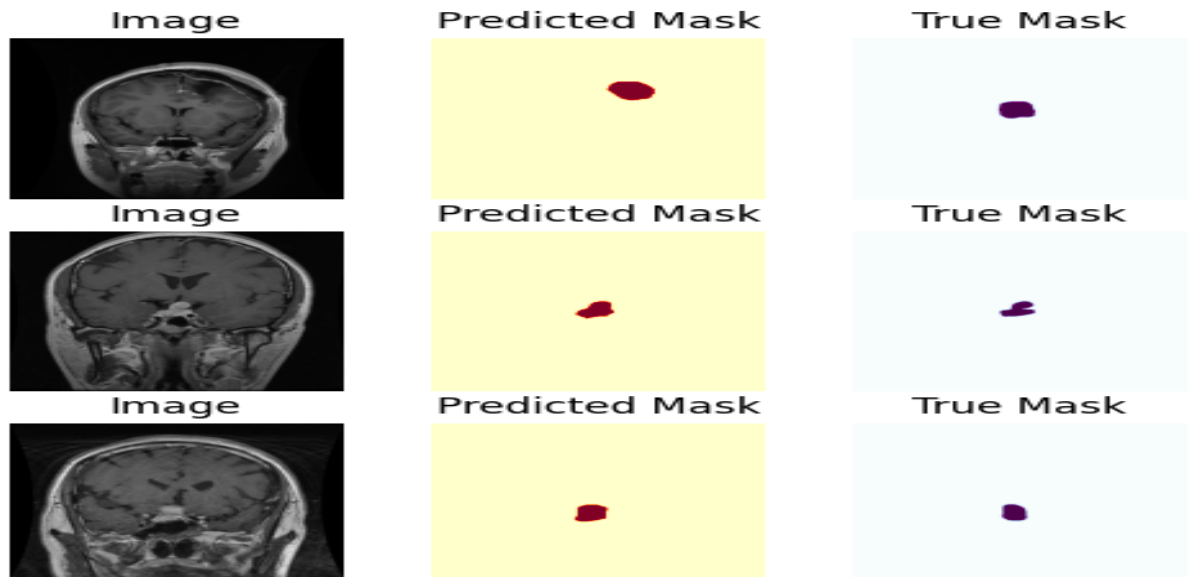
- **Model Evaluation:**

The trained models were evaluated using the validation dataset to assess their segmentation performance. Metrics like Dice coefficient and accuracy were computed to gauge the models' ability to accurately segment brain tumor regions.

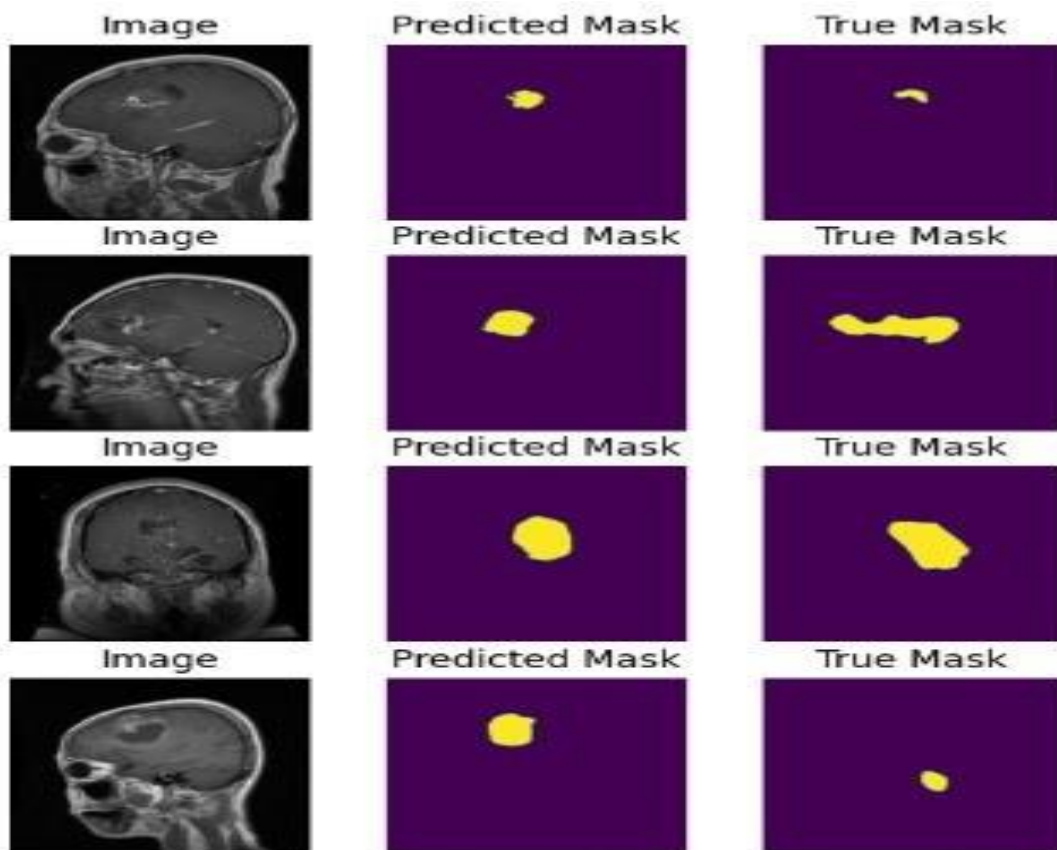
Architecture	Loss	Dice Coefficient	Accuracy	recall	precision	f1score
3D U-Net	0.5536	0.4422	98.42	0.3669	0.6036	0.4563
Inception U-Net	0.6516	0.3462	98.29	0.2718	0.5303	0.3594

Sample Of Predicted and Actual Masks

Inception U-Net



U-Net



Results and Discussion

The study evaluated the performance of different convolutional neural network (CNN) architectures - U-Net and Inception U-Net - for segmenting brain tumors in MRI images.

- **3D U-Net:** Achieved a Dice coefficient of 0.4266 and an accuracy of 98.29%.
- **Inception U-Net:** Showed a Dice coefficient of 0.3508 and an accuracy of 98.19%.

U-Net exhibited better segmentation performance compared to Inception U-Net.

Despite the additional complexity in Inception U-Net with multi-scale feature extraction, its segmentation effectiveness was slightly lower than the standard U-Net.