Ministry of Higher Education and Scientific Research

University of La Manouba

National School of Computer Science

ÉCOLE NATIONALE DES SCIENCES DE L'INFORMATIQUE

جامعة منوبة
Université de la Manouba

OntarioTech UNIVERSITY

MRI Brain Tumour Segmentation Using Transformers

Supervised by:
Professor Mehran Ebrahimi

Realized by:
Ines Bouhelal
ines.bouhelal@ensi-uma.tn

Co-Supervised by:
Professor Anja Habacha

CONTENT

Introduction

Hosting Organism

01

Ontario Tech University:

- Ontario Tech University was **founded** in 2002.
- It is a public research university **located** in Oshawa, Ontario, Canada.
- It **operates** seven faculties and **focuses** on research and innovation.

OntarioTech
UNIVERSITY

Imaging Lab:

- Research is **focused** on machine learning, mathematical imaging, and inverse problems.
- Their **long-term** research objective is solving real-world problems in the field of medical imaging

Context

Problem Statement & Objectives of the Project

02

Background Context: Brain tumours, Glioma

Gliomas, short for **Glioblastoma**:

- Is a highly **complex** and **heterogeneous** form of brain tumour.
- Is one of the most **deadly**, and **treatment-resistant** cancers.
- Is a widely **spread** type of brain tumour in the population.

Problem Statement:

- **Gliomas** presents unique challenges for accurate segmentation.
- **Current** deep learning and computer vision **methods** often **suffer** from reduced accuracy and efficiency in the segmentation of brain tumours.
- The segmentation has a **crucial role** in various clinical phases, such as diagnosis, treatment, and monitoring.

Objectives of the internship:

Literature review:
Exploring existing segmentation models and their applicability to MRI data.

Enhanced Accuracy:
Develop a state-of-the-art MRI brain tumour segmentation model using a Transformers-based approach.

Performance Evaluation:
Evaluate the performance of the produced model in terms of accuracy, efficiency.

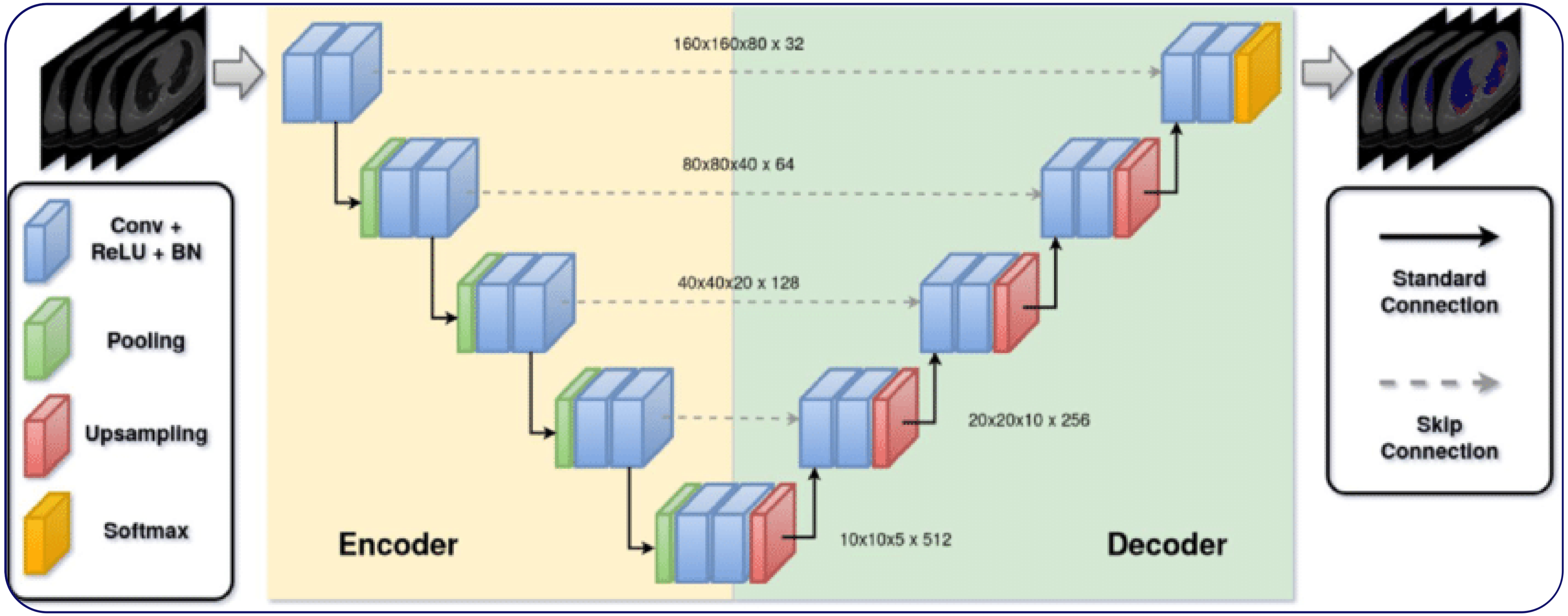
Existing Solutions

State-of-the-art Models & Critiques

03

State-of-the-art Models: 3D U-Net

U-Net is a convolutional neural network that was developed for biomedical image segmentation at the Computer Science Department of the University of Freiburg



Critique of 3D U-Net:

Spatial Information Capture: It excels at capturing spatial information within three-dimensional data

YES

NO

Demanding Model: It requires significant resources for training and inference.

Accurate Segmentation: It retains fine-grained details during the encoding and decoding proces

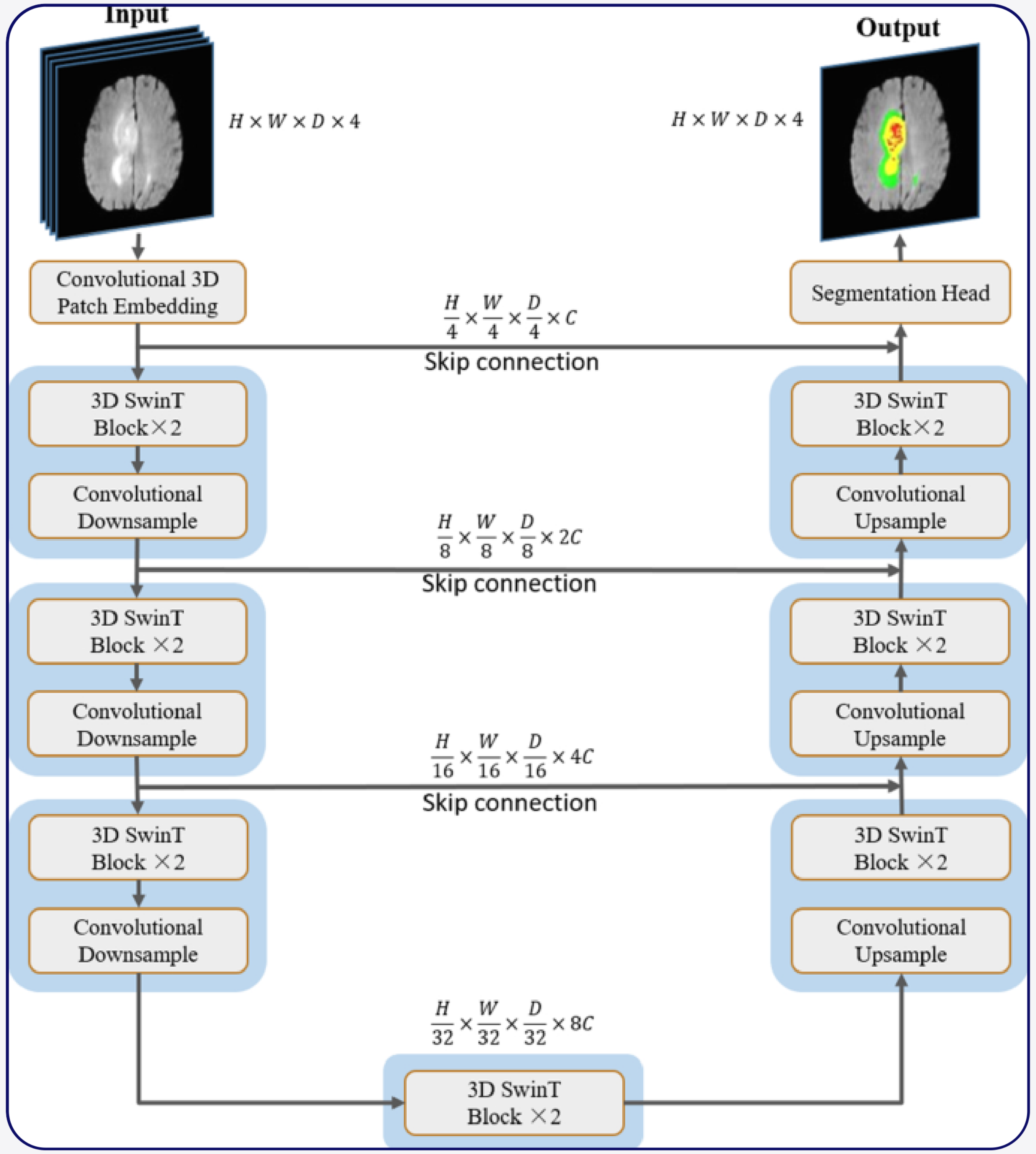
YES

NO

Data Availability: High-quality 3D labelled data for training can be scarce, especially in medical imaging applications

State-of-the-art Models: Swin-Unet

Swin-Unet refers to a specialized neural network architecture that combines the U-Net architecture with the Swin Transformer model.



Critique of Swin-UNet:

Enhanced Long-Range Dependencies: It is able to effectively capture long range dependencies in images.

YES

NO

Complexity: the model is hard to understand, implement, and fine-tune compared to simpler architectures.

Global Context Understanding: The model allows a better understanding of the overall composition of an image.

YES

NO

Edge Cases and Artifacts: The model still struggle with certain edge cases or artifacts

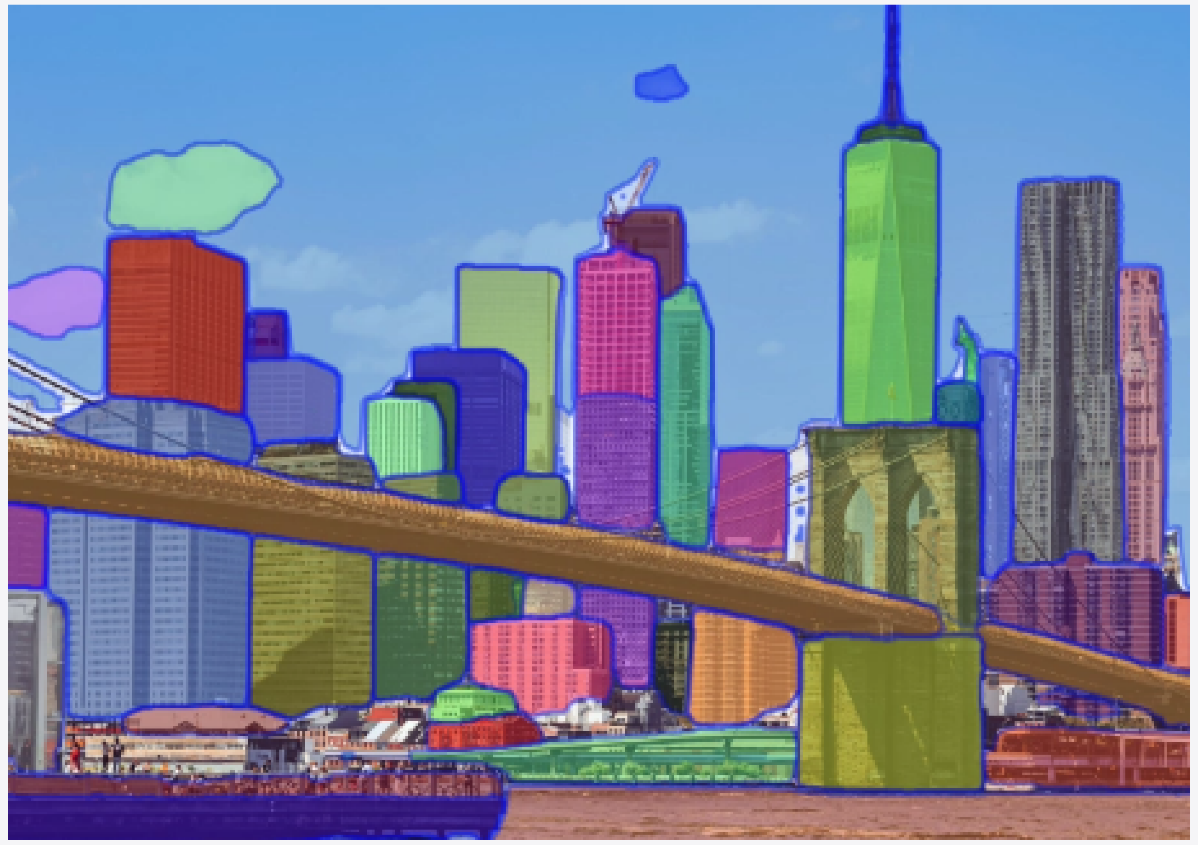
Proposed Solution

Proposed Model: Segment Anything Model

04

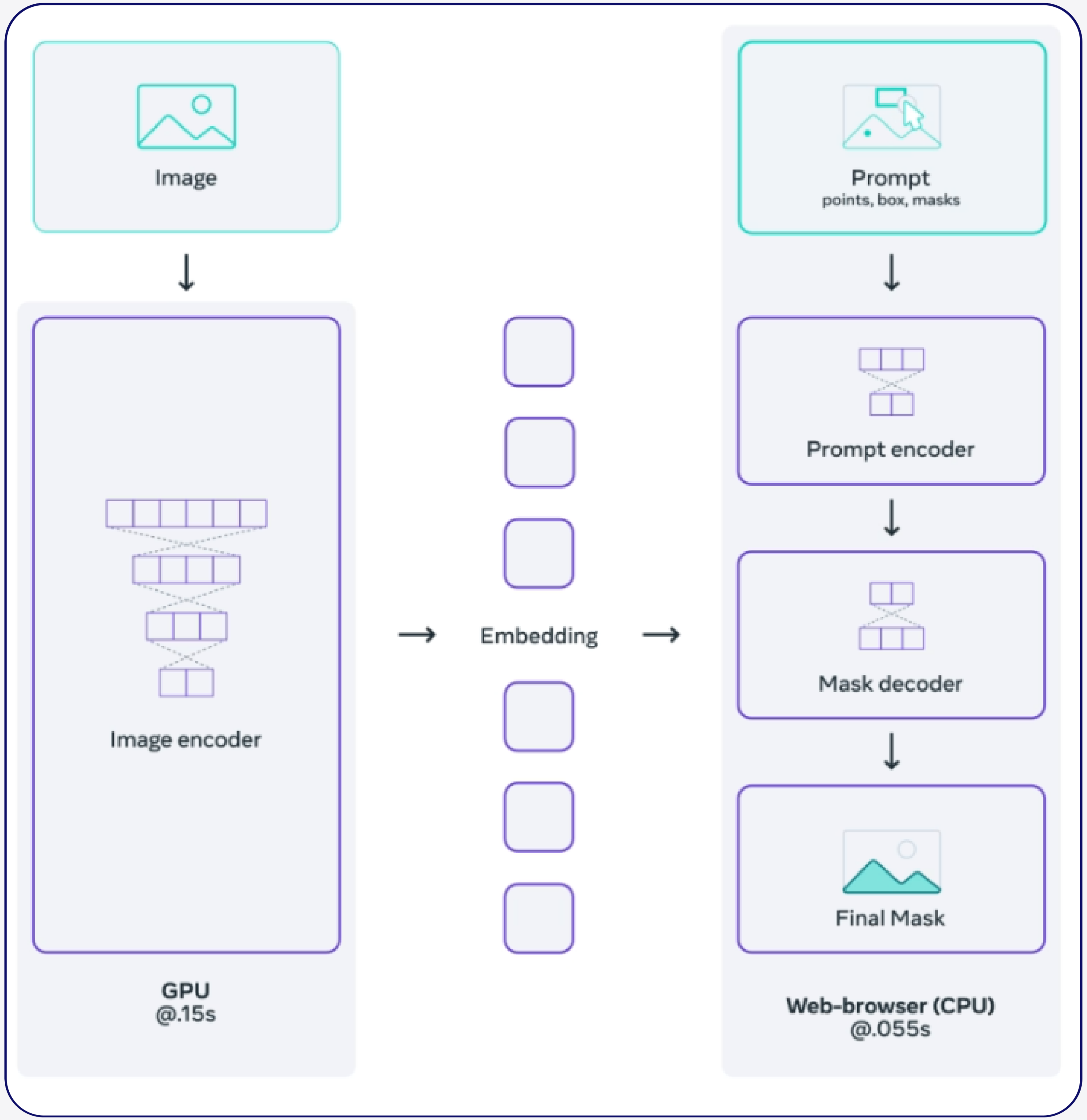
Segment Anything Model (SAM):

- SAM is a **promptable segmentation system** with zero-shot generalization to unfamiliar objects and images.
- **Developed by Meta Research** and released in April 2023, SAM is an instance segmentation model that underwent training on an extensive dataset comprising **11 million images and 1.1 billion** segmentation masks.



Architecture of SAM:

- **A ViT-H image encoder** that runs once per image and outputs an image embedding.
- **A prompt encoder** that embeds input prompts such as clicks or boxes.
- **A lightweight transformer-based mask decoder** that predicts object masks from the image embedding and prompt embeddings.



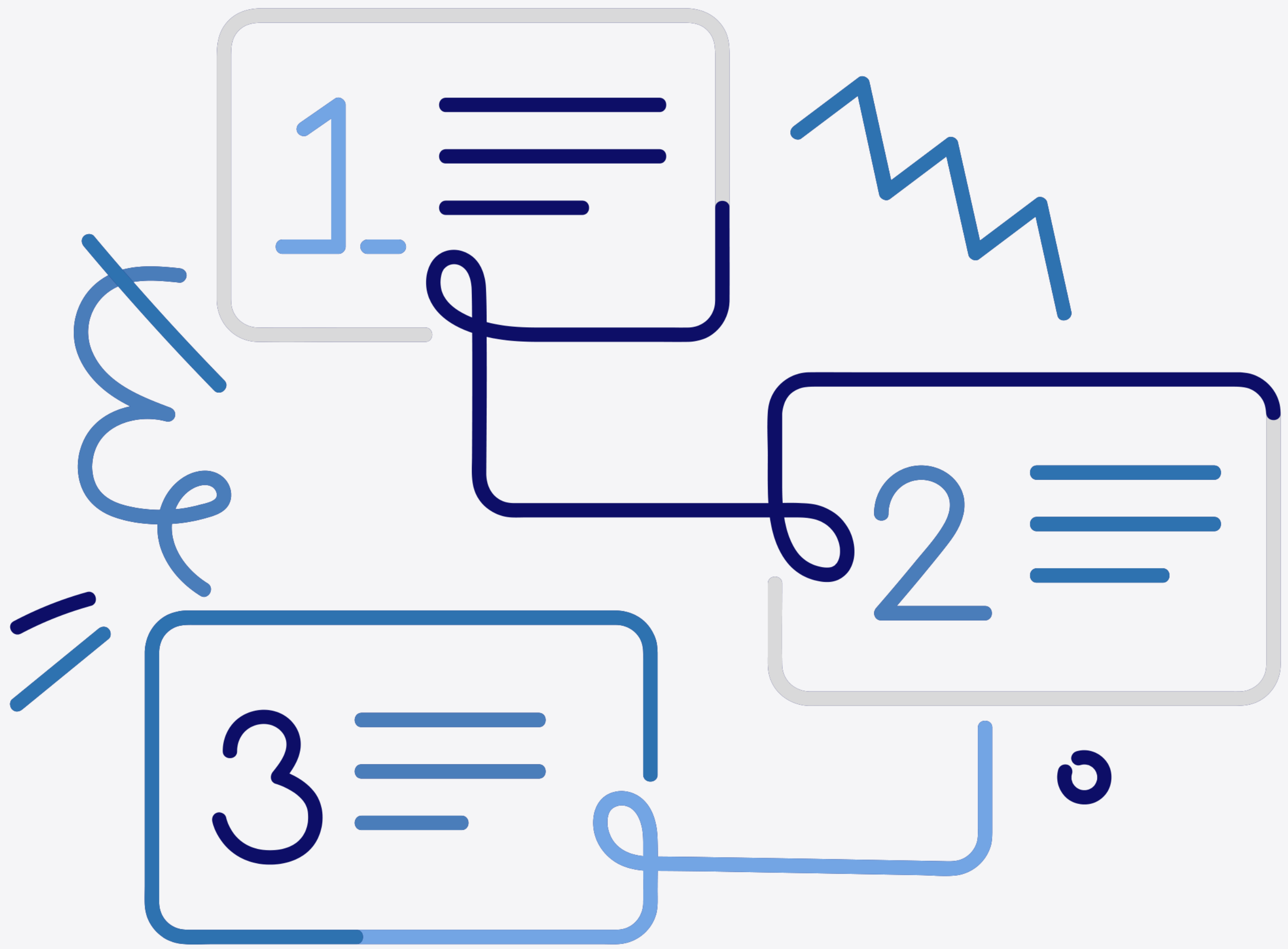
The technical side of SAM: Libraries & Programming Language

- The image encoder is **implemented in PyTorch** and requires a **GPU** for efficient inference.
- The prompt encoder and mask decoder **can run directly with PyTroch.**
- We also used various tools to handle the data we were feeding to SAM.

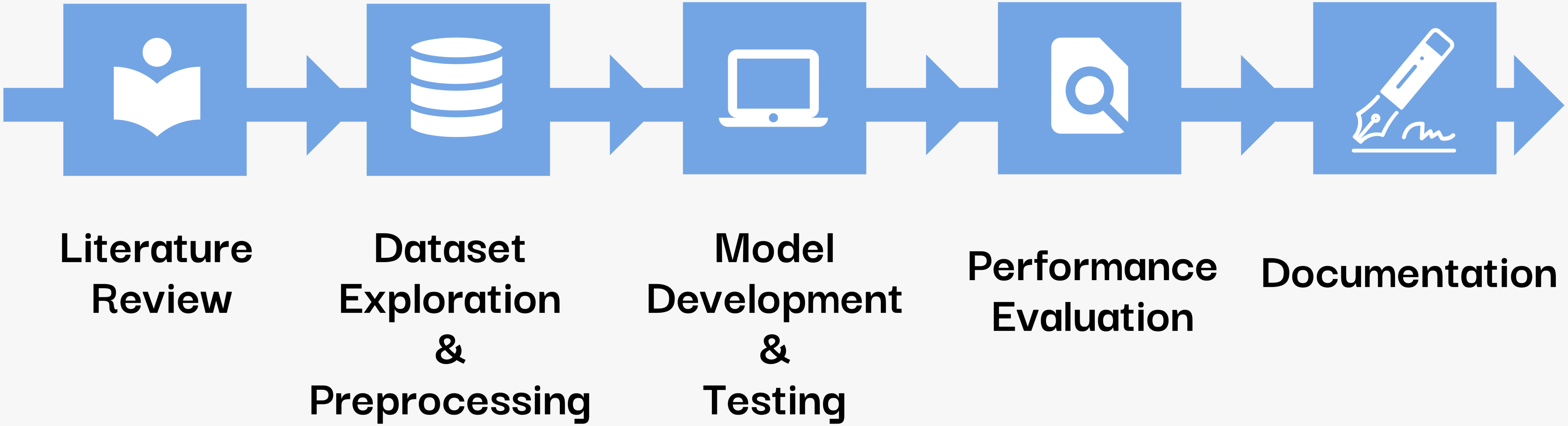
Workflow & DataFlow

Work Plan and Data manipulation

05

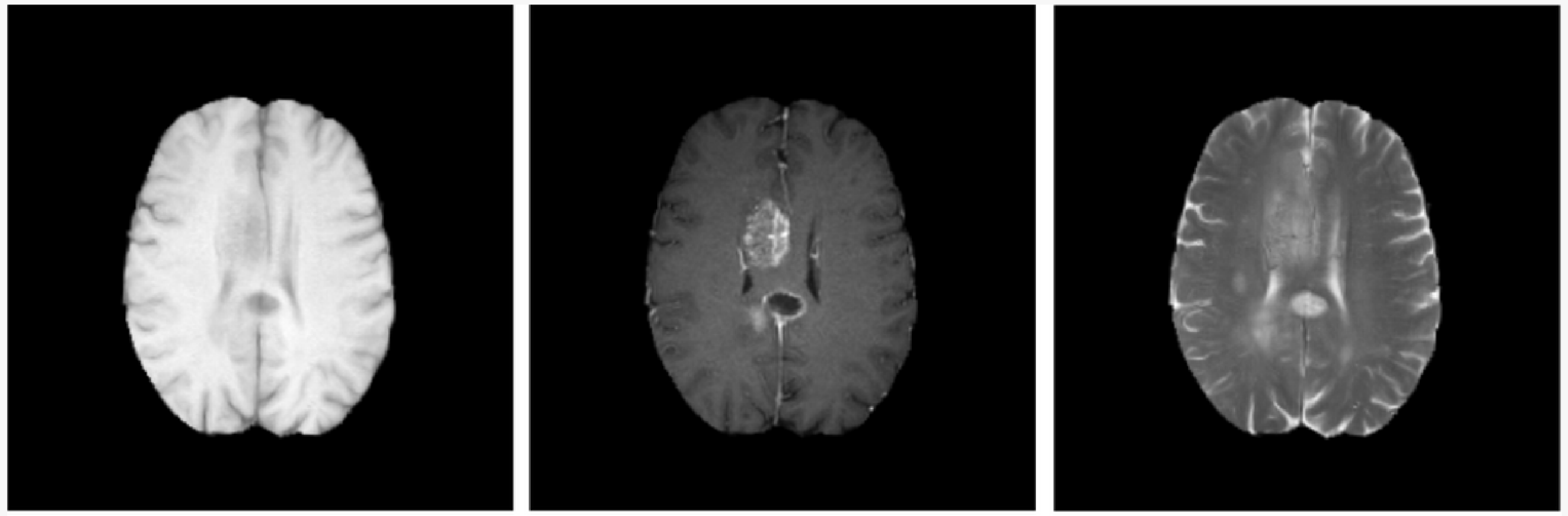


WorkFlow:


Literature Review
Dataset Exploration & Preprocessing
Model Development & Testing
Performance Evaluation
Documentation

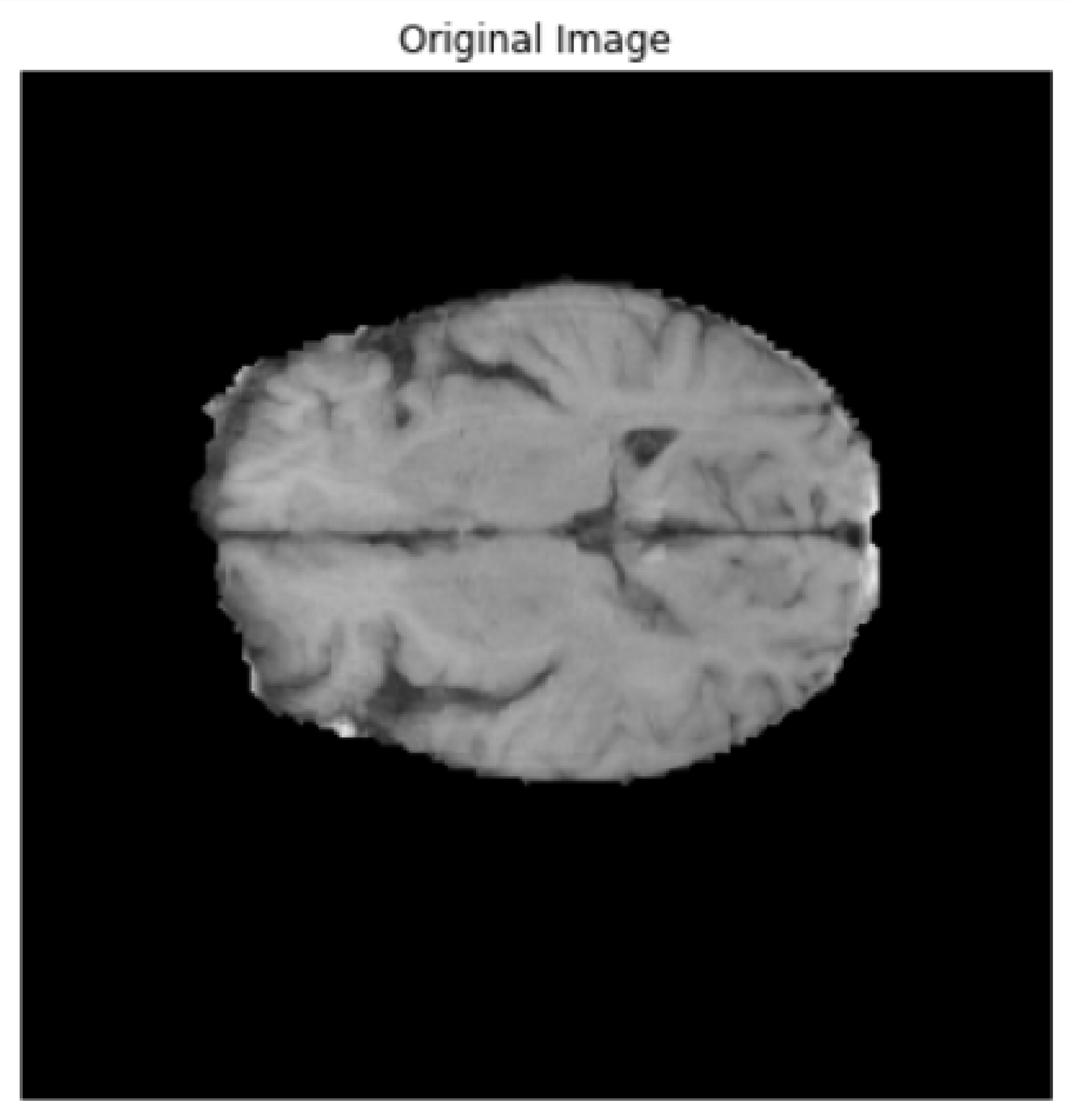
Data : BraTs Dataset (1)

All BraTS mpMRI scans are available as NIfTI files (.nii.gz) and describe a) native (T1) and b) post-contrast T1-weighted (T1w), and c) T2-weighted (T2w) volumes, and were acquired with different clinical protocols and various scanners from multiple data contributing institutions.

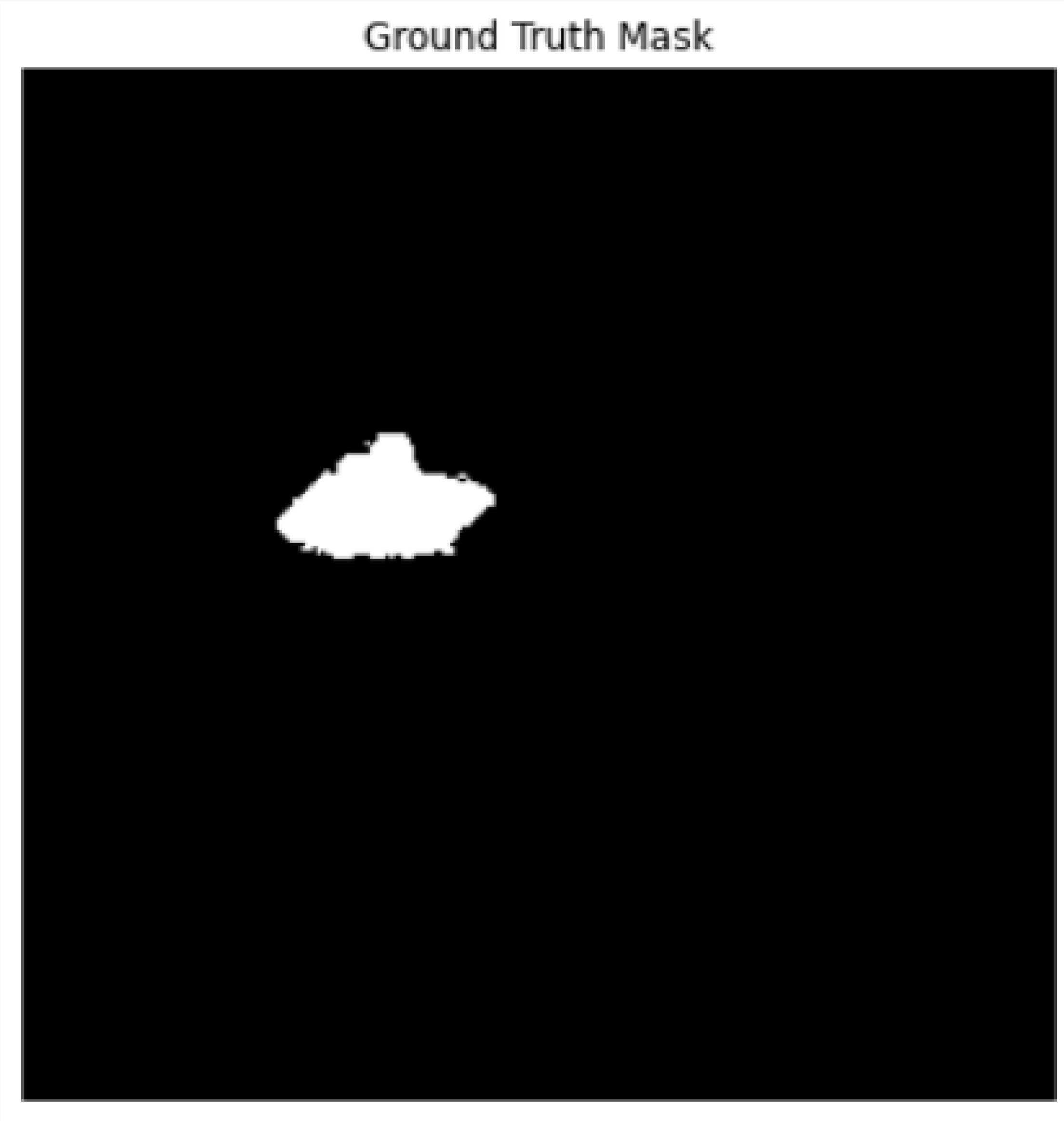


(a) T1 (b) T1c (c) T2

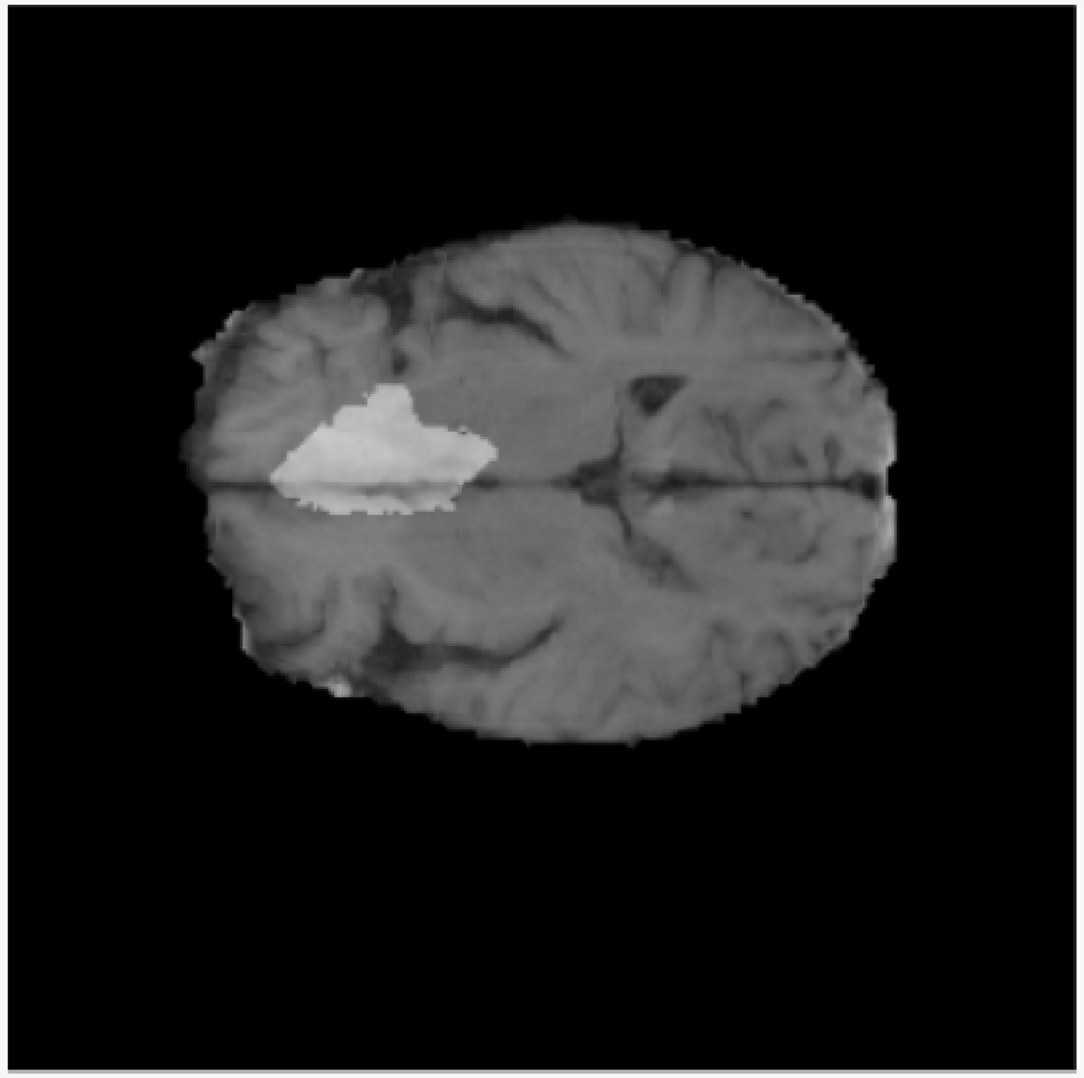
Data : BraTs Dataset (2)



T1n

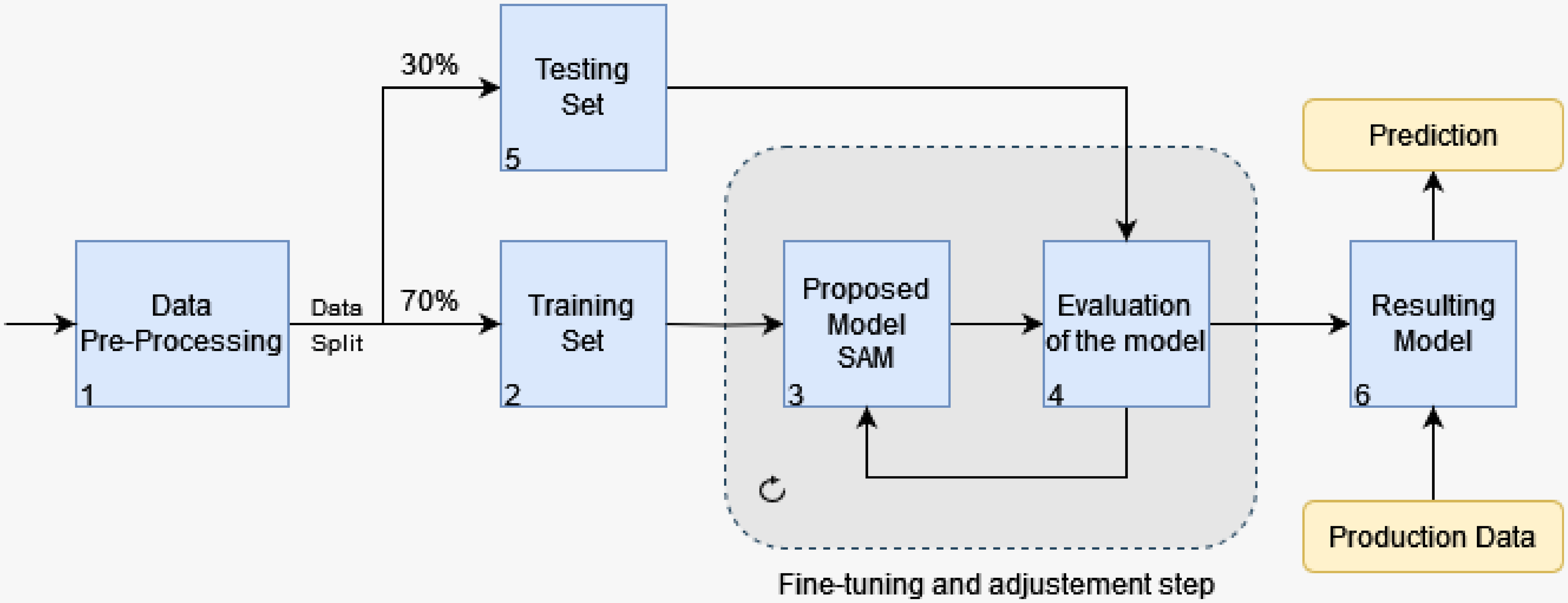


Corresponding segmentation mask



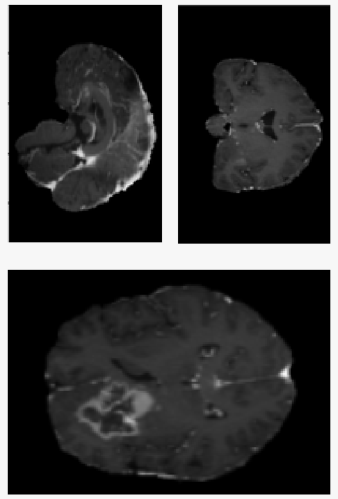
Segmented T1n

Dataflow:

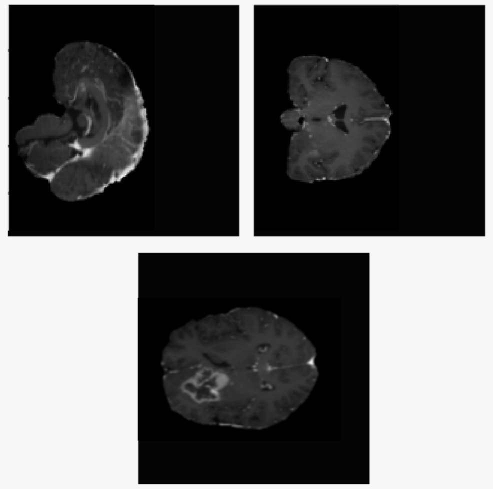

30%
Testing Set
5
Prediction
Data Pre-Processing
1
Data Split
70%
Training Set
2
Proposed Model SAM
3
Evaluation of the model
4
Resulting Model
6
Production Data
Fine-tuning and adjustement step

Dataflow: Data Pre-Processing

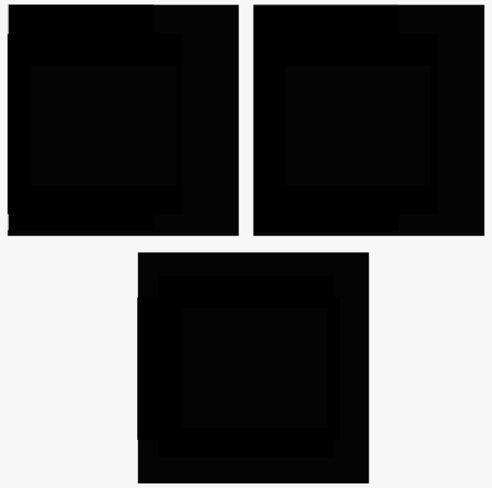
Extracting from Nifti files
the images in slices and remove
the excess generated



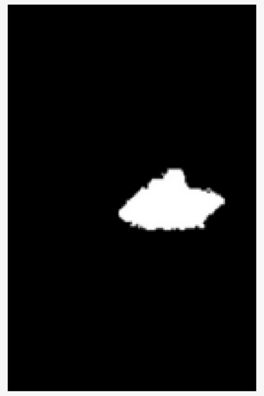
Padding
the slices
into 256x256



Normalizing
the images
with Sam Preprocessor

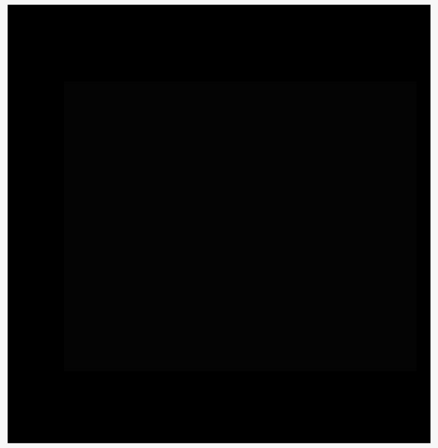


Extracting from Nifti files
the masks in slices and remove
the excess generated



Padding
the slices
into 256x256

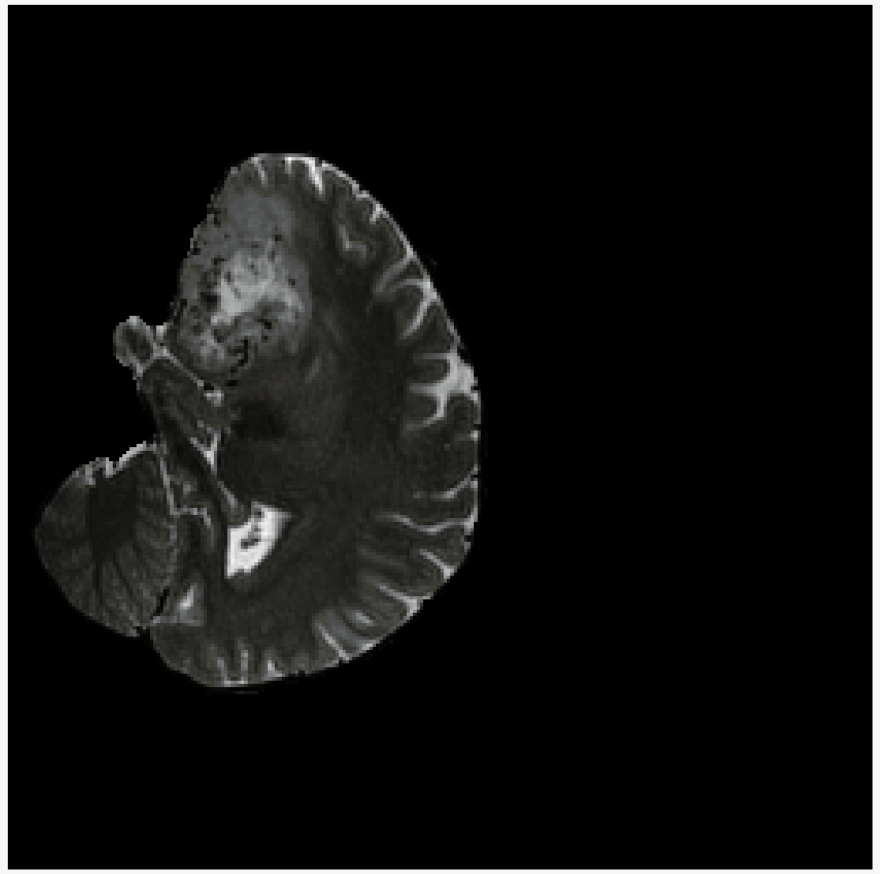
Normalizing
the masks
with Sam Preprocessor



Dataflow: Data Pre-Processing (optional Step)

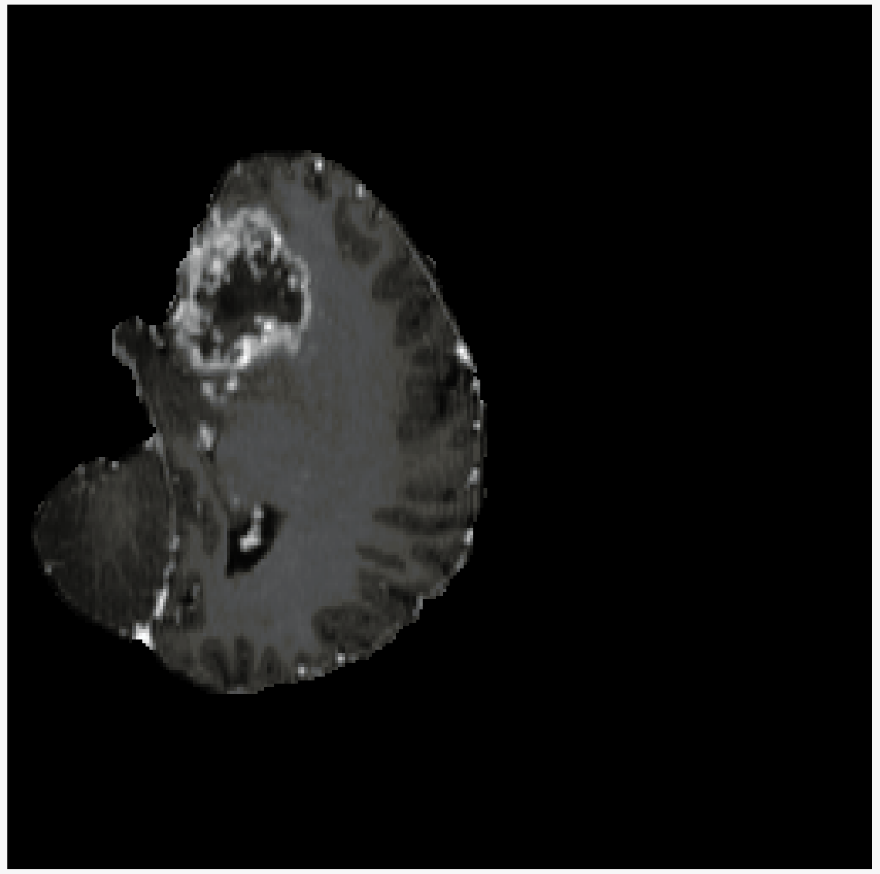
Fusion of Two Modalities T1c & T2w

Before the step of **normalizing** and after the step of **padding**:

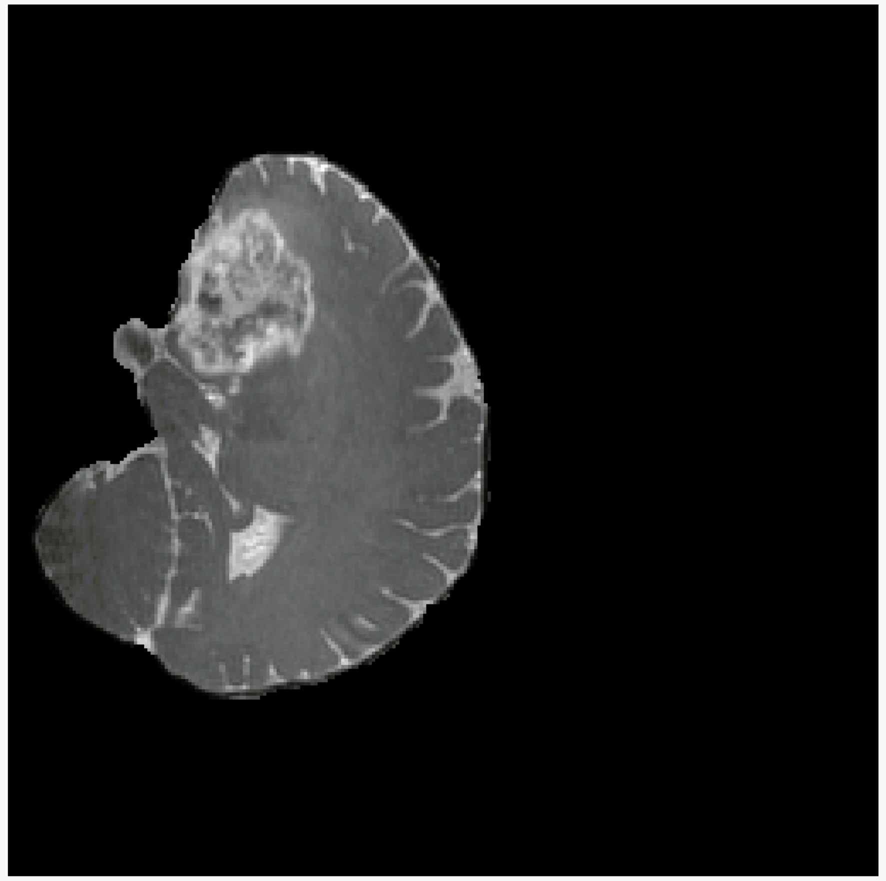


T2w

+



T1c



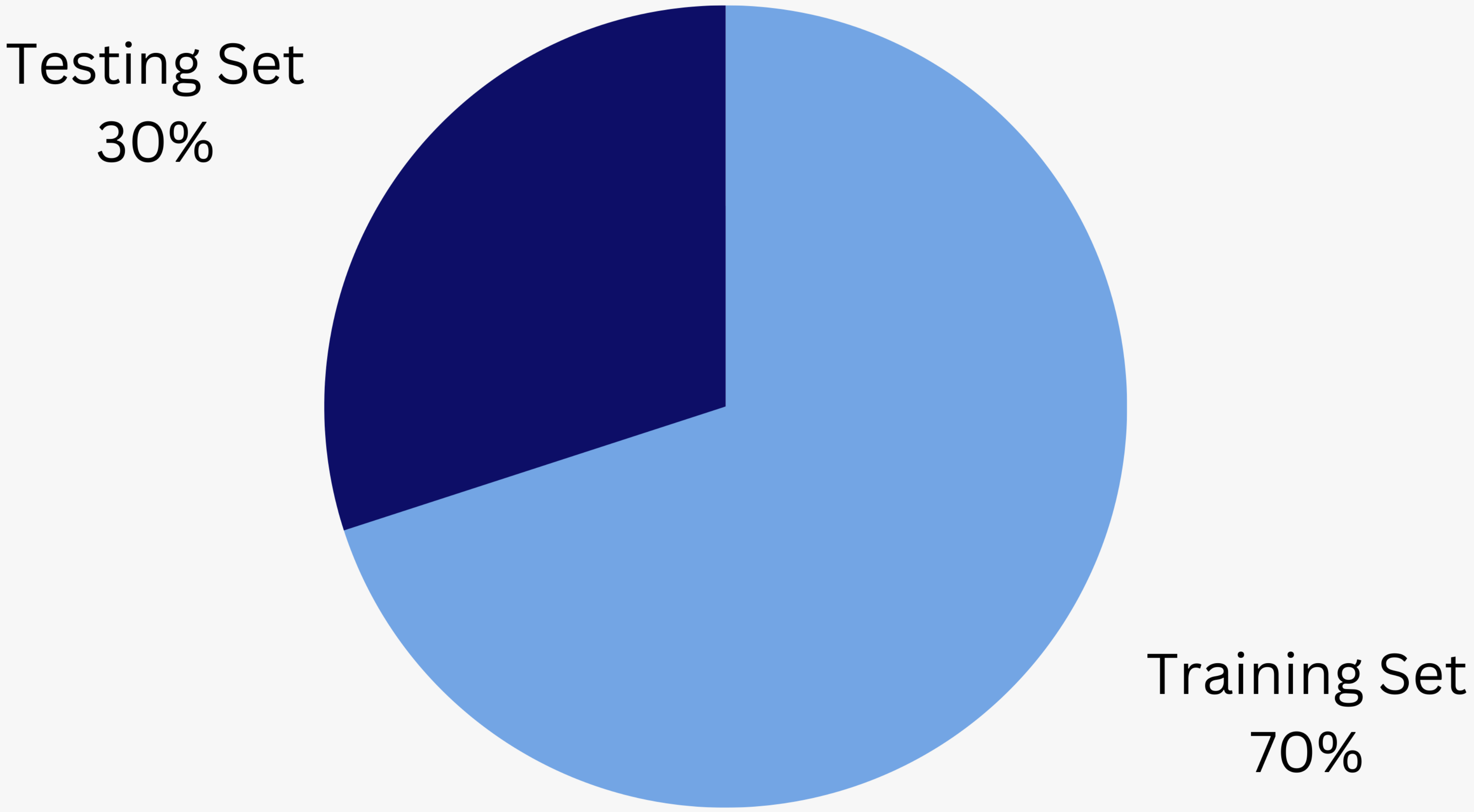
Fusion of T1c & T2w

Dataflow: Data Split

In total, there are
1133 patients

70% 30%

758 375



Research Results

Quantitative and Qualitative Results

06

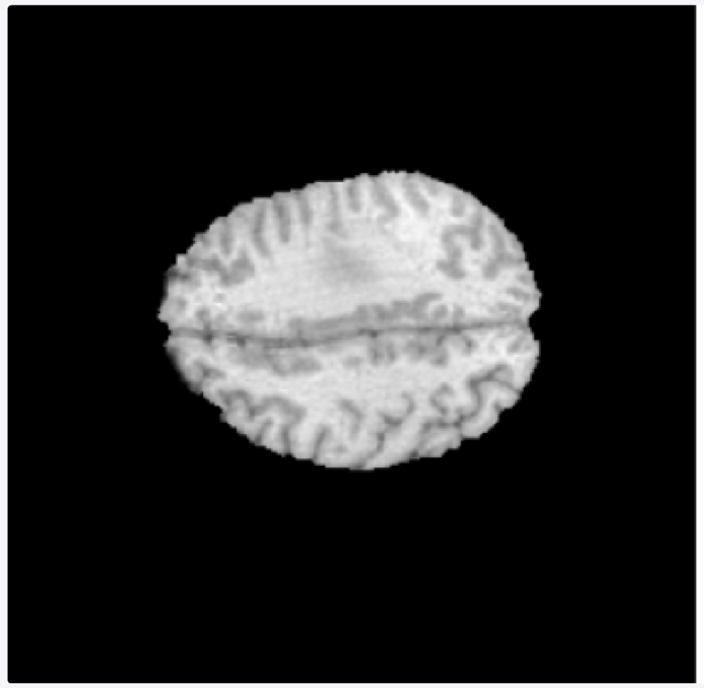
Performance of SAM: (Quantitative Results)

	Epoch	Dice Score	Jacard Index	Specificity	Sensitivity
Normal data	1	0.737	0.614	0.993	0.840
	2	0.741	0.617	0.993	0.841
With fused data	1	0.559	0.429	0.995	0.537
	2	0.710	0.581	0.992	0.794

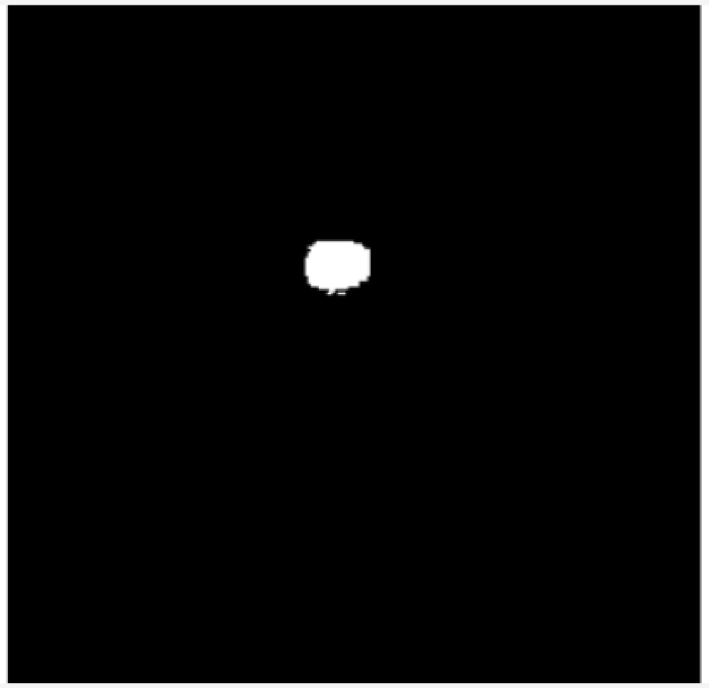
Best Results!

Performance of SAM: (Qualitative Results)

Original Image

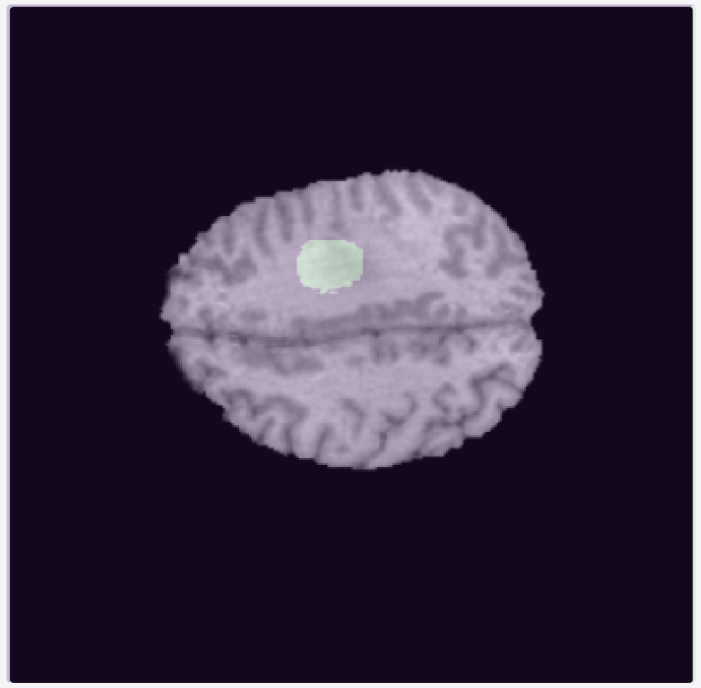


Ground Truth



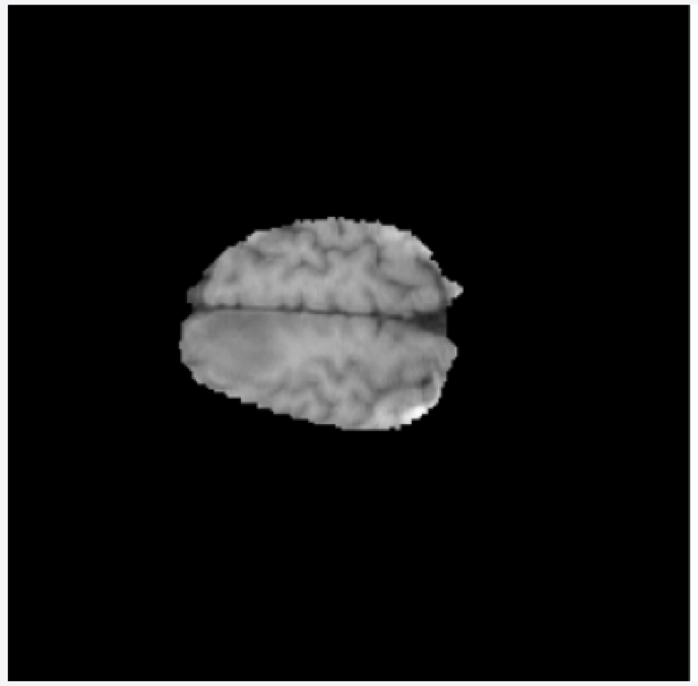
Predicted

Predicted



```
Dice Score : 0.8089330024813896
Jaccard Index : 0.6791666666666667
SSIM : 0.9998710879085113
Specificity : 0.9990478823059676
Sensitivty : 0.7799043062200957
raTS-GLI-01202-000\t1n\Slice_dim2_108.png
```

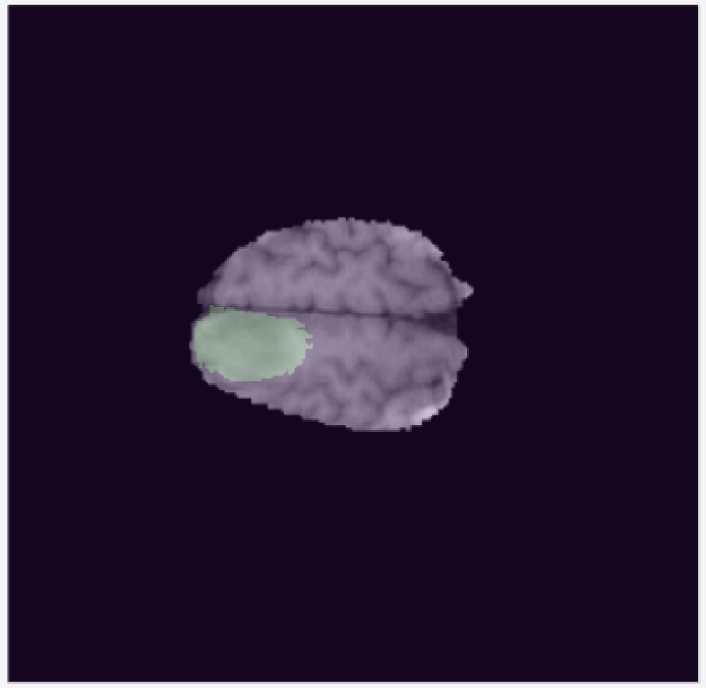
Original Image



Ground Truth

Predicted

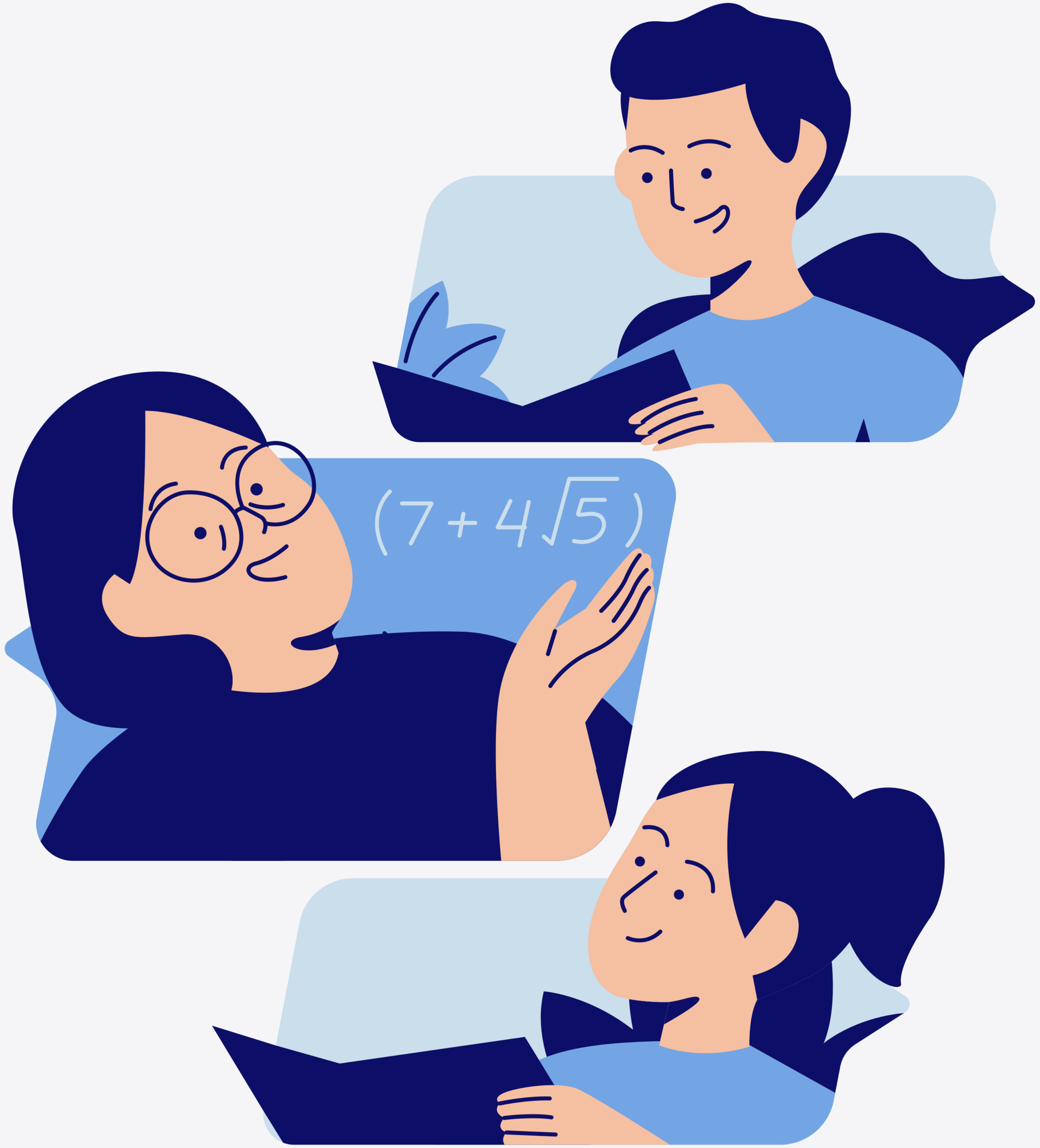
Predicted



```
Dice Score : 0.9225806451612903
Jaccard Index : 0.8562874251497006
SSIM : 0.9999066187832748
Specificity : 0.9993031790520138
Sensitivty : 0.896551724137931
raTS-GLI-01176-000\t1n\Slice_dim2_124.pn
```

Conclusion & Perspectives

07



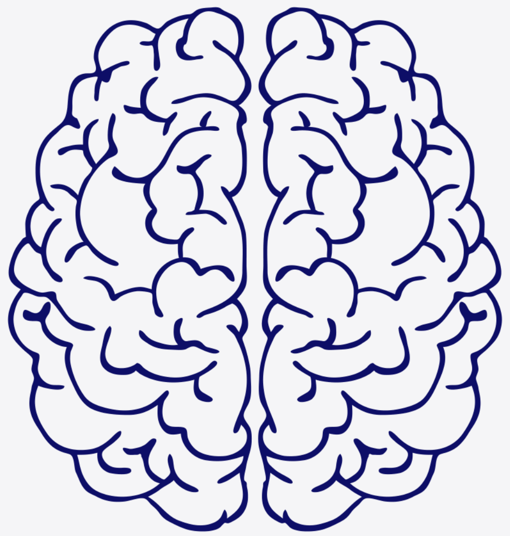
Conclusion:

SAM demonstrated remarkable capabilities **in accurately segmenting brain** tumours, supported by strong quantitative metrics and qualitative visualizations.

Sam is an **efficient, and reliable approach** for segmenting brain tumours, and it would make a great computer-aided diagnosis (CAD) tool.

Future Endeavors:

Investigation into hybrid model approaches



Incorporating a broader range of modalities like CT-Scans

Thank you
for listening!