



# **AUTO-SEGMENTATION OF BRAIN TUMOUR IN MRI**

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MINOR PROJECT  
EC788

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# OVERVIEW

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- Introduction
- Problem Statement
- Objective
- Dataset Analysis
- U-Net
- Methodology
- Results



# INTRODUCTION

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- 5-year relative survival rate for a cancerous brain tumour is almost 36%
- Types of tumours
  - Primary and Secondary (metastatic) tumours
  - Malignant (cancerous) and benign (non-cancerous) tumour
- Severity of symptoms depends on size and position of tumour
- Imaging techniques - MRI, CT Scan, etc





# ***INTRODUCTION***

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## ***WHY AUTO SEGMENTATION?***

- Early and accurate detection is crucial in treatment planning
- Time efficient
- Enhanced precision
- Ability to Process Large Volumes of Data
- Reduced inter observer variability

# ***PROBLEM STATEMENT***

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Manual segmentation of brain tumours presents significant challenges, including inter-observer variability, time inefficiency, susceptibility to human error, limited scalability, and difficulties in handling heterogeneous or big datasets

# OBJECTIVE

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“To build deep learning model for auto segmentation of brain  
tumour in MRI ”





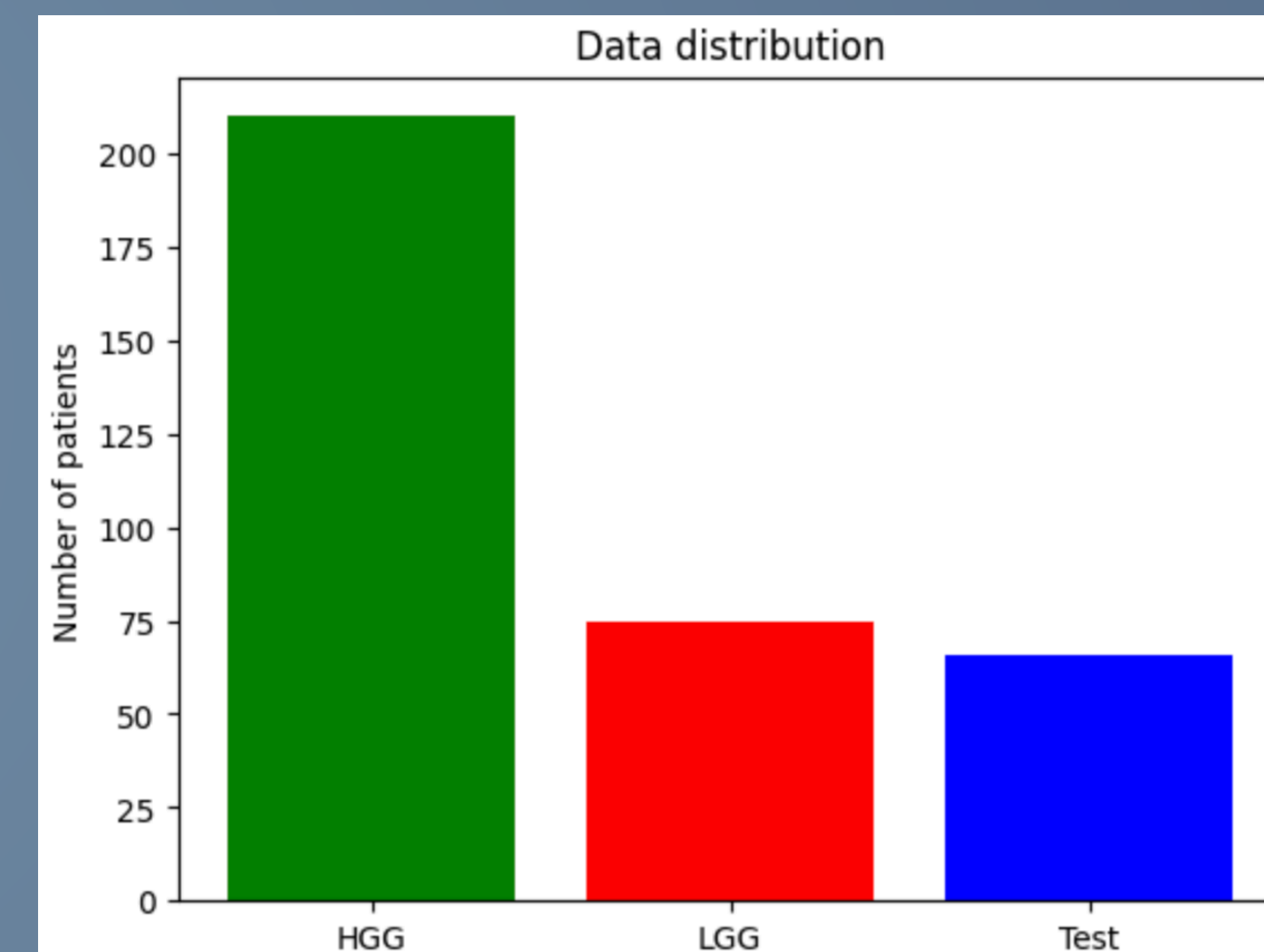
# ***DATASET ANALYSIS***

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## ***MICCAI BRATS 2018***

- Benchmark dataset for BT detection algorithms assessment
- Data for two grades of glioma
  - HGG: High-Grade Glioma
  - LGG: Low-Grade Glioma
- Training data size- 210 HGG, 75 LGG    Testing data size- 67
- Survival data (Age, Survival, ResectionStatus)

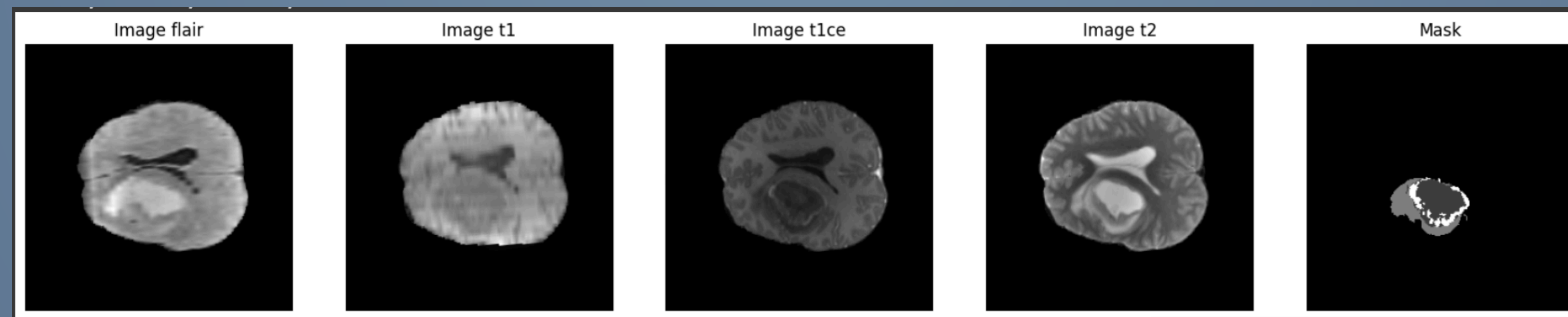
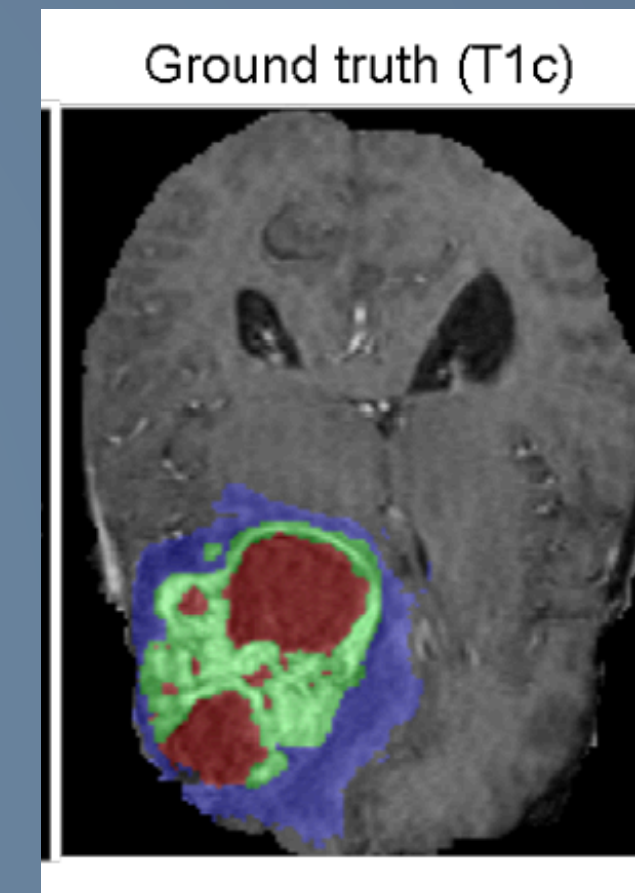


# ***DATASET ANALYSIS***

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- 4 modalities ( T1-weighted, T2-weighted, FLAIR, T1-weighted with contrast )
- Volumetric data - 240 x 240 x 155
- Nifty images



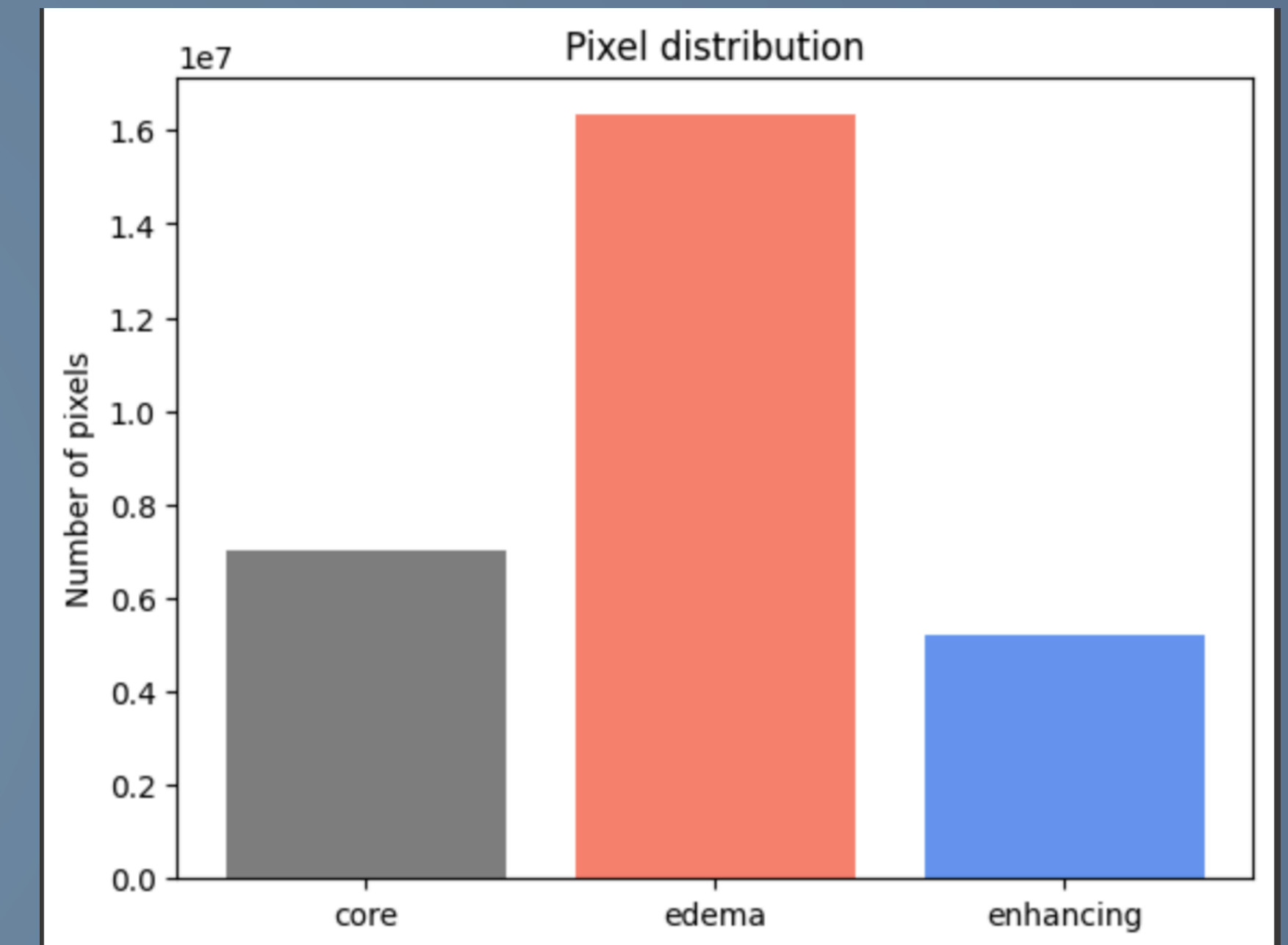
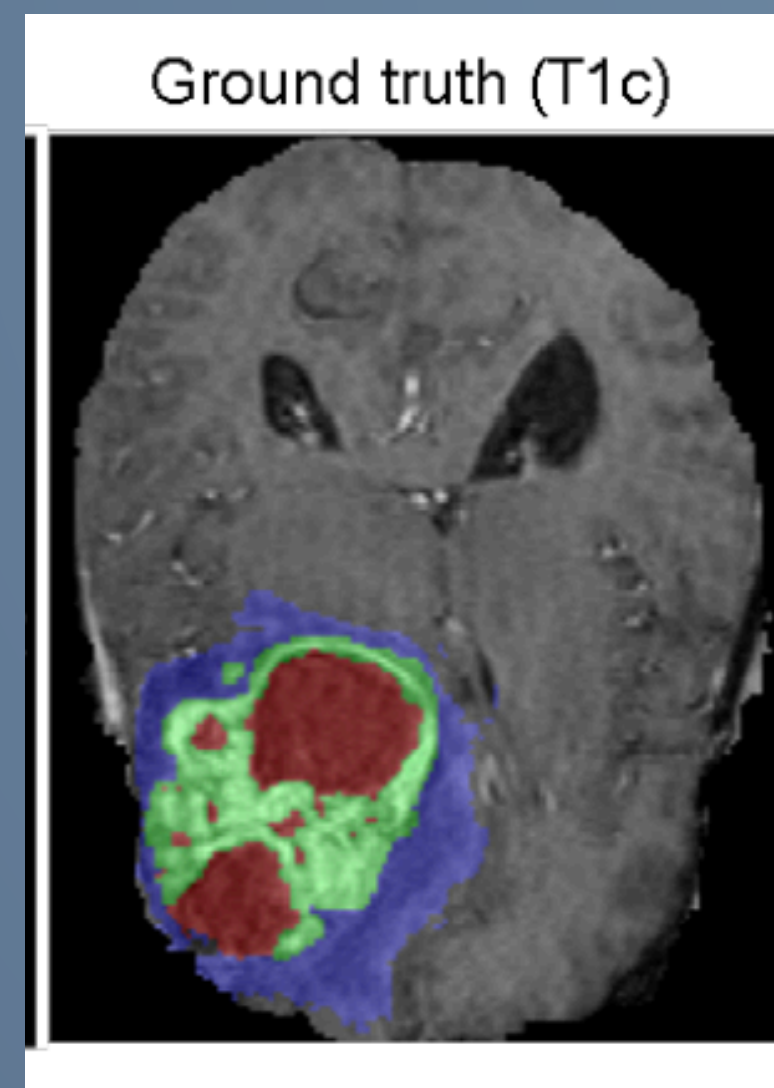
Sample images from dataset



# ***DATASET ANALYSIS***



- Different tumours as different labels
  - Edema - blue (class label 2)
  - Enhancing tumour - green (class label 4)
  - Non enhancing & necrotic tumour - red (class label 1)



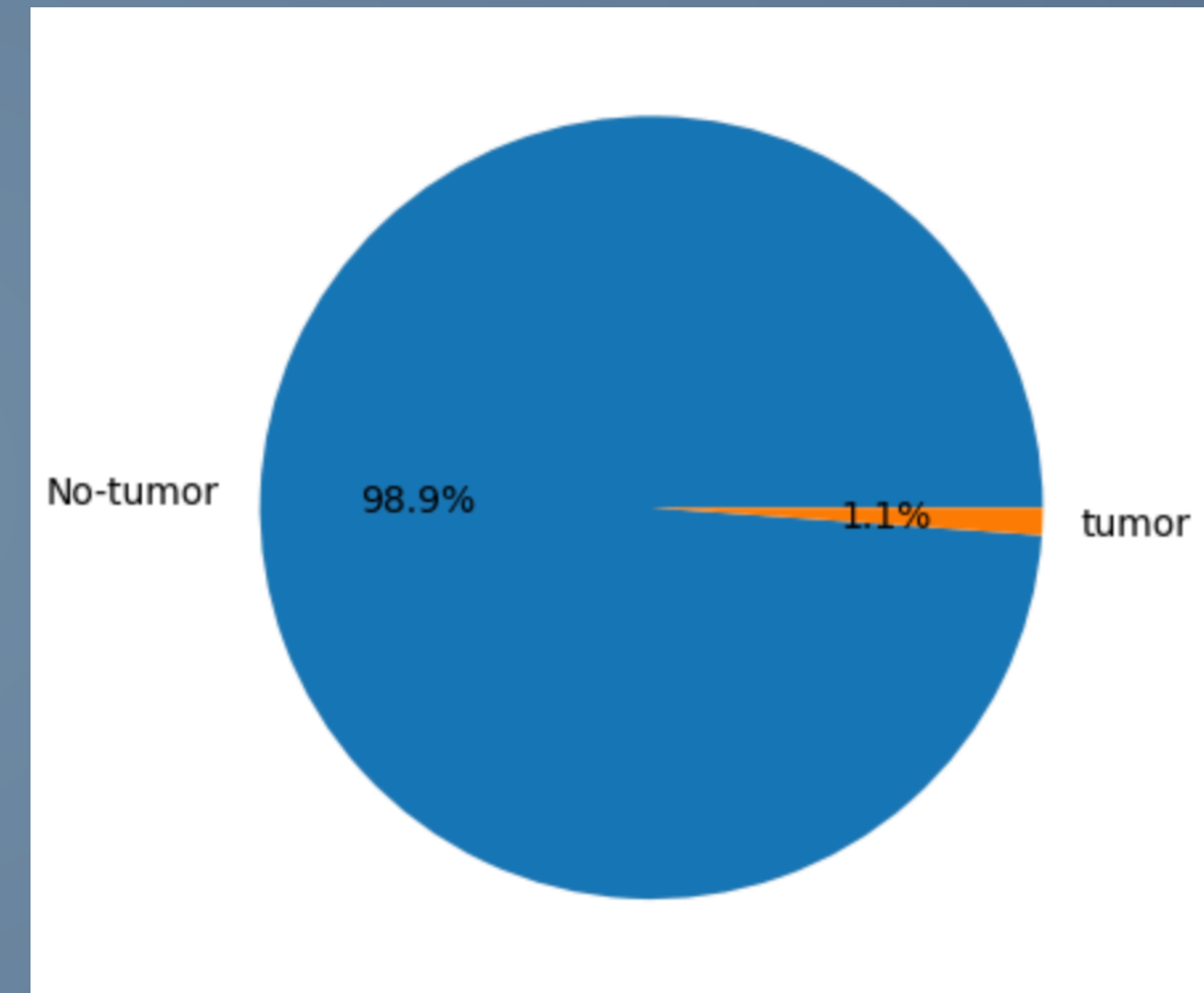
Pixels with 3 different type of tumour region

# ***DATASET ANALYSIS***

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Slices with foreground data vs no foreground data

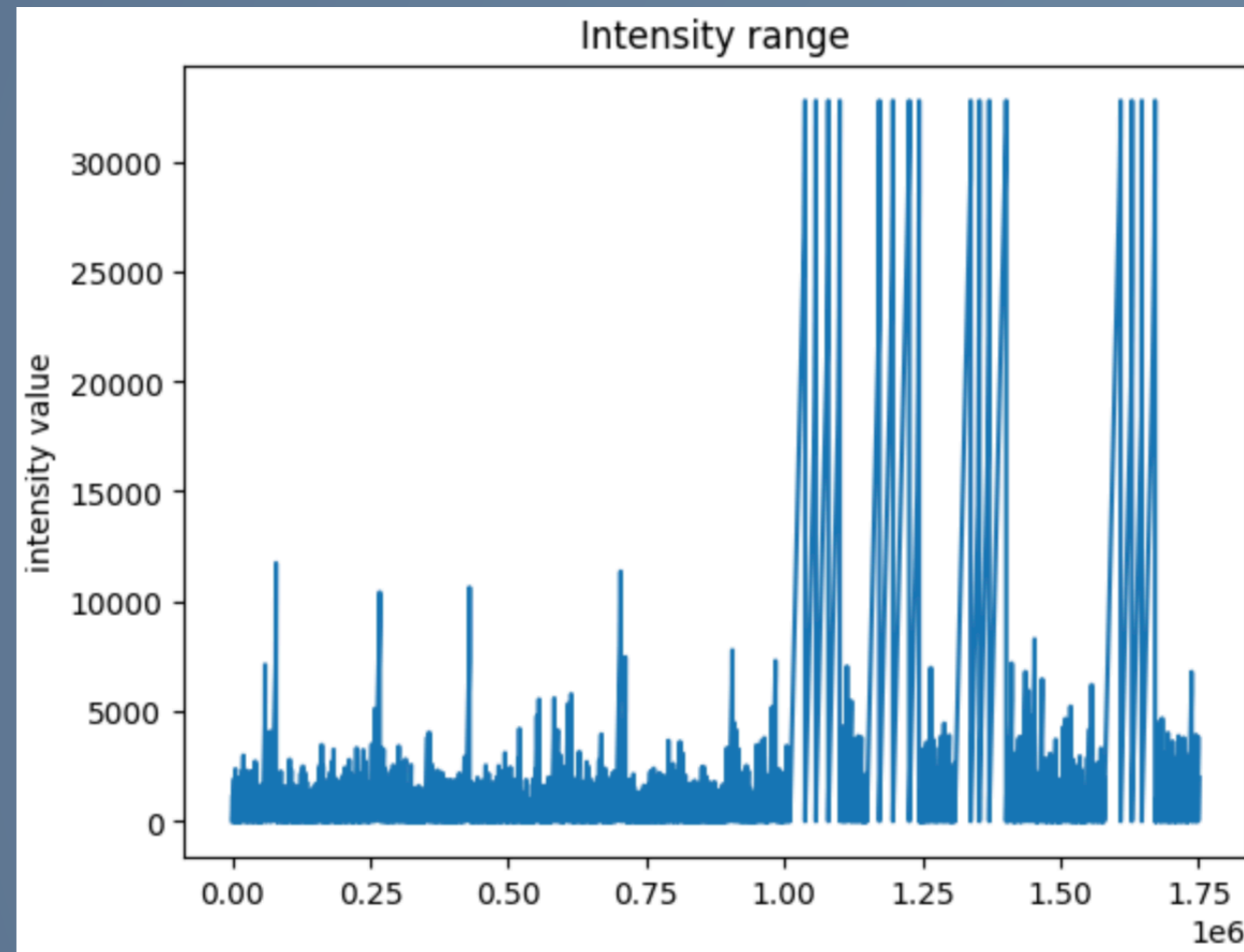


Tumour pixels vs non tumour pixels

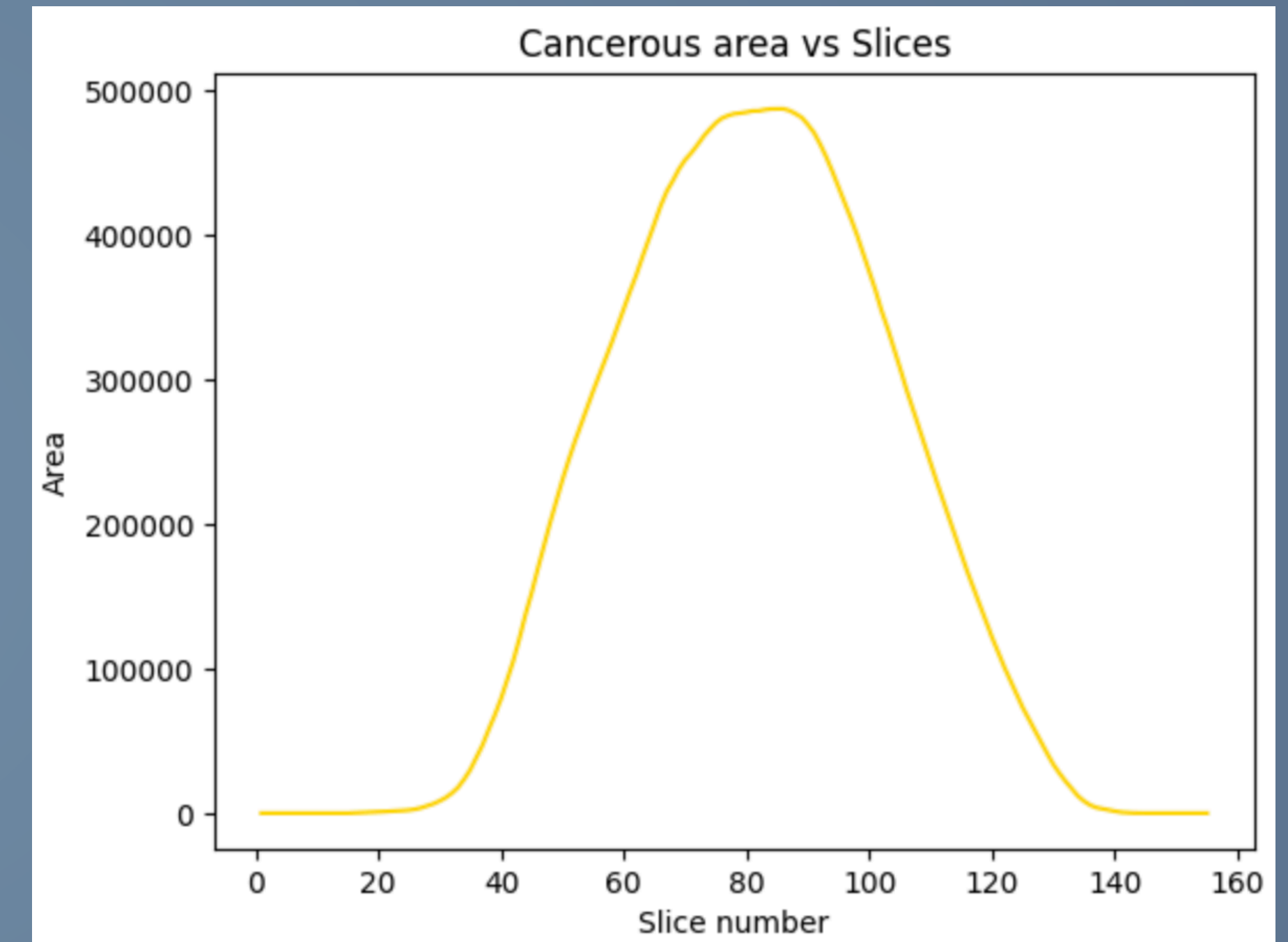


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Intensity range of input

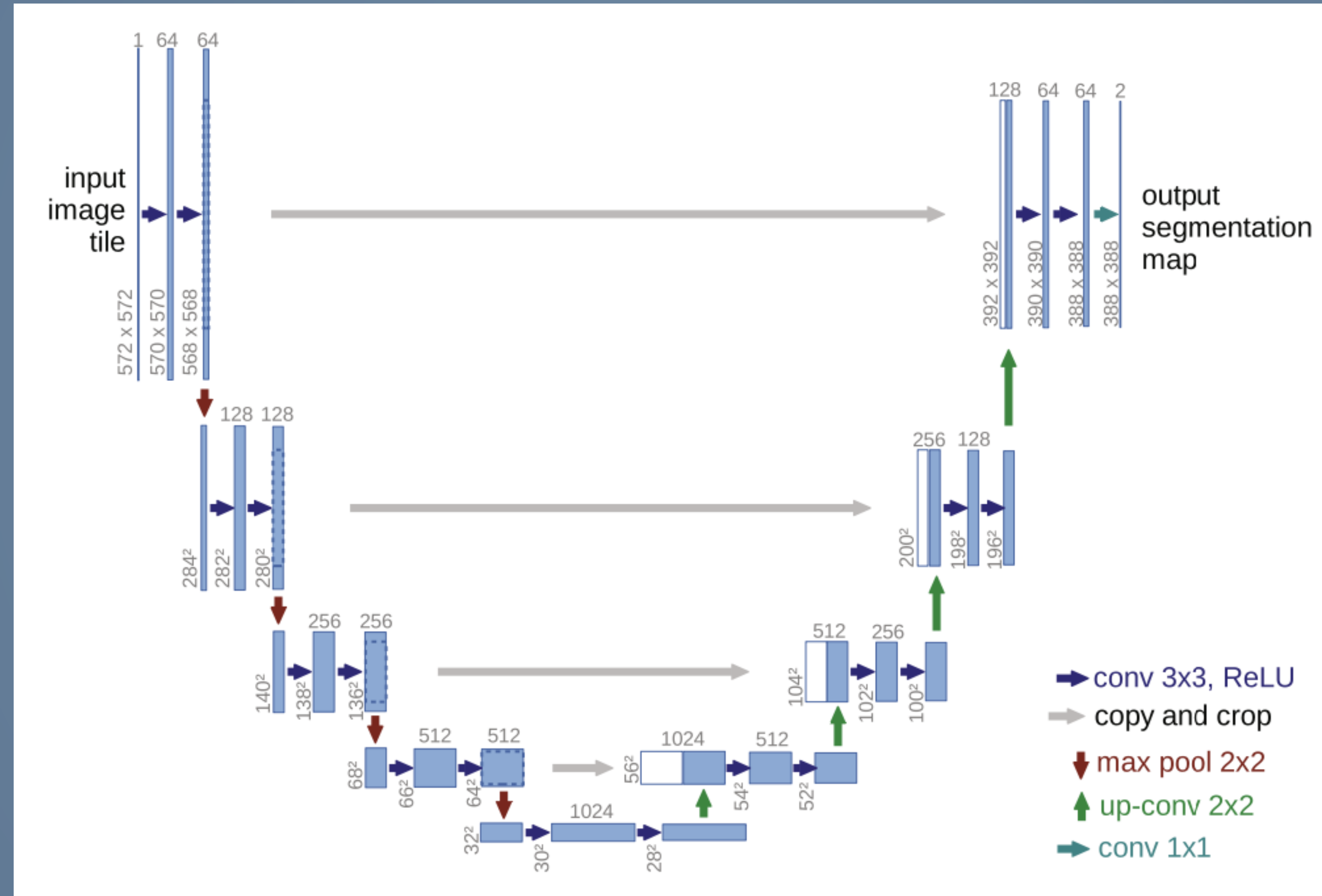


Slice number and cancerous tumour pixels

- Max value = 32767
- Min value = 0

# U-NET

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U-Net architecture





- **Data preparation**

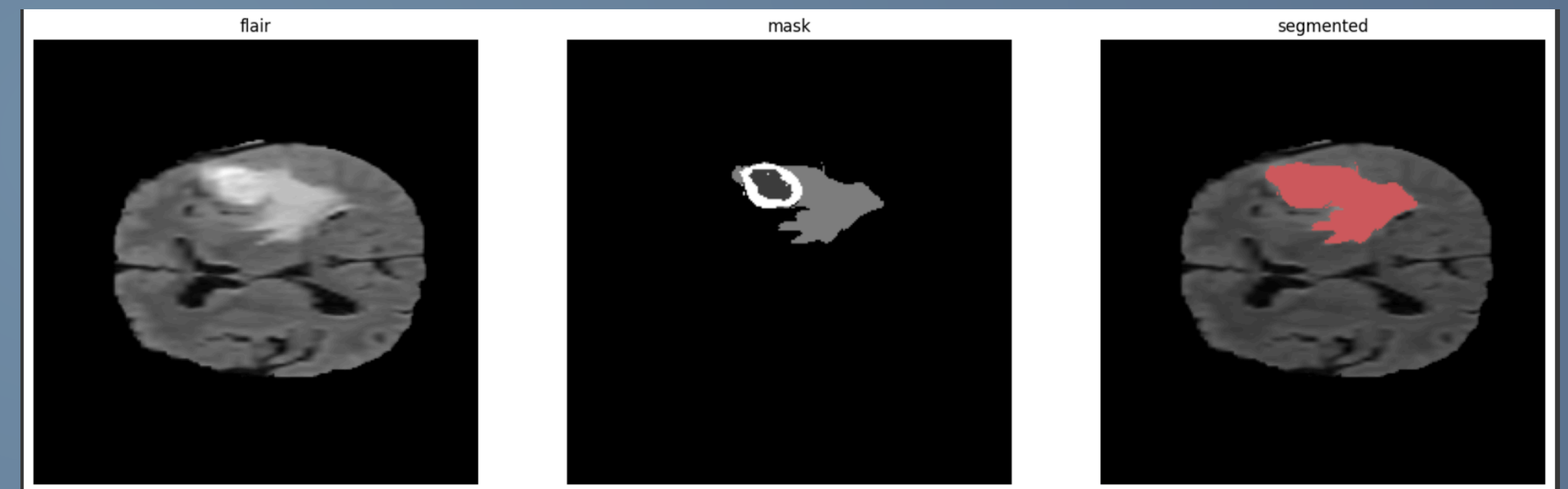
- ▶ Reduced dataset- 60 patients data is used
- ▶ 1 modal from each patient at random
- ▶ Resized input to 128x128x146 (cv2.resize function and thresholding with 0.4)
- ▶ Intensity values normalised to 0 to 255
- ▶ Mask is converted to binary mask- one hot encoding
- ▶ Slices without foreground data is removed to avoid overfitting

# METHODOLOGY

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- **Model training and Evaluation**
  - 3373 slices - Training & Validation (20%)
  - 375 slices - Testing
  - Binary cross entropy loss function
  - Adam Optimizer
  - Learning rate= 0.0001
  - 50 epochs
  - Evaluation metric- BinaryIoU



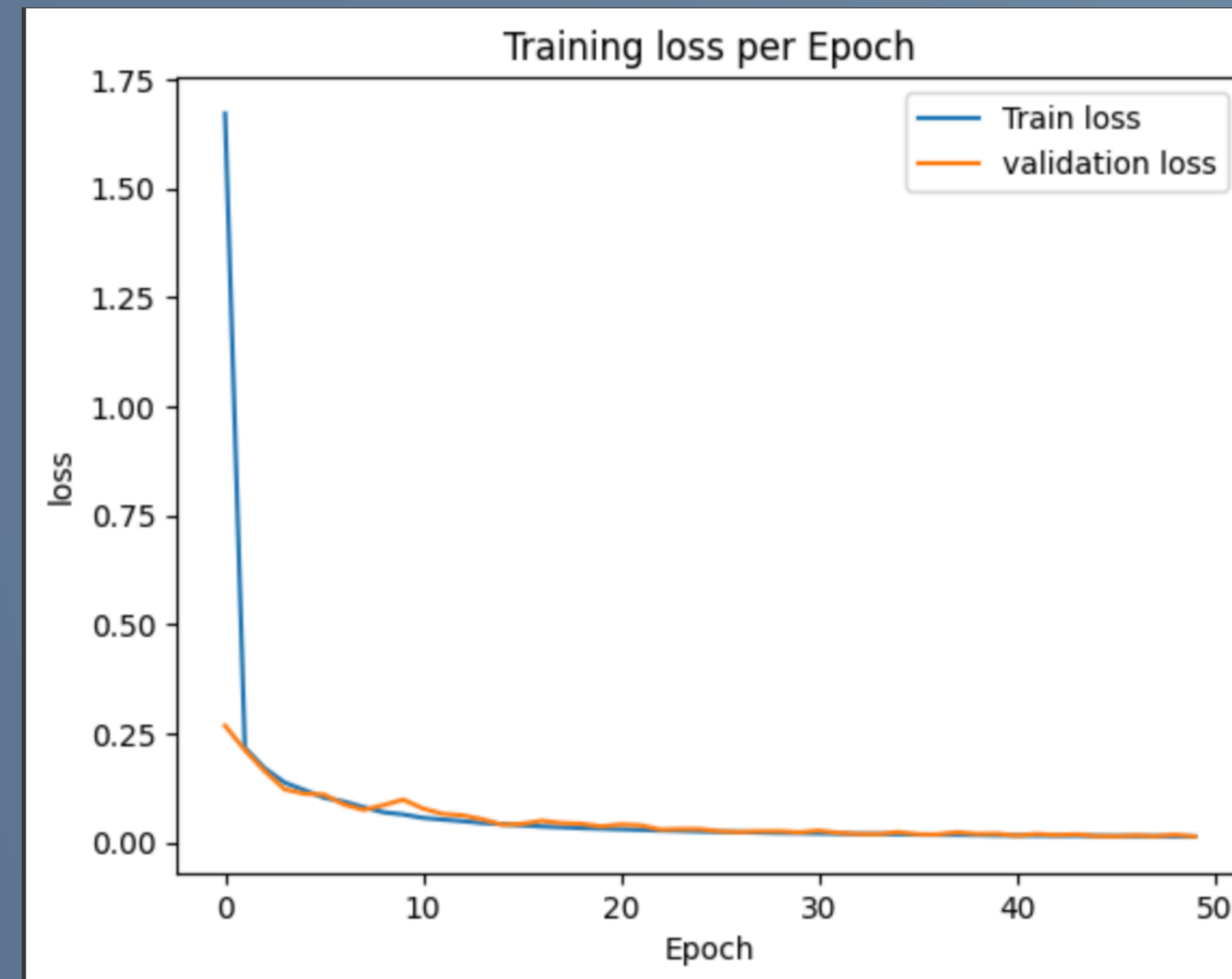
Input, mask and super imposed image after binary segmentation



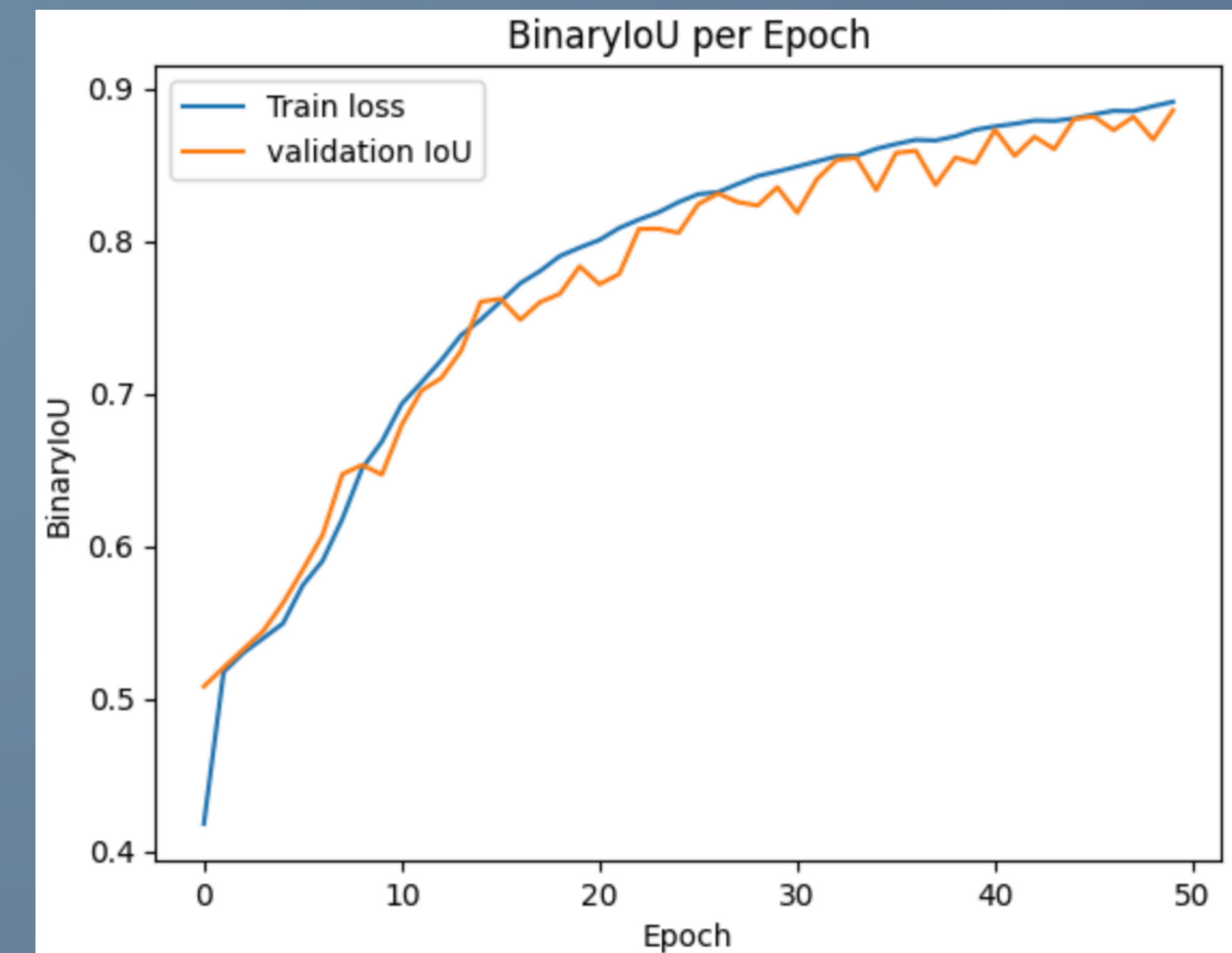
# RESULTS



- Trained BinaryIoU of 0.8913 and validation IoU of 0.8858
- Testing loss of 0.3669 and BinaryIoU of 0.4886



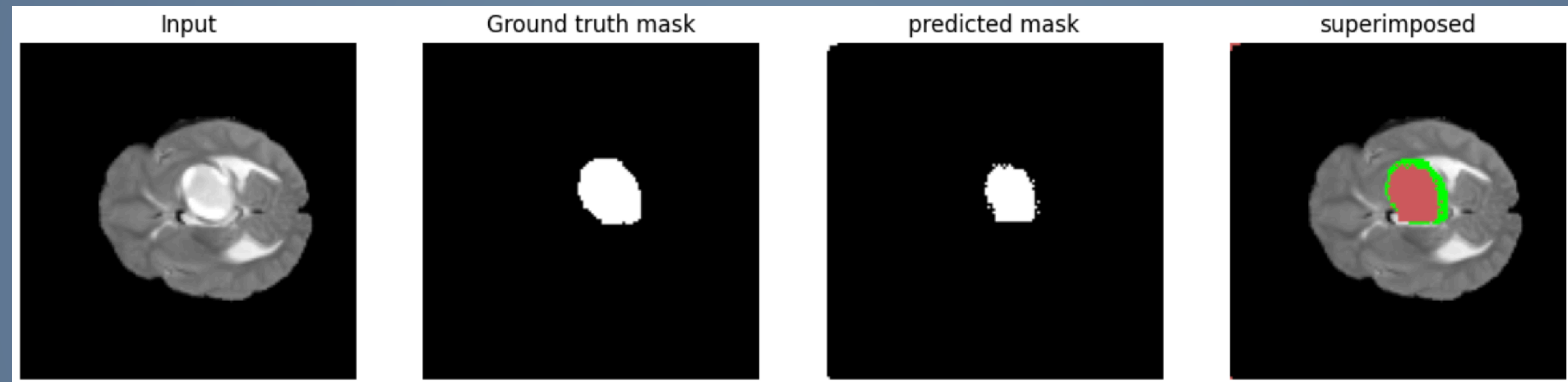
Binary cross entropy in training



BinaryIoU in training

# RESULTS

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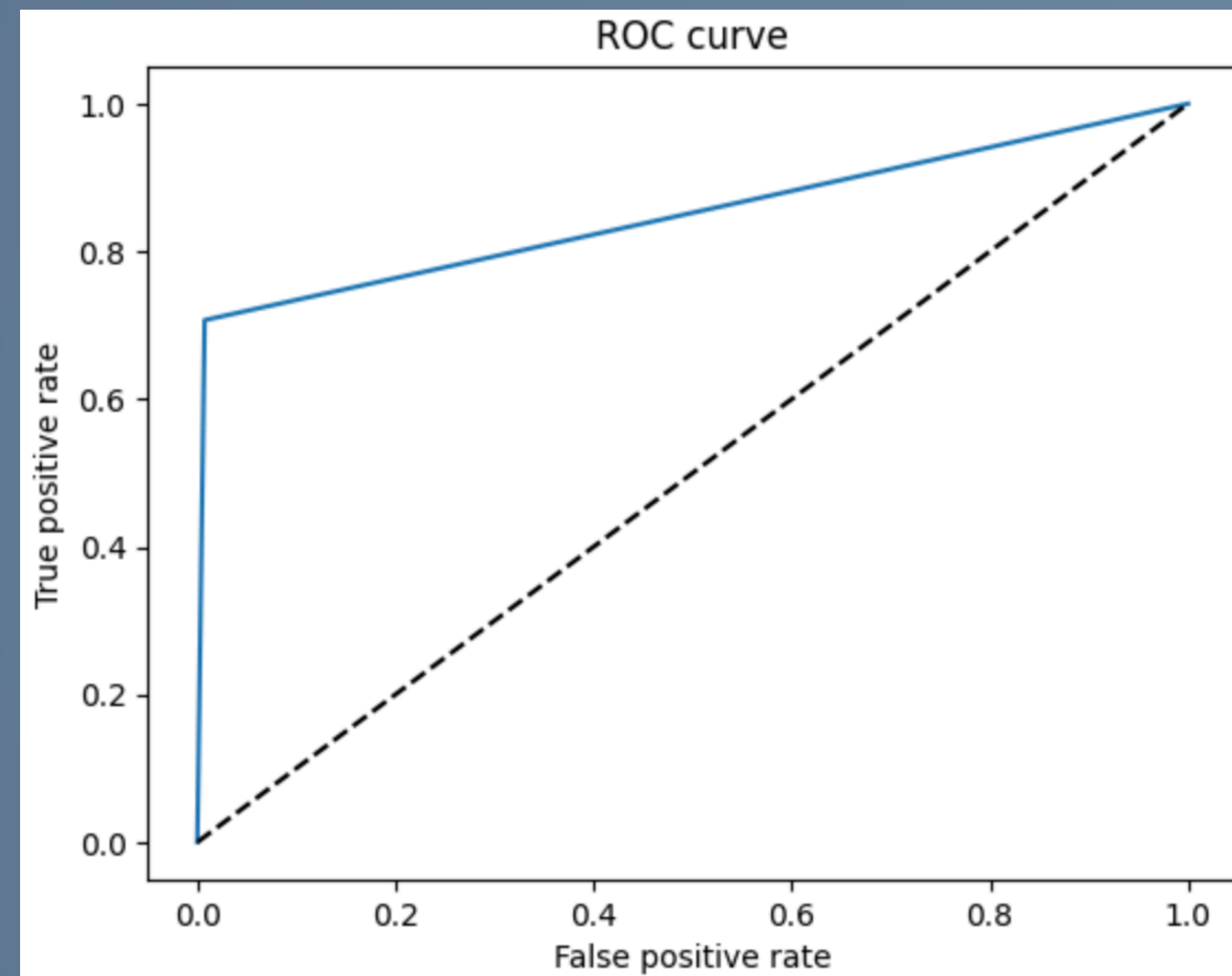


Prediction results

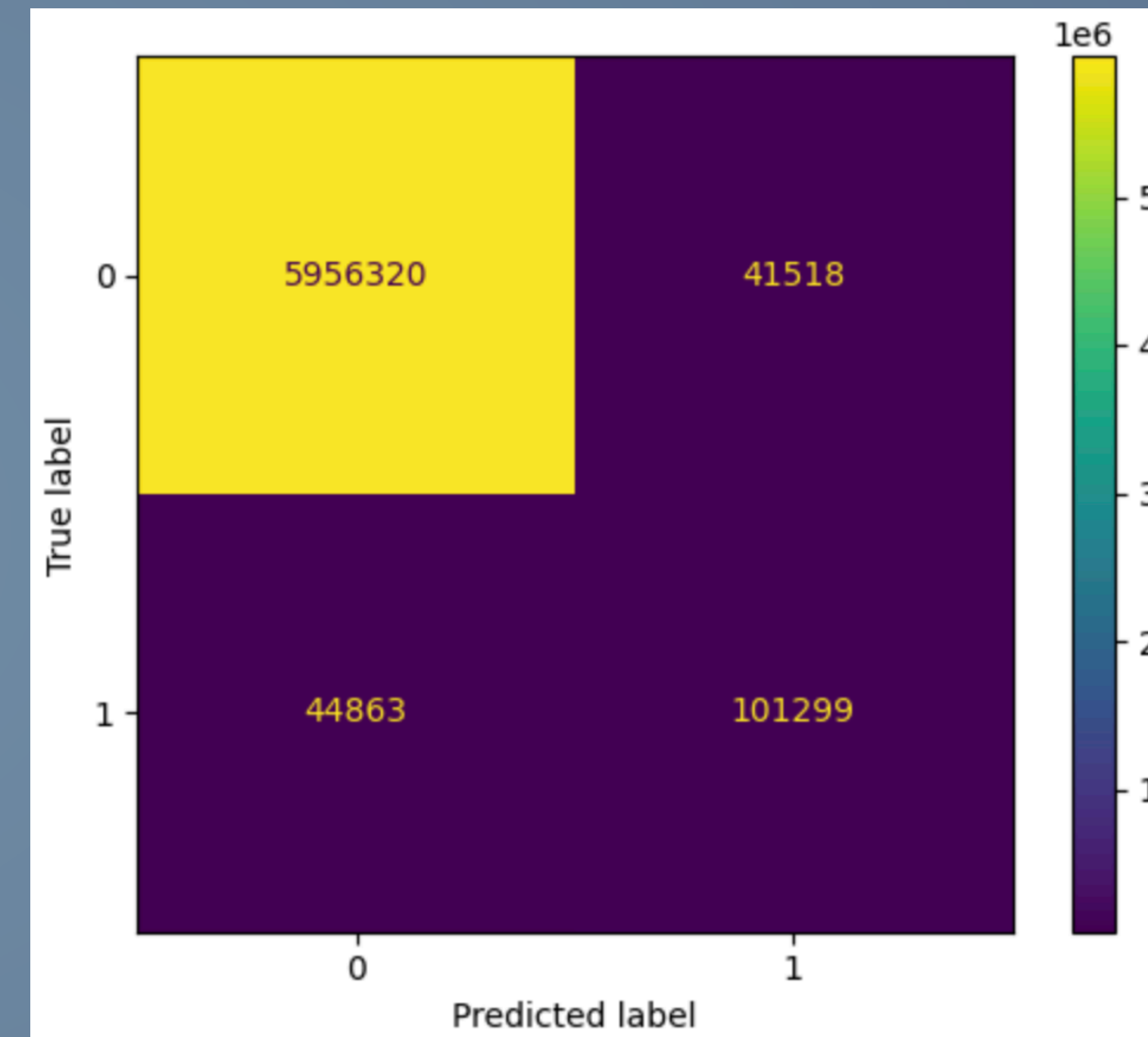


# RESULTS

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ROC curve



Confusion matrix

# RESULTS



METRIC	SCORE
ACCURACY	0.9859
PRECISION	0.7092
RECALL (SENSITIVITY, TPR)	0.693
SPECIFICITY	0.993
F1 SCORE	0.7009



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**THANK YOU!**