XRAI PIPELINE – THE CREATION OF A CONDITIONALLY ADAPTIVE LOSS FUNCTION FOR MEDICAL SEGMENTATION TASKS

GROUP-1

Masa Cirkovic

Bashir Alam

Md Kaf Shahrier

Mete Harun Akcay

AGENDA

01 Problem Statement

02 Our approach

03 Pipelines

04 Results

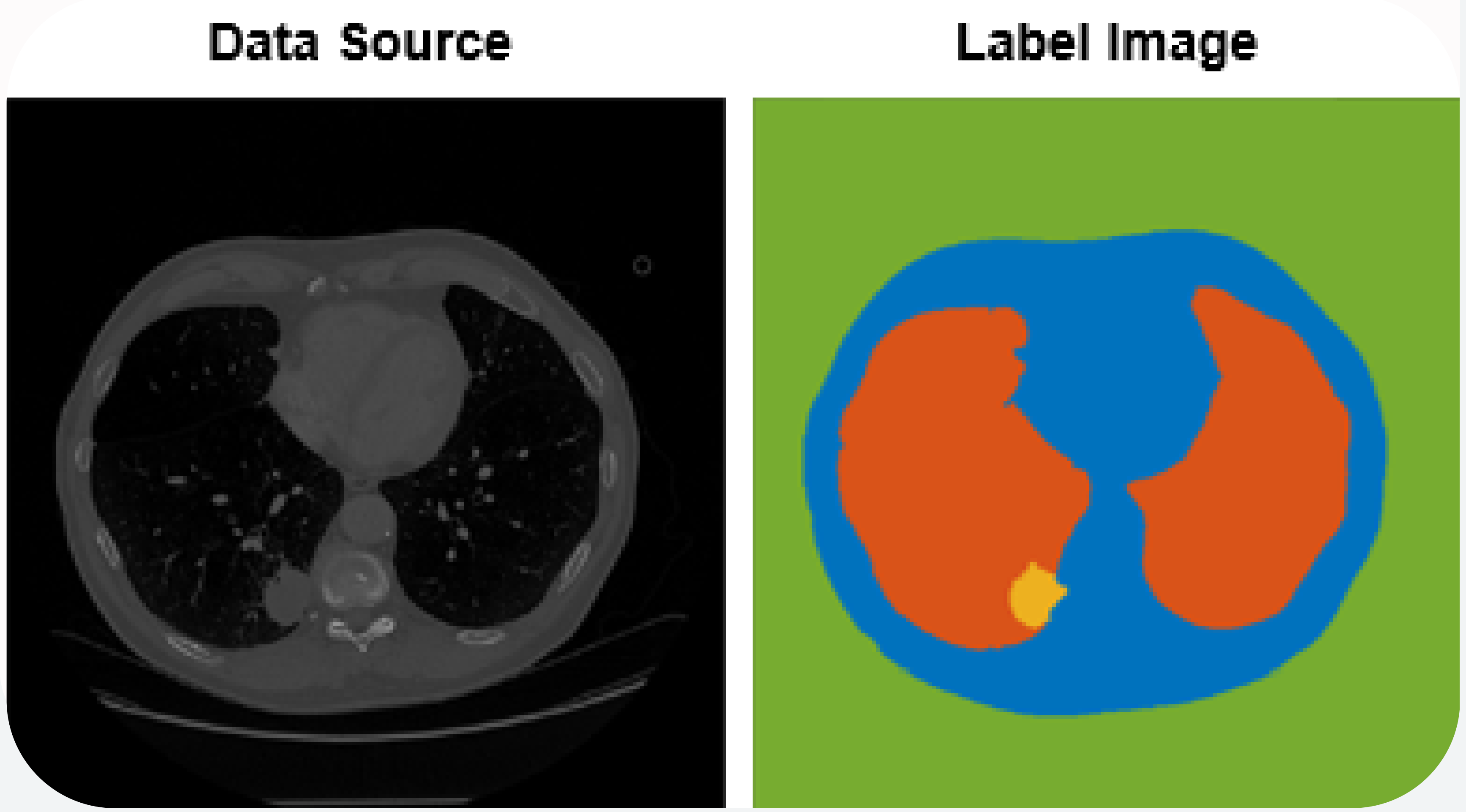
05 Next tasks

06 Conclusion

PROBLEM STATEMENT

AI ENROLLMENT IN MEDICAL DOMAIN

MEDICAL SEGMENTATION

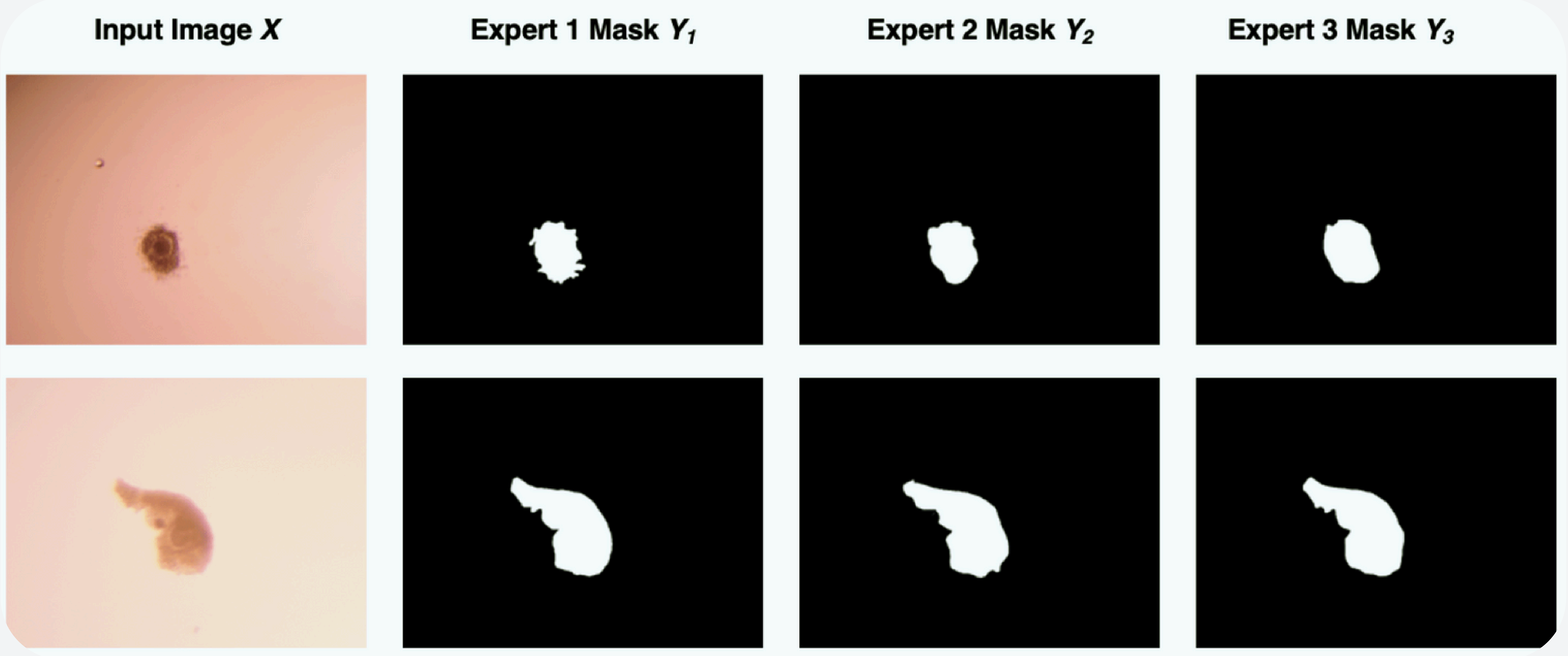


CHALLENGES OF MEDICAL SEGMENTATION

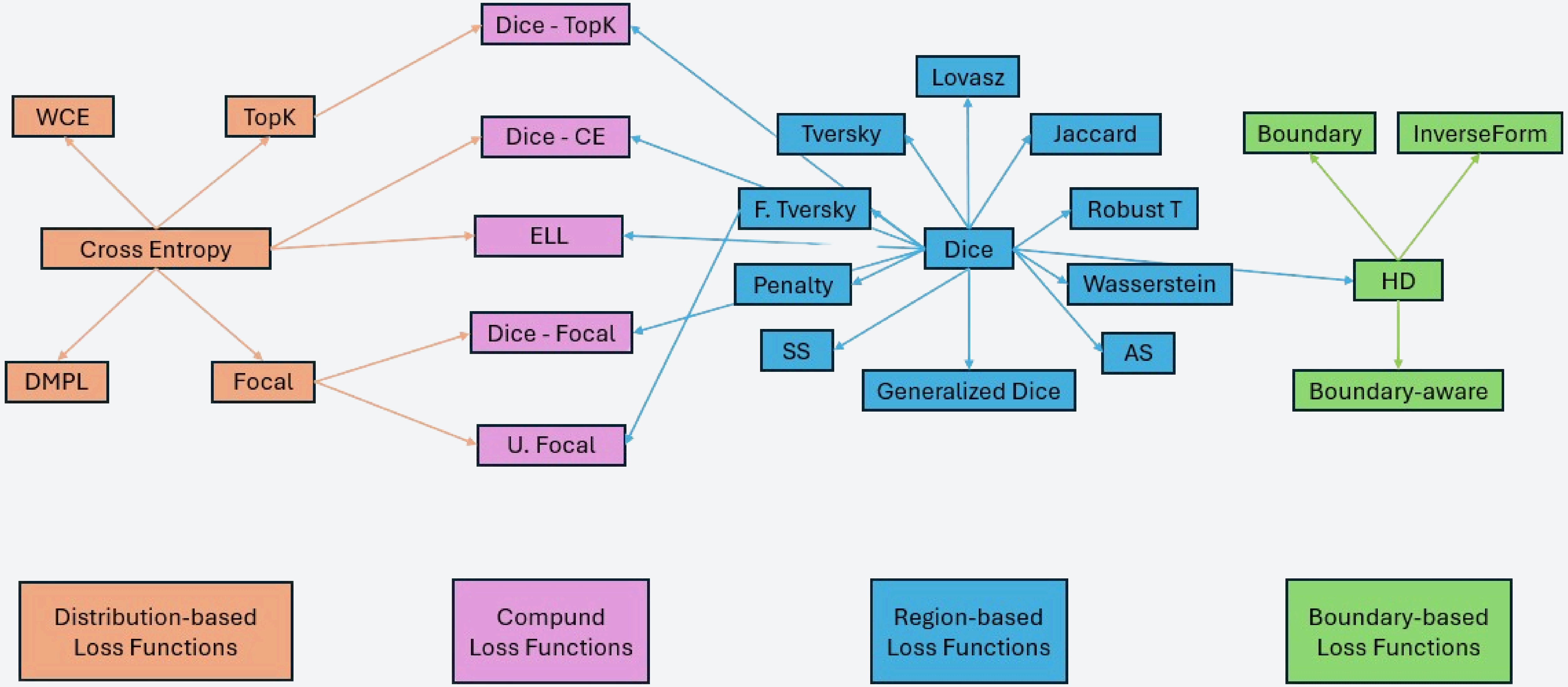
MANUAL SEGMENTATION → TIME CONSUMING

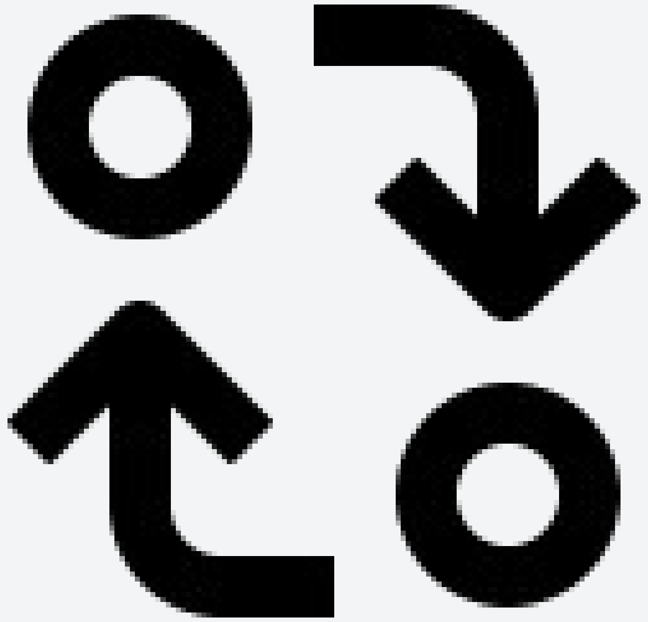
TRAINING DATA → SCARCE, IMBALANCED

ANNOTATIONS → RUSHED, INACCURATE



STATE-OF-THE-ART ~ LOSS FUNCTIONS

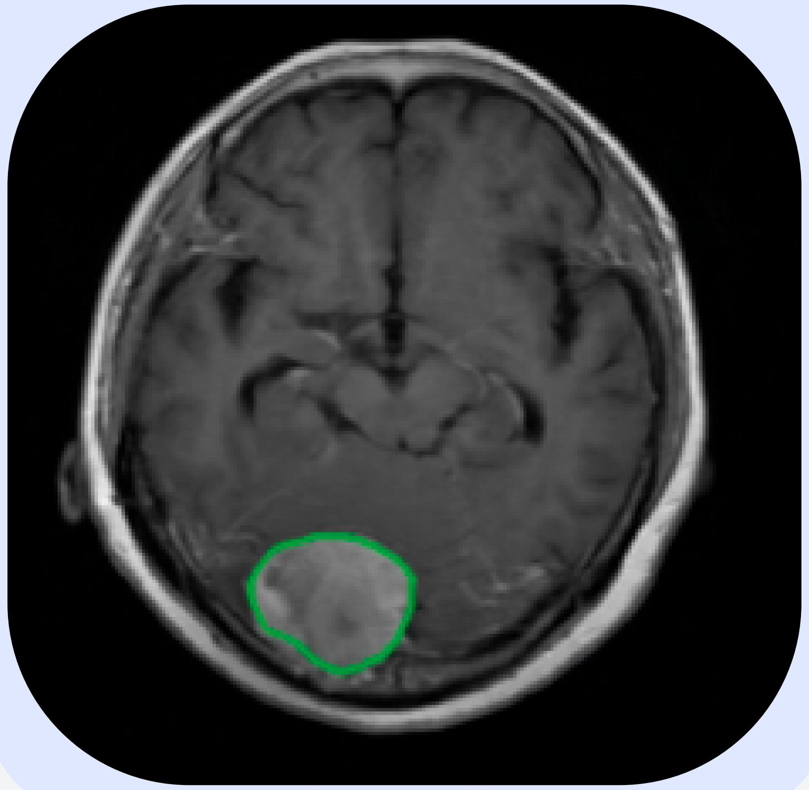




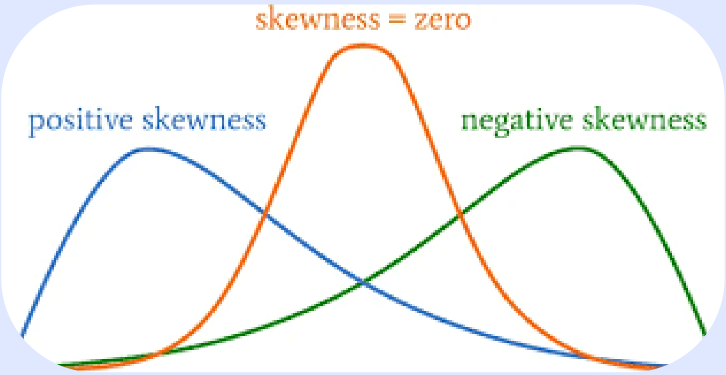
- HANDLING **CLASS IMBALANCE**
- IMPROVING **BOUNDARY PRECISION**
- CAPTURING **SMALL STRUCTURES**
- MINIMIZING **FALSE NEGATIVES**
- MINIMIZING **FALSE POSITIVES**
- HANDLING **MULTI-CLASS DATA**

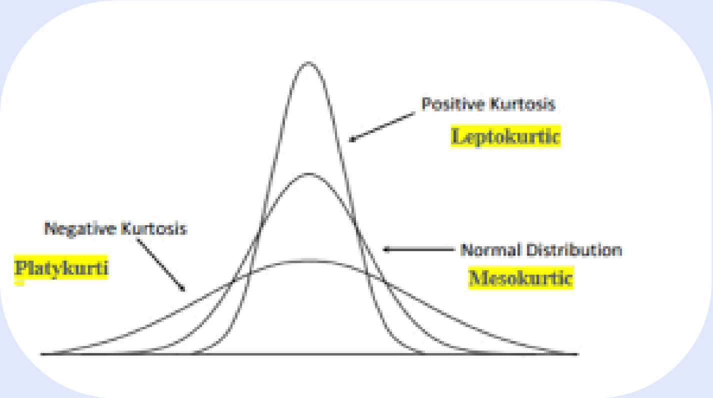
OUR UNIQUE ADAPTIVE LOSS FUNCTIONS

Calculate Foreground and Background

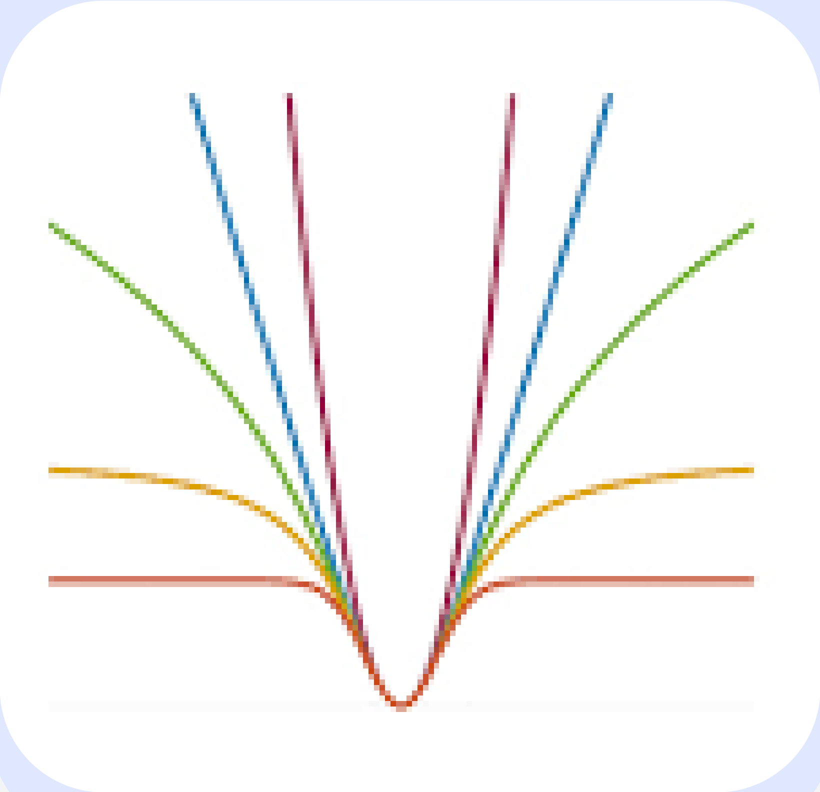


Calculate Statistical Properties





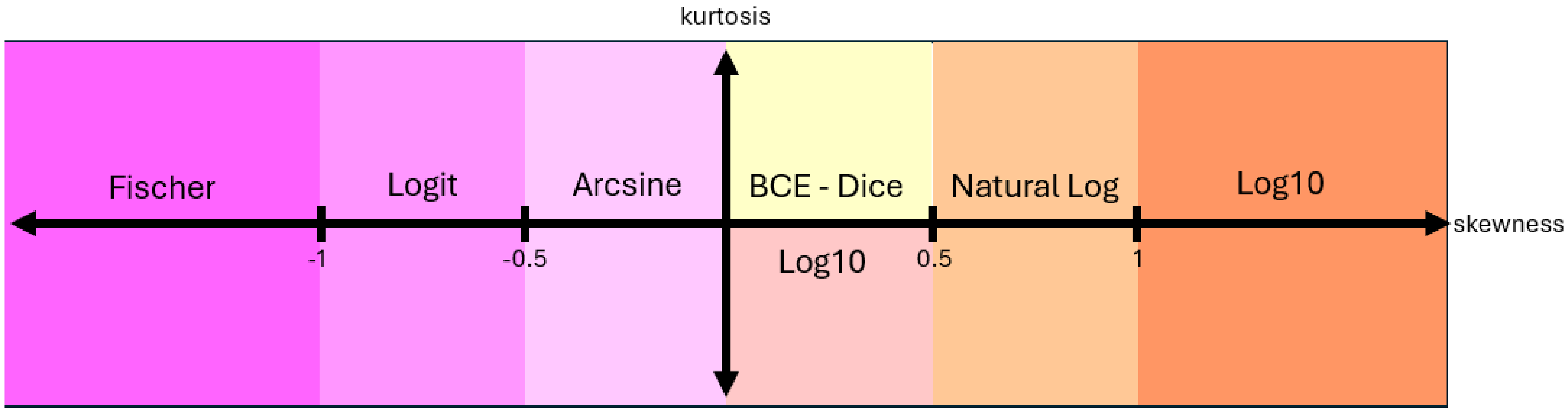
Adaptive Loss Function Based on Distribution

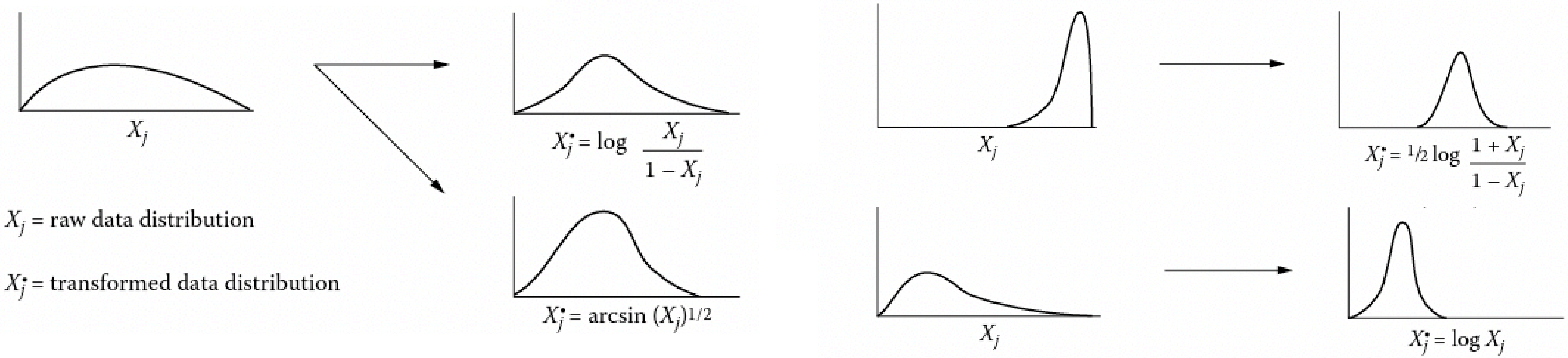


Adaptive Distribution Loss Function

Region-based Adaptive Loss Function

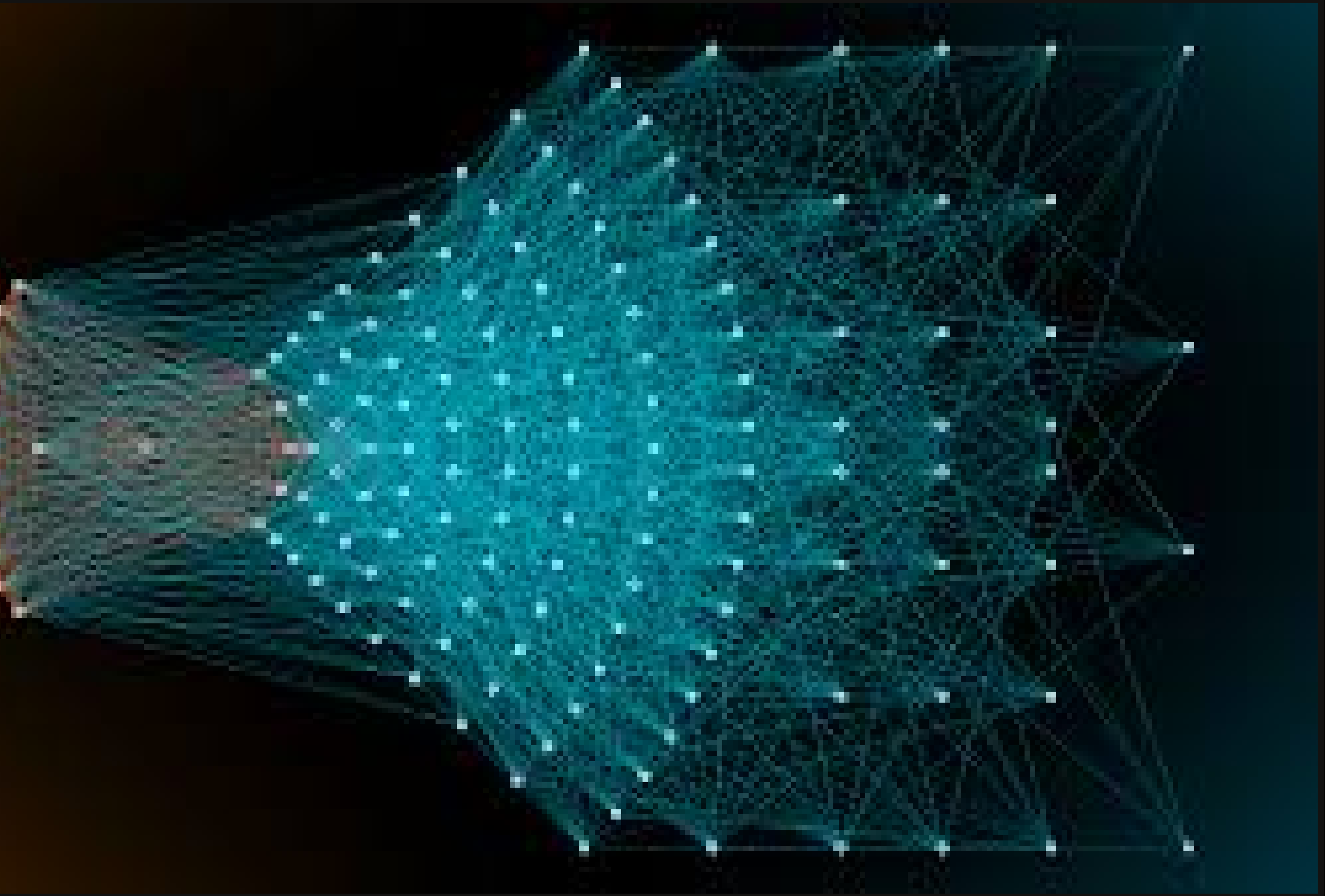
OUR UNIQUE ADAPTIVE LOSS FUNCTIONS





MAIN OBJECTIVE

*“**Test our unique adaptive loss function** on different **deep learning models** with the most popular **loss functions** on various **datasets**”*



COMPONENTS OF WORK FLOW

- Datasets
- Loss functions
- Models
- Training pipeline

DATA REPORT

DATASETS (TCIA)	4 (3 PUBLIC AND 1 PRIVATE)
PATIENTS	1410
MEDICAL IMAGE FORMATS	2 TYPES
MRI SCANS	3 TYPES
IMAGING PLANES	3 TYPES
SEGMENTATION	BINARY OR GRAYSCALE
CANCER TYPES	4 TYPES

DATA REPORT

MEDICAL IMAGE FORMATS

- **DICOM** (DIGITAL IMAGING AND COMMUNICATIONS IN MEDICINE)
- **NIFTI** (NEUROIMAGING INFORMATICS TECHNOLOGY INITIATIVE)
- **NRRD** (NEARLY RAW RASTER DATA)

CANCER TYPES

- GLIOBLASTOMA
- CENTRAL NERVOUS SYSTEM NEOPLASMS
- DIFFUSE GLIOMA
- LOW-GRADE GLIOMA

MRI SCAN TYPES

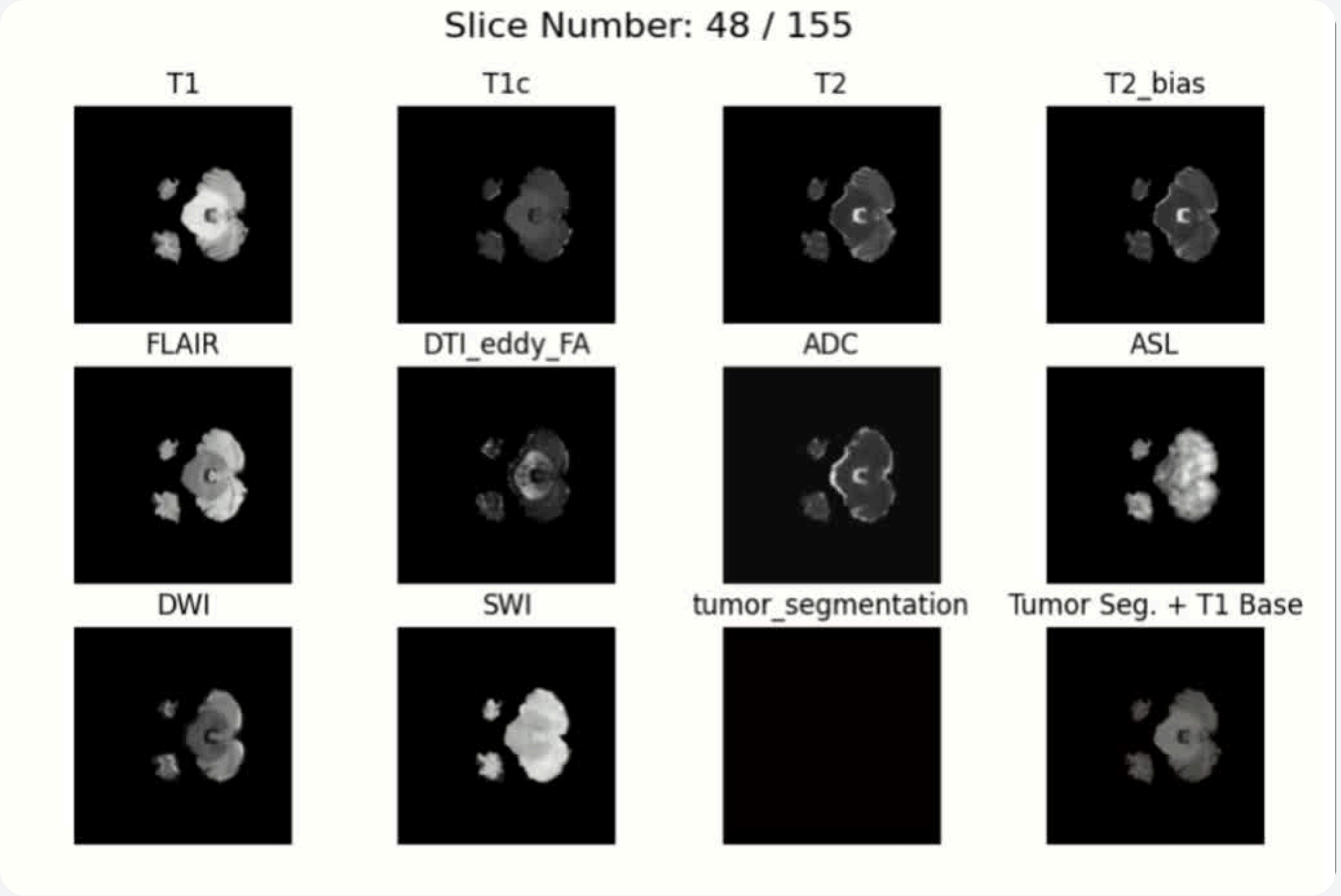
- **T1WI** (T1 AND T1-WEIGHTED IMAGING)
- **T2WI** (T2 AND T2-WEIGHTED IMAGING)
- **FLAIR** (FLUID-ATTENUATED INVERSION RECOVERY)
- **DWI** (DIFFUSION-WEIGHTED IMAGING)
- **SWI** (SUSCEPTIBILITY-WEIGHTED IMAGING)
- **ASL** (ARTERIAL SPIN LABELING)

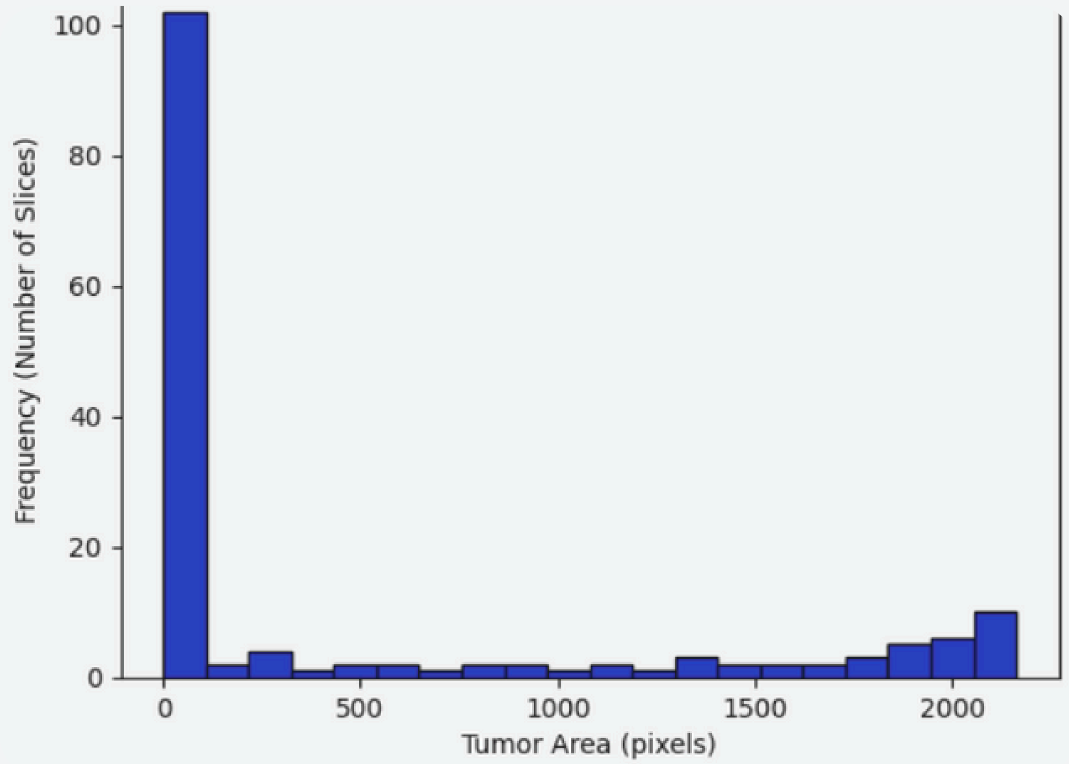
DATASETS

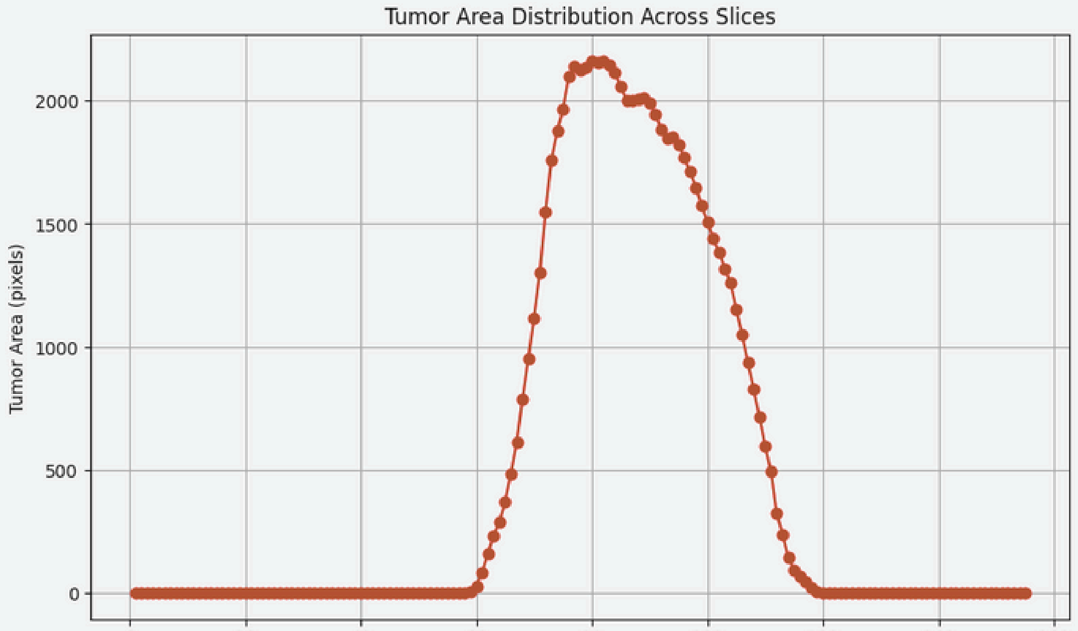
MRI Images — T1, T2, FLAIR

Planes — Axial

Distribution — Right Skewed







DATA PREPROCESSING

3D MRI IMAGES

FORMAT

1. NIFTI
2. DICOM

NON BINARY
SEGMENTATION

2D IMAGES

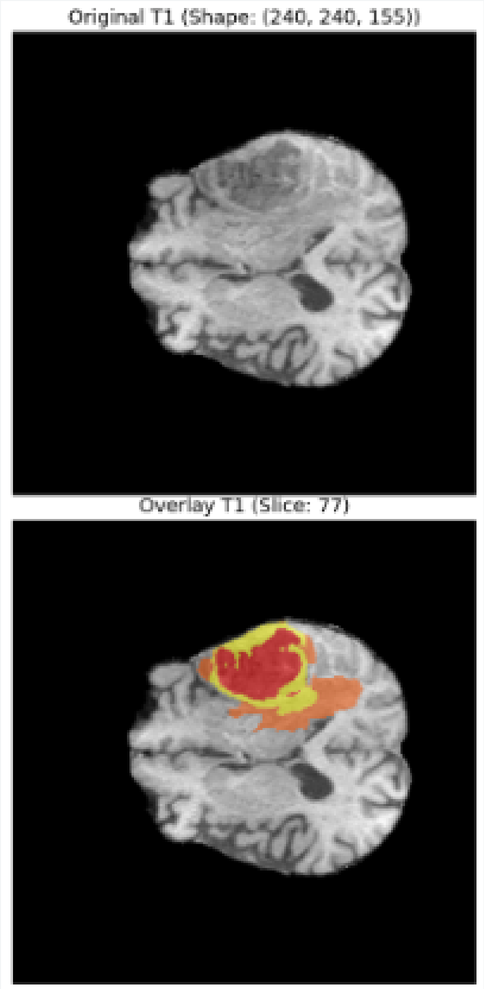
FORMAT

PNG

BINARY
SEGMENTATION

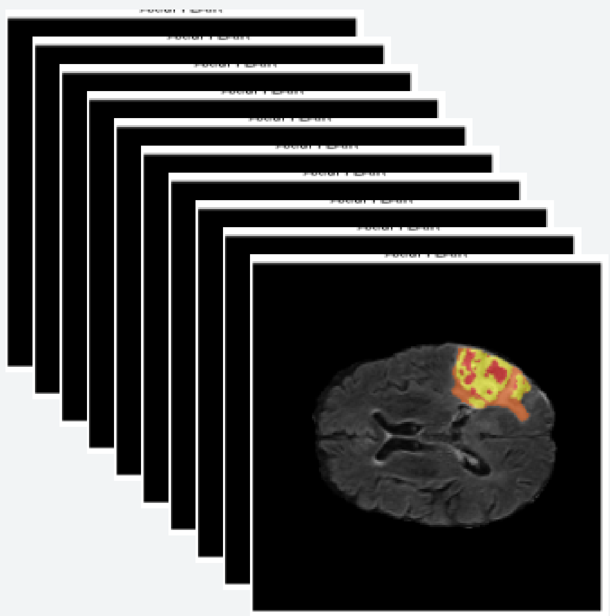
IMAGE CONVERSION

3D



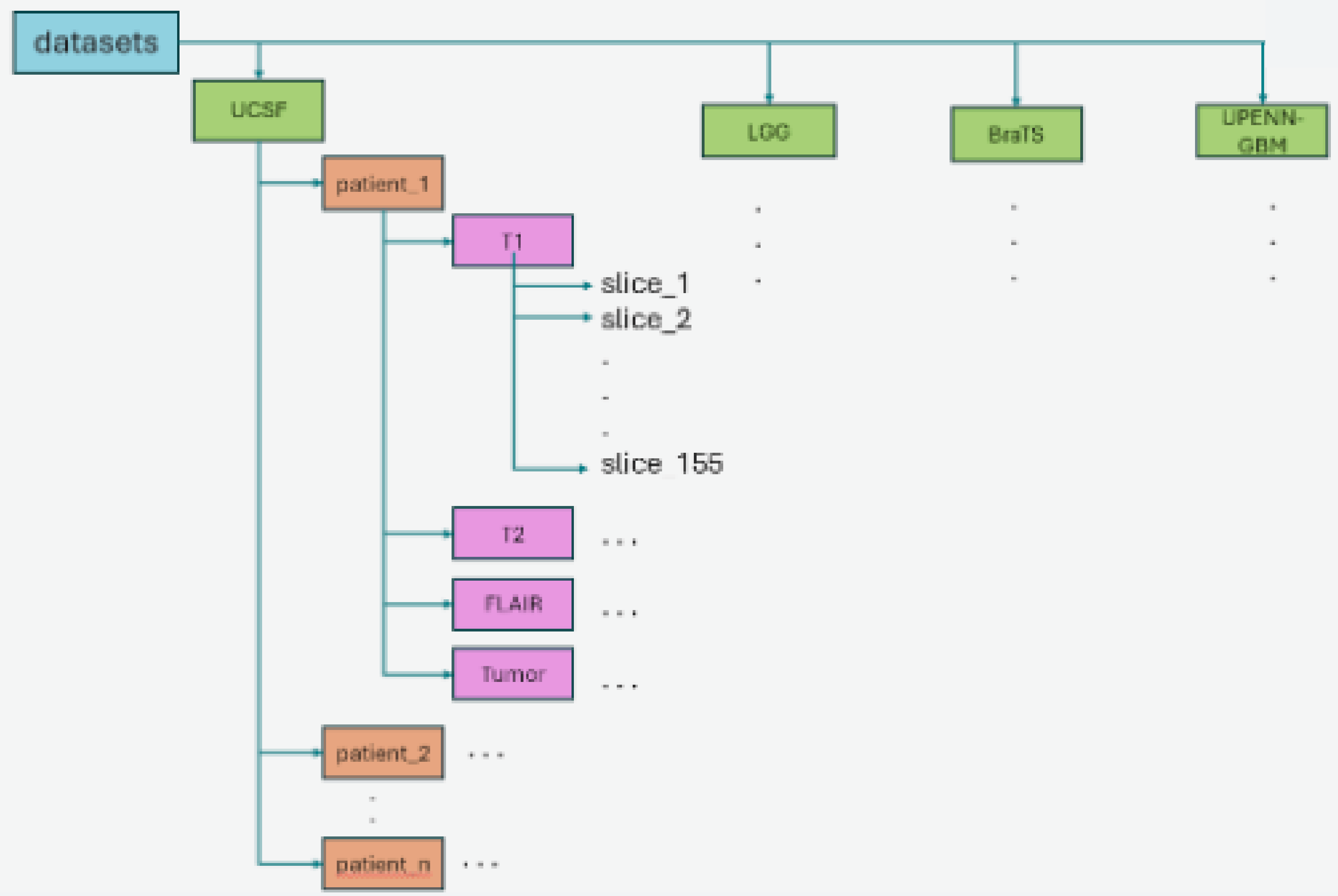
M x N x Slices

2D



Slices
M x N

DIRECTORY STRUCTURE



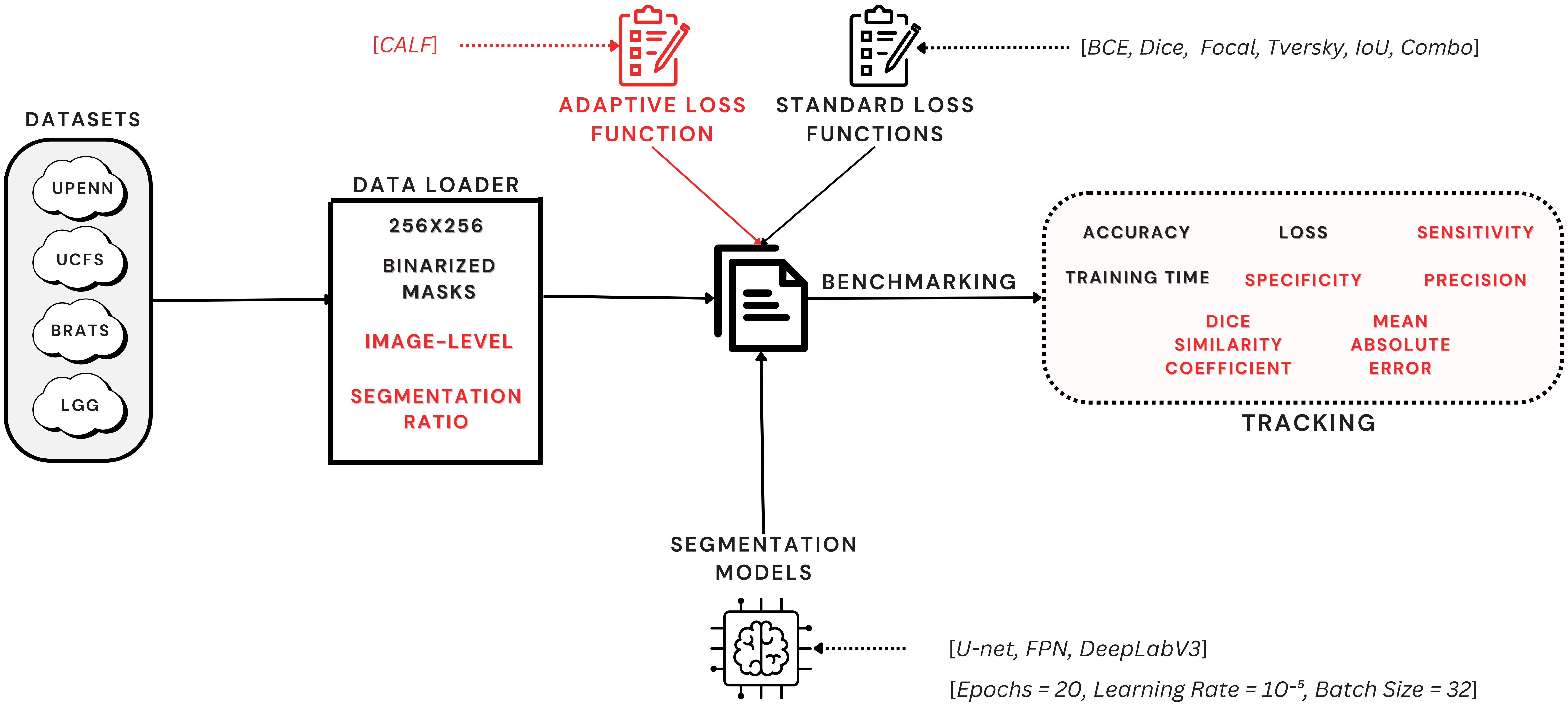
LOSS FUNCTIONS

Name	Class	Domain	Year	Citations to Original Paper	Publications	Citations in total	Purpose	Use Cases - Pros/Cons
Cross Entropy	Distribution	Binary Classification	2015	94542	477	100000	Minimize cross entropy H(P,Q)	Works best in equal data distribution among classes
WCE	Distribution	Binary Classification	2015	94542	66	96000	Minimize CE, penalize majority weights	Widely used in skewed datasets
TopK	Distribution	Ranking	2016	187	4	343	Force networks to focus on hard samples during training	Used in imbalanced data
Focal	Distribution	Object Detection	2017	199	336	5000	Adapt the standard cross entropy to focus on hard examples	Works best with highlt imbalanced datasets, down-weight the contribution of easy examples, enabling model to learn hard e
Distance Map enalizing Loss	Distribution	Segmentation	2019	104	22	215	Guide the network's focus towards hard-to-segment boundary regions	Used for hard-to-segment boundaries
Dice	Region	Segmentation	2016	10882	557	22000	Optimize the Dice Similarity Coefficient (DSC)	Does not require class re-weighting for imbalanced segmentat
IoU (Jaccard)	Region	Segmentation	2016	1033	183	3000	Optimize the object category segmentation metric	Highly effective for tasks where boundary precision is crucial
Lovász	Region	Segmentation	2018	613	37	1000	Optimize the Jaccard index	Optimizing with cross entropy first is needed
Tversky	Region	Segmentation	2017	1056	154	3000	Achieve a better trade-off between precision and recall	Used where the cost of false positives and false negatives diff significantly and it is wanted to adjust the model's behavior ac
Focal Tversky	Region	Segmentation	2018	930	46	2000	Focus on hard cases with low probabilities	Focus on hard examples
Robust T-Loss	Region	Segmentation	2023	8	1	8	Emphasize robustness	Used in noisy data
ensitivity-specificity	Region	Binary Classification	2015	52	26	164	Address the class imbalance problem by weighting specificity higher	Used when there is more focus on True Positives
Asymmetric similarity	Region	Ranking	2018	206	10	463	Make a better adjustment of the weights of FPs and FNs	Used in imbalanced data
eneralized Dice	Region	Segmentation	2017	2688	37	5000	Multi-class extension of Dice loss	Used in multi-class segmentation
G. Wasserstein Dice loss	Region	Segmentation	2018	184	4	296	To improve multi-class segmentation	Used in multi-class segmentation, tackles hierarchical classes take advantage of known relationships between classes
Penalty	Region	Segmentation	2019	37	4	67	Penalize the FNs and the FPs in generalized Dice	Used in multi-class segmentation, focused on false negatives positives
Boundary Loss	Boundary	Segmentation	2018	558	63	1000	Use integral framework to compute distance between two boundaries	Time-consuming, should be coupled with region-based loss
oundary-aware Loss	Boundary	Segmentation	2017	170	101	1000	Pay attention to boundary regions	Used in data having precise boundaries
InverseForm	Boundary	Segmentation	2021	123	2	124	Assign lower loss to predictions that do not perfectly align with ground truth but have similarities	Complements cross-entropy with boundary transformation and outperforms while not adding time complexity
Hausdorff Distance Loss	Boundary	Segmentation	2019	503	6	845	Avoid unstable training	Time-consuming, should be coupled with region-based loss
BCE - Dice	Compound	Binary Segmentation	2018	388	6	701	Handle input and output imbalance in multi-organ segmentation	Used for lightly class imbalanced
Dice - Focal	Compound	Segmentation	2018	514	18	566	Alleviate the imbalanced organ segmentation problem and force the model to learn from poorly segmented voxels better	Good in multi-class segmentation
Dice - TopK	Compound	Segmentation	2020	29	4	89	Used for automated volumetric assessment of multiple sclerosis	Good in multi-class segmentation
Unified Focal	Compound	Segmentation	2022	406	33	671	Mitigate the issues associated with loss suppression and over-enhancement	Used in imbalanced data
Exponential Logarithmic Loss	Compound	Segmentation	2018	251	3	441	Address the issues of highly unbalanced object sizes	Focuses on less accurately predicted cases

MODELS

- U-Net
- Hr-Net
- Deeplabv3
- FCN
- FCN-Net
- Link-Net
- FPN

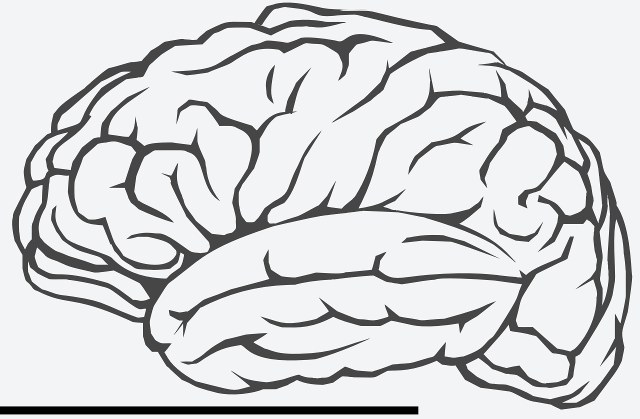
GENERAL WORKFLOW



ACHIEVEMENTS

- Results
- User-interface
- MICCAI Submission

1. RESULTS



Models

- U-net
- FPN
- Deeplabv3

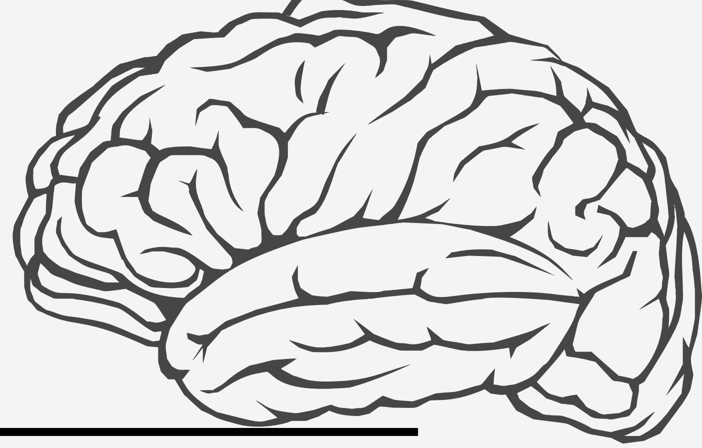
Loss Functions

- BCE
- DICE
- Tversky
- IoU
- Combo
- Focal
- Adaptive

Segmentation ratio

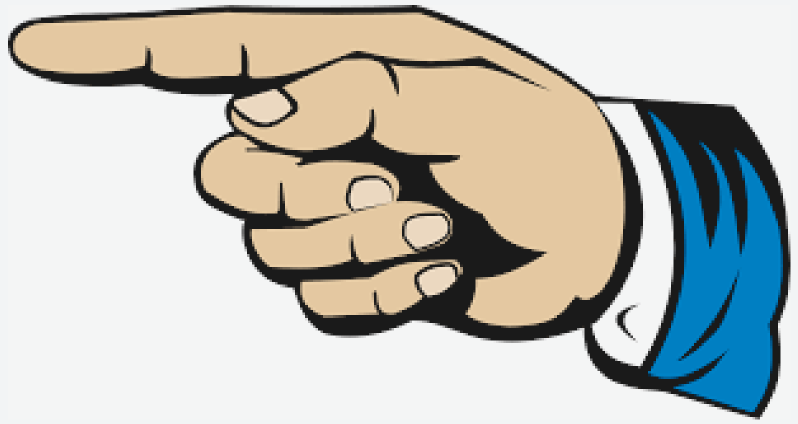
- 0.41
- 0.10
- 0.25
- 0.6
- 0.85

56 Trained models



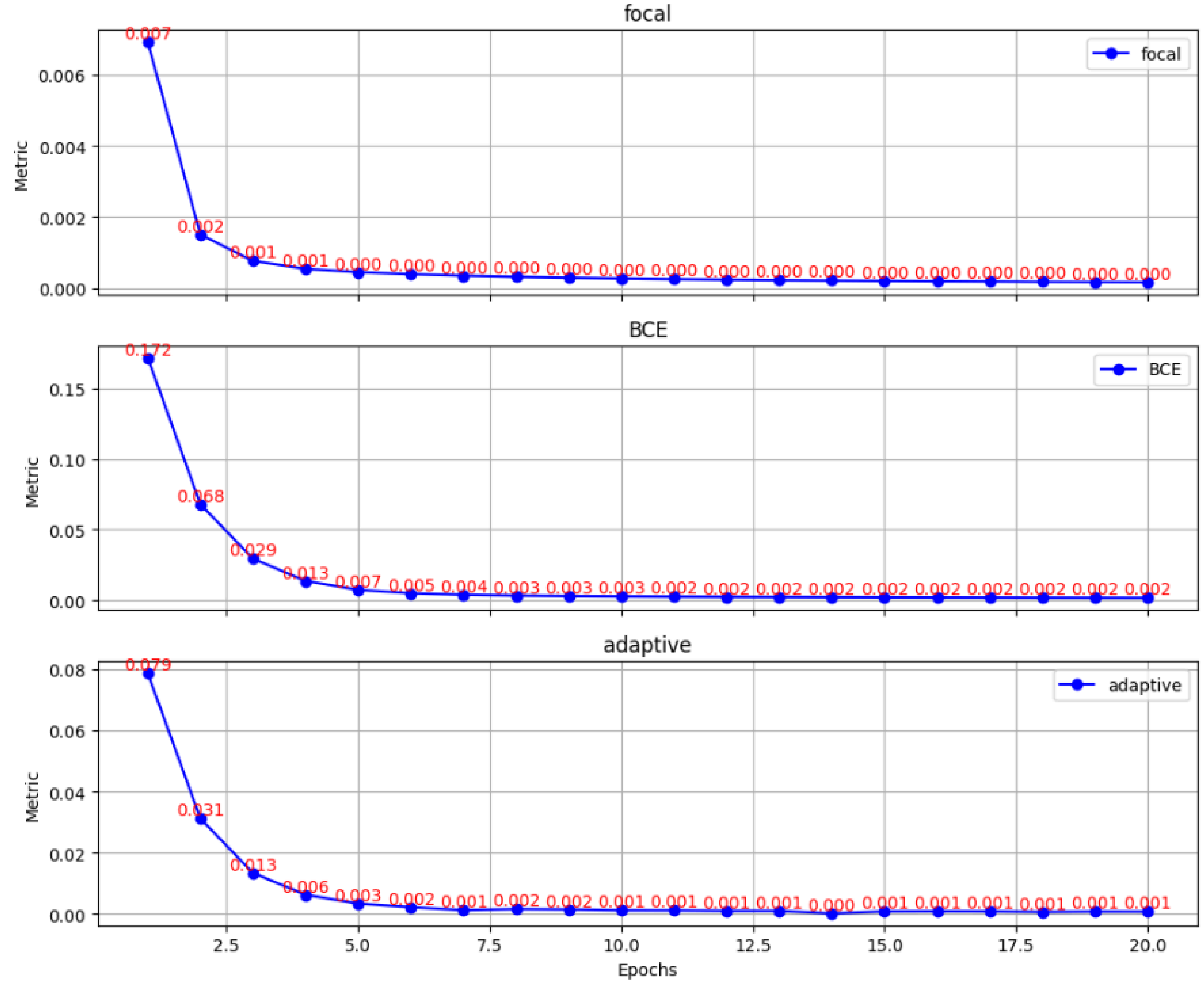
1. RESULTS

Results are HERE

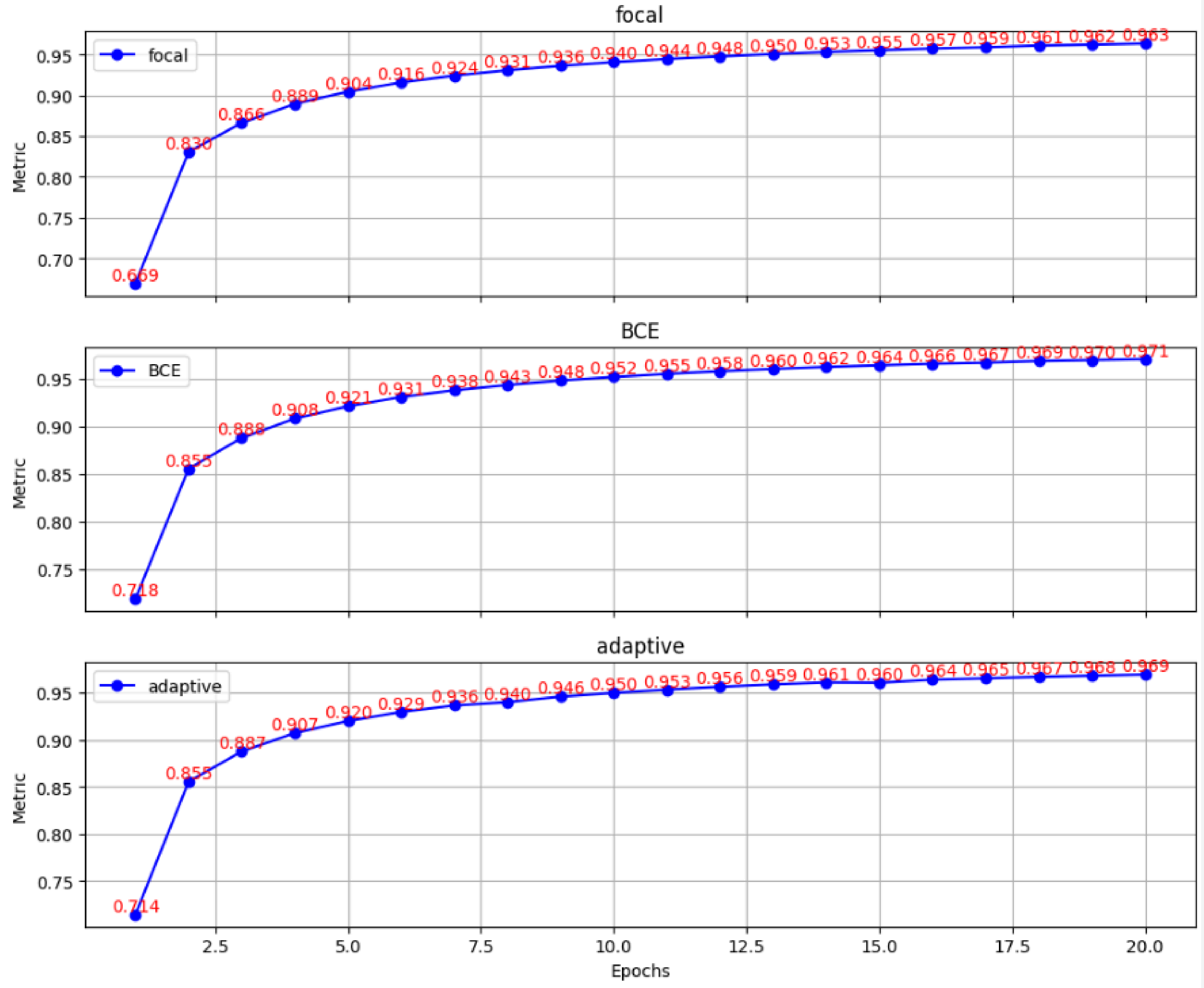


PERFORMANCE OF ADAPTIVE LOSS FUNCTION

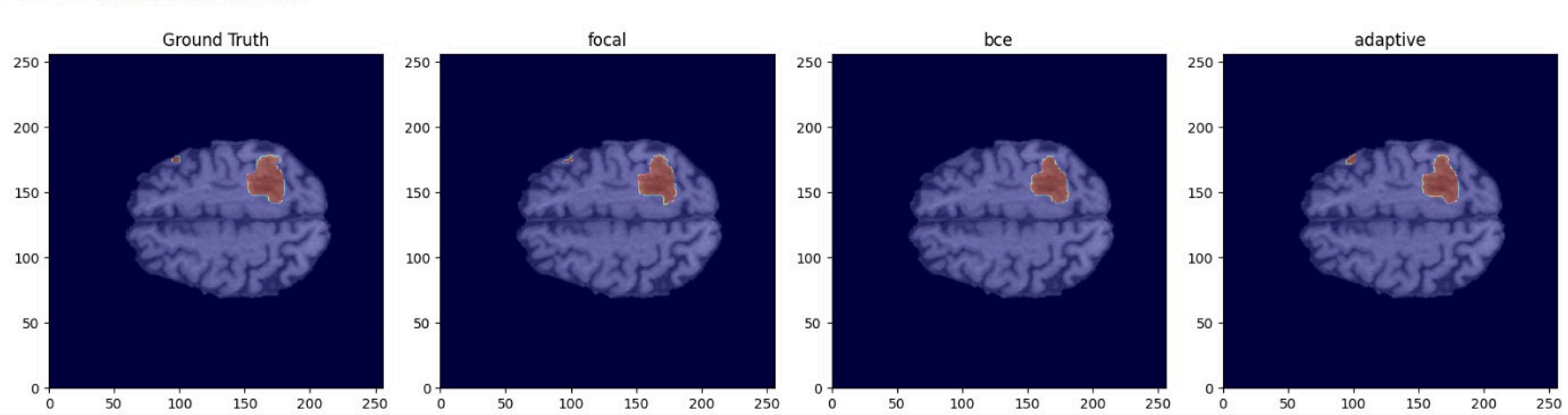
LOSS HISTORY

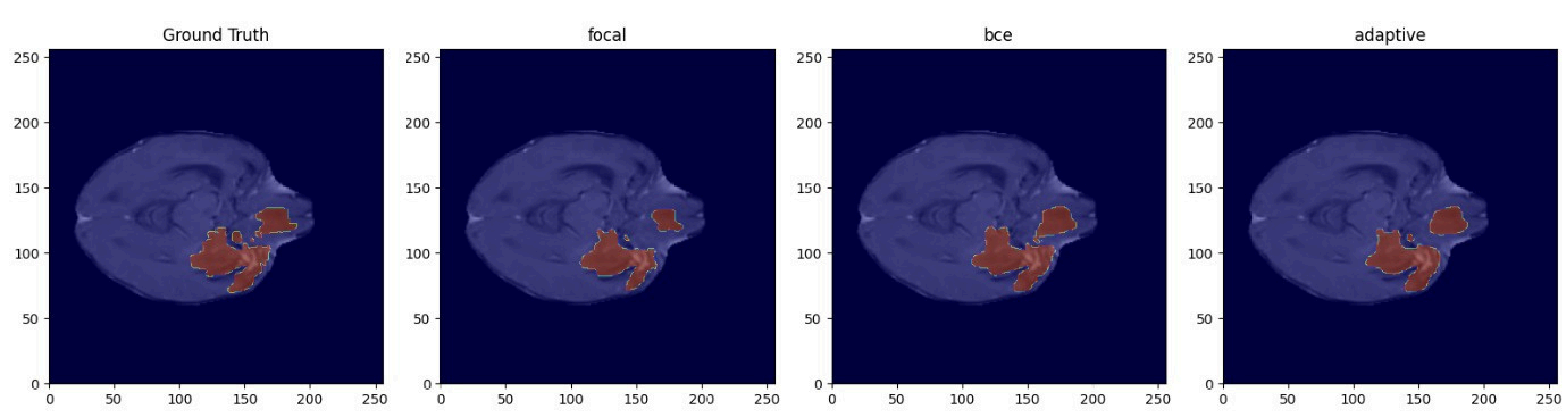


DICE SIMILARITY COEFFICIENT HISTORY



PERFORMANCE OF ADAPTIVE LOSS FUNCTION





2. USER INTERFACE

Upload a Tumor Image (JPG Format)

Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

Browse files

Configuration

Select a Segmentation Model

UNet

Select a Loss Function

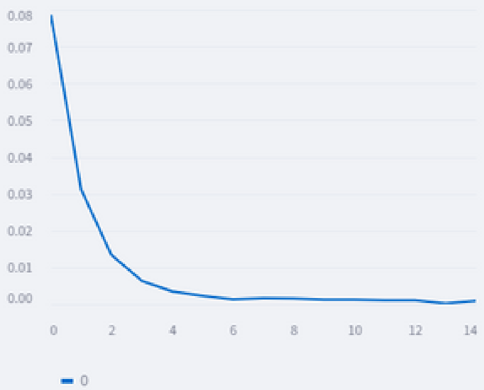
Adaptive

UNet - Adaptive Model Performance

	epochs	actual_epochs	learning_rate	batch_size
0	20	15	0	32

Select an option

- loss_history
- dsc_history



Upload Ground Truth Image (JPG Format)

Drag and drop file here

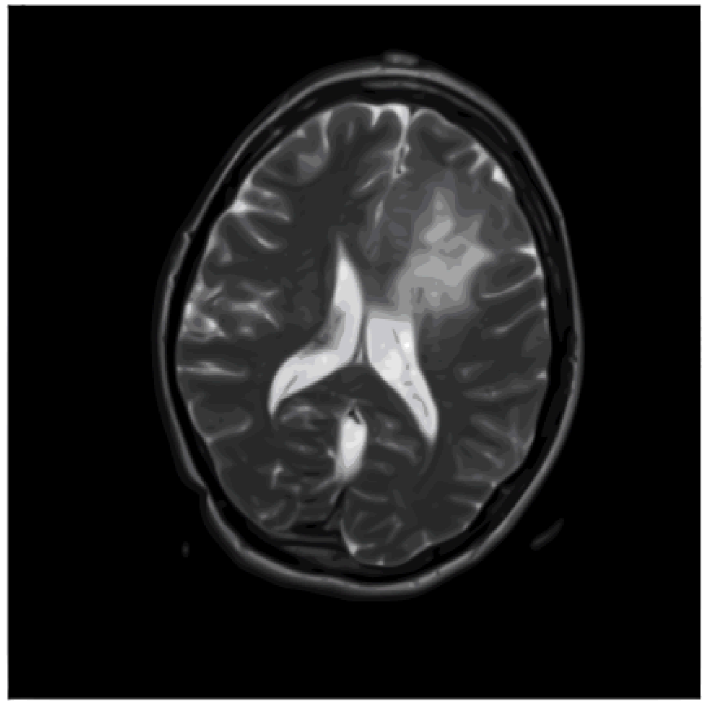
Limit 200MB per file • JPG, JPEG, PNG

Browse files

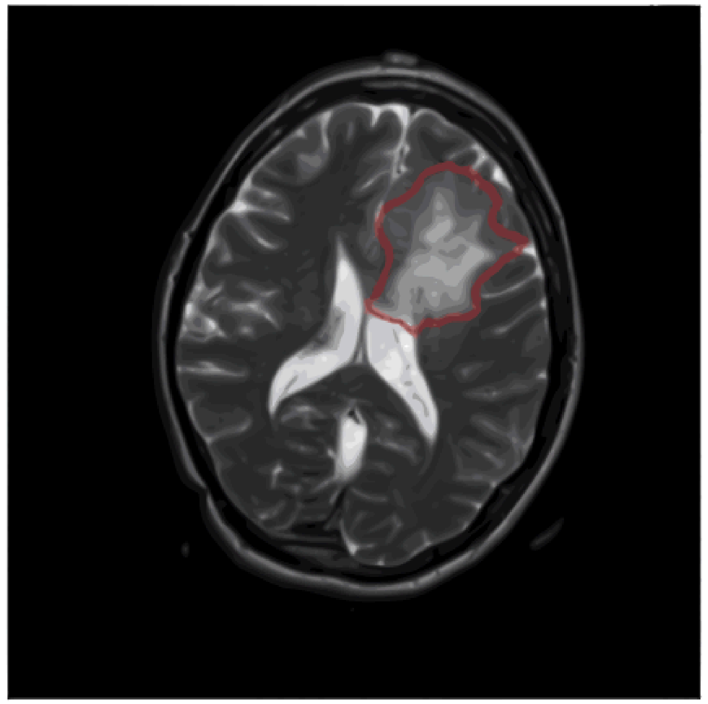
✅ Correct Tumor (Green): 1887 pixels (91.07%)

❌ Missed Tumor (Red): 185 pixels (8.93%)

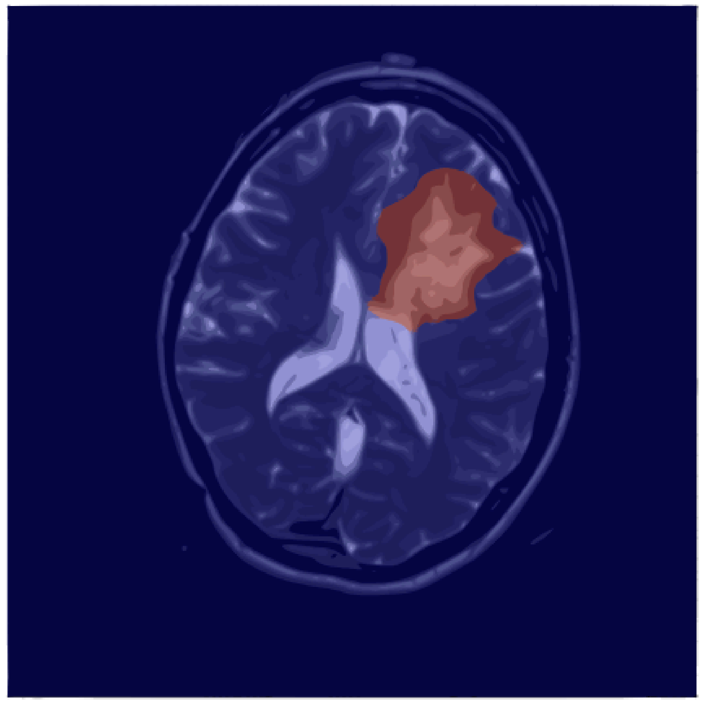
🔵 Over-Predicted Tumor (Blue): 243 pixels (11.73%)



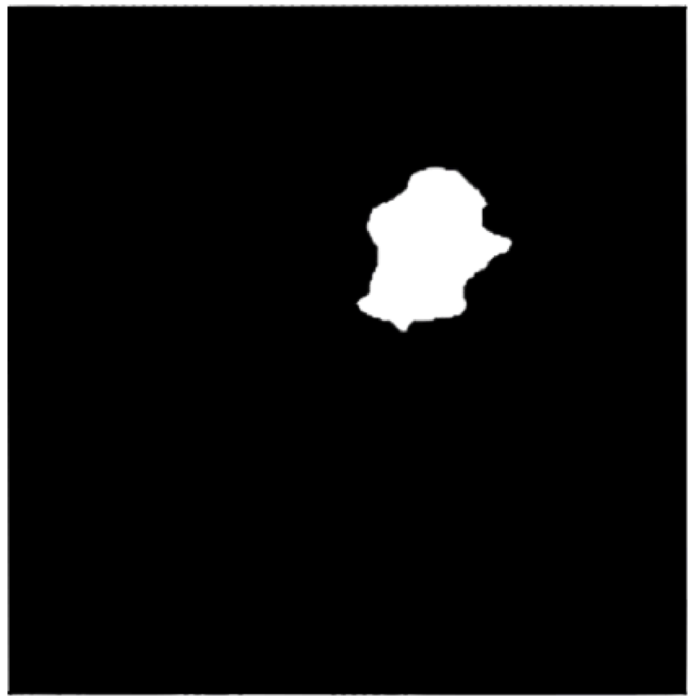
Uploaded Image



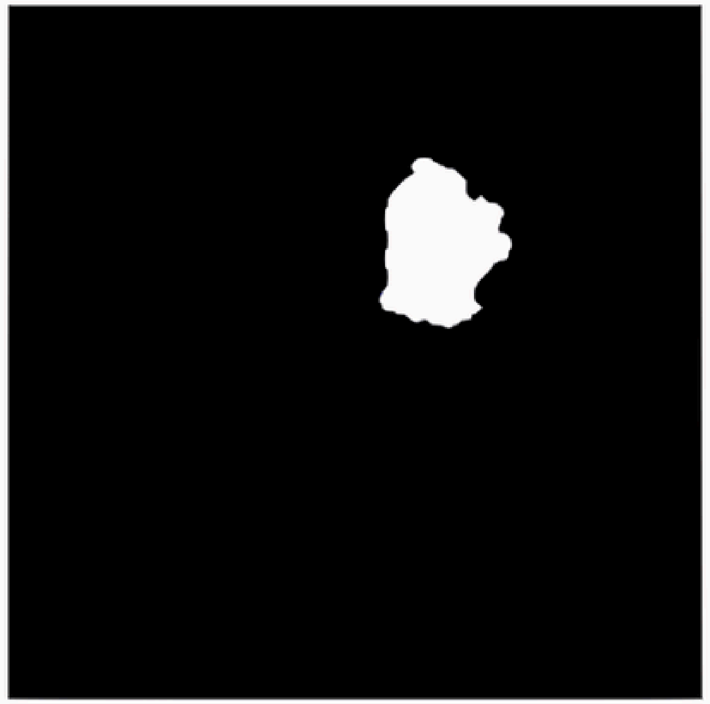
Contour Overlay



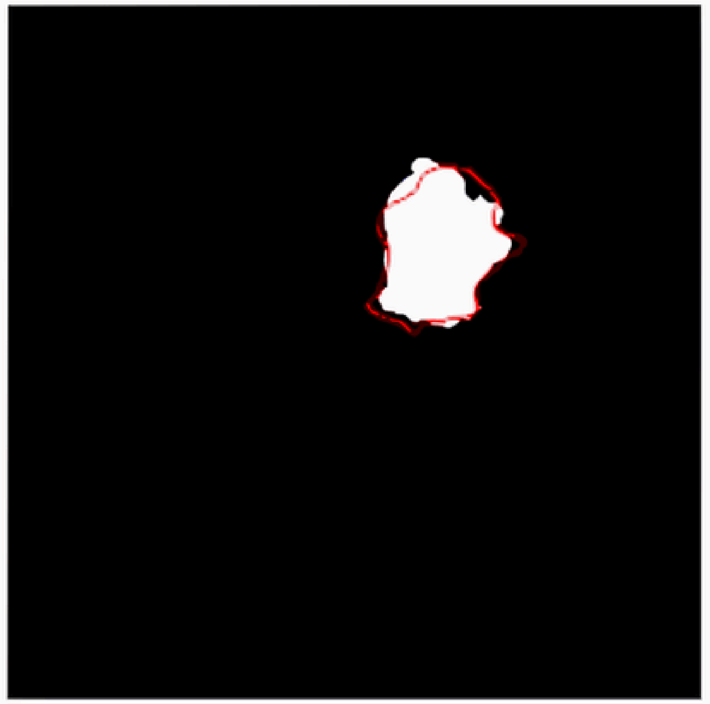
Overlayed Tumor Region



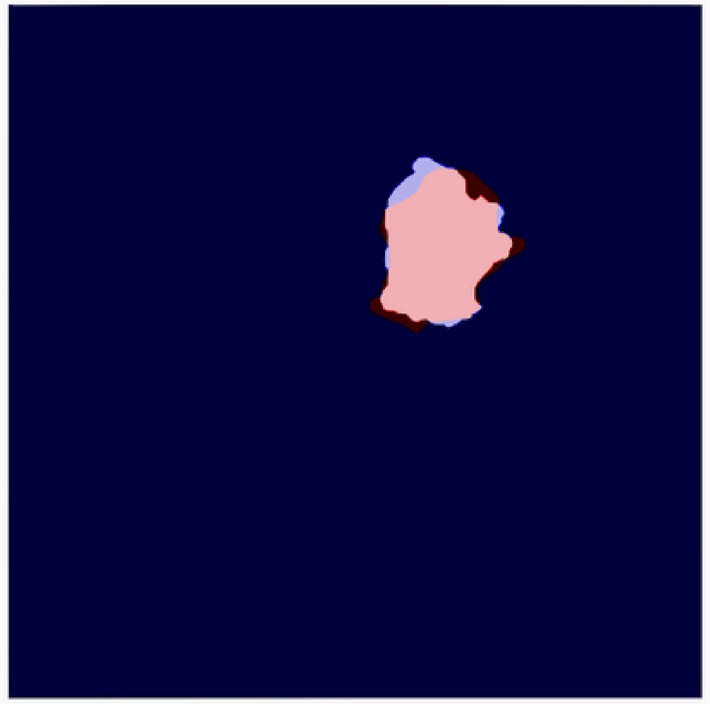
Segmentation Output



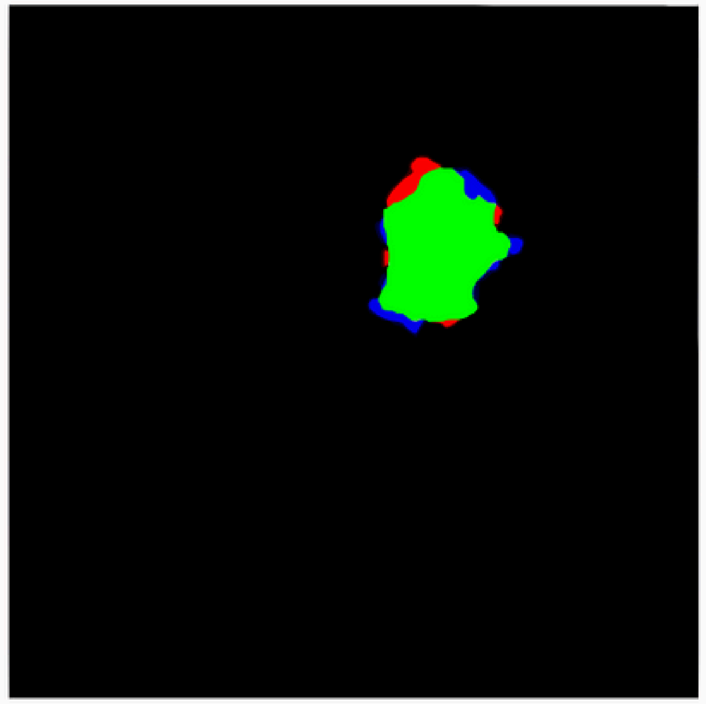
Ground Truth Image



Contour Overlay



Overlayed Tumor Region



Difference Overlay

3. PAPERS

ADAPTIVE LOSS FUNCTION

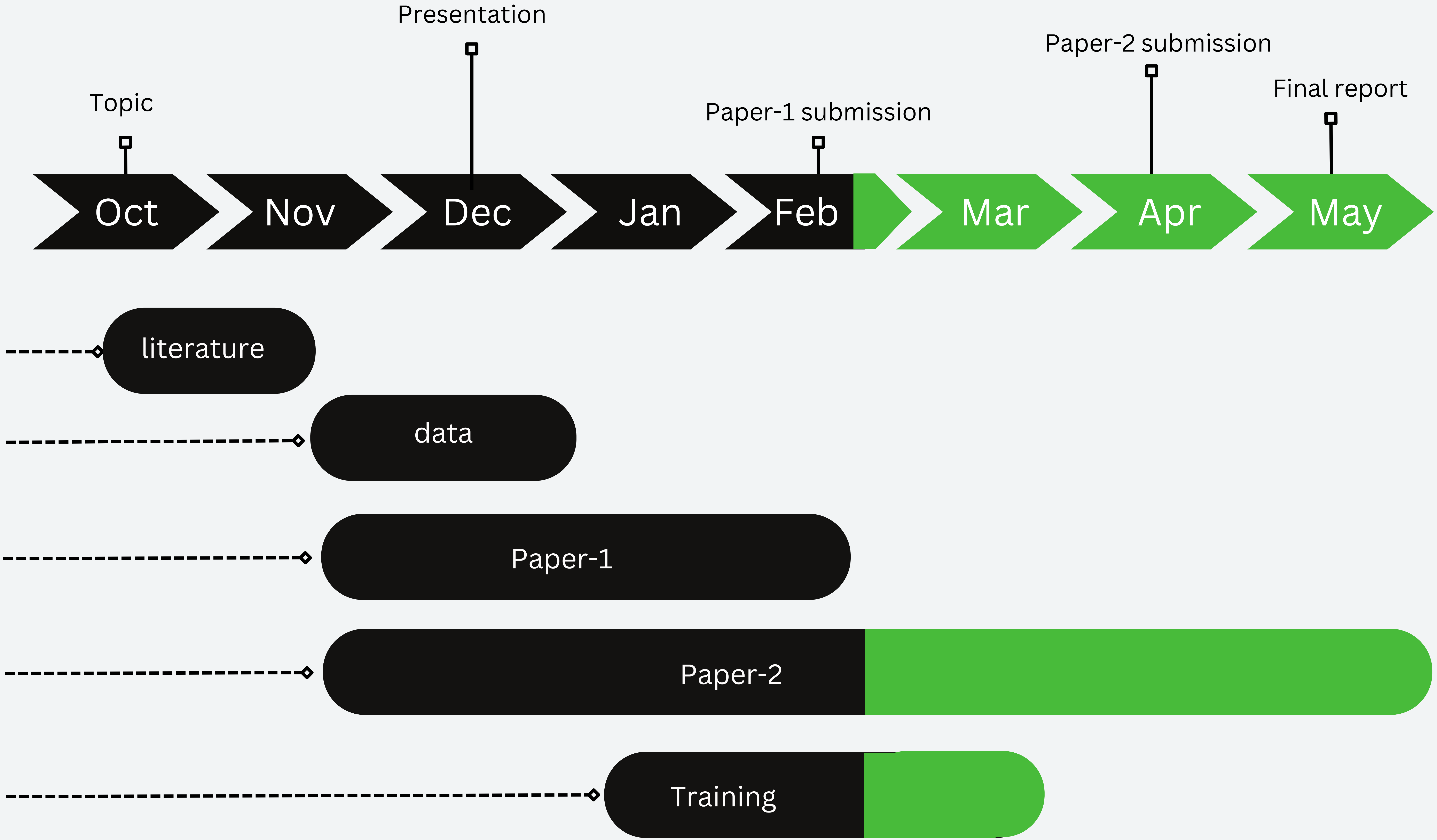
MICCAI

TITLE: [CALF]: A CONDITIONALLY ADAPTIVE LOSS FUNCTION TO MITIGATE CLASS-IMBALANCED SEGMENTATION THROUGH MODEL HARMONIZATION

GUIDE TO EXISTING LOSS FUNCTIONS

CURRENTLY IN PROGRESS

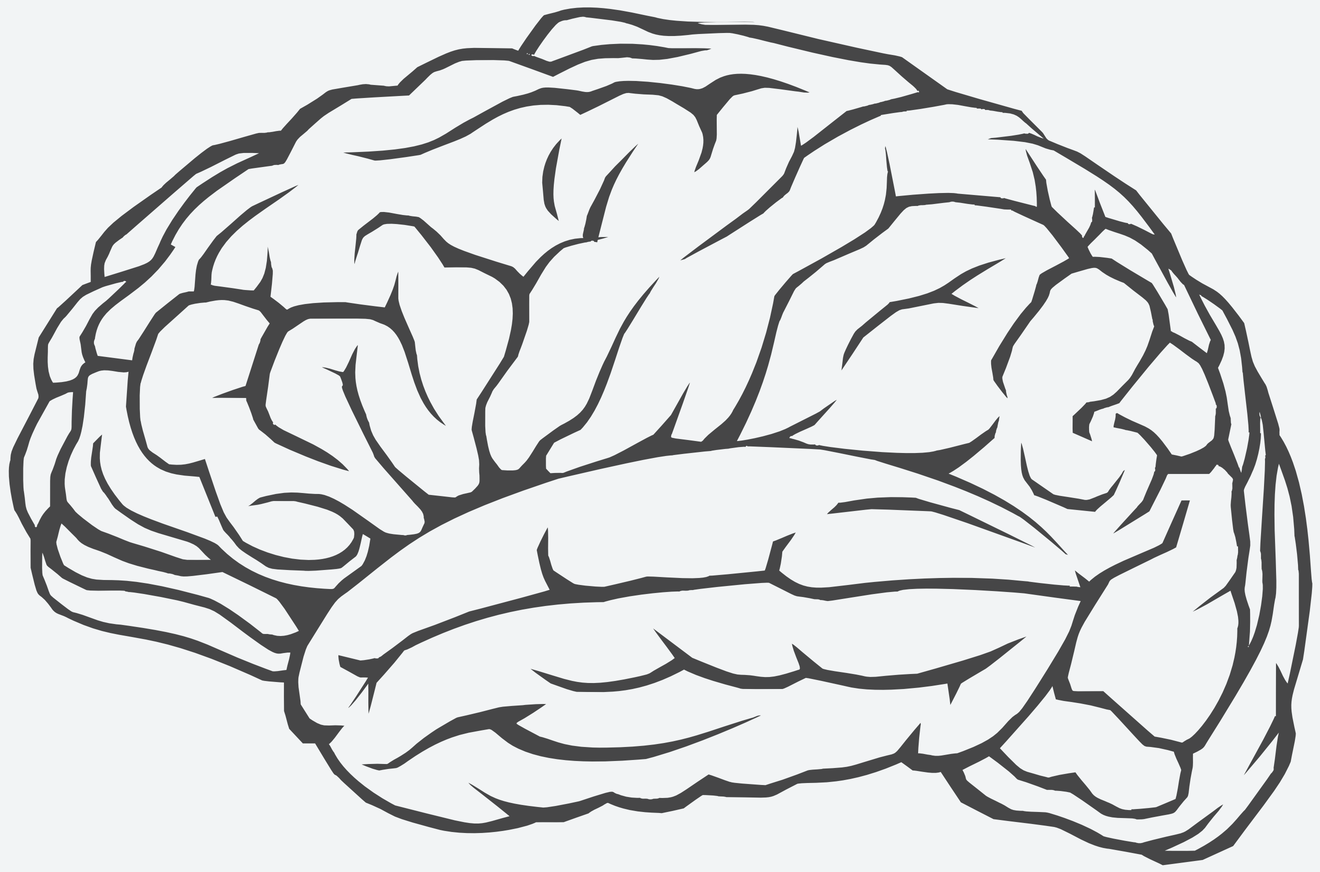
NEXT STEP


Presentation
Paper-2 submission
Topic
Paper-1 submission
Final report
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
literature
data
Paper-1
Paper-2
Training

CONCLUSION

"We have achieved a great deal, but there is still more to accomplish"

THANK YOU



REFERENCES

A GENERAL AND ADAPTIVE LOSS FUNCTION - CVPR 2019

ADAPTIVE REGION-SPECIFIC LOSS FOR IMPROVED MEDICAL IMAGE SEGMENTATION - IEEE 2023

LGG-1P19QDELETION | LGG-1P19QDELETION

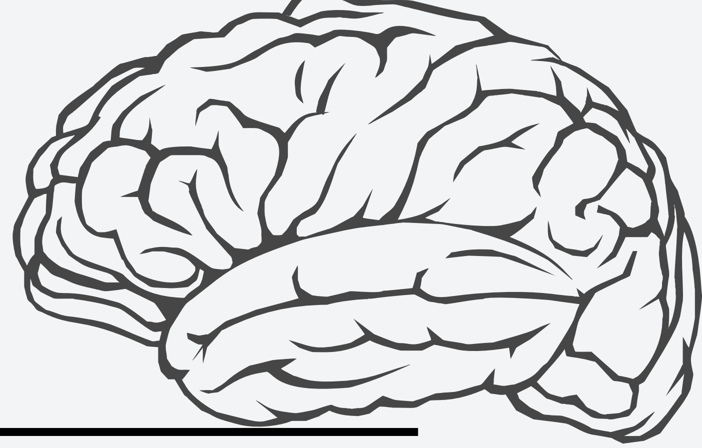
UCSF-PDGM | THE UNIVERSITY OF CALIFORNIA SAN FRANCISCO PREOPERATIVE DIFFUSE GLIOMA MRI

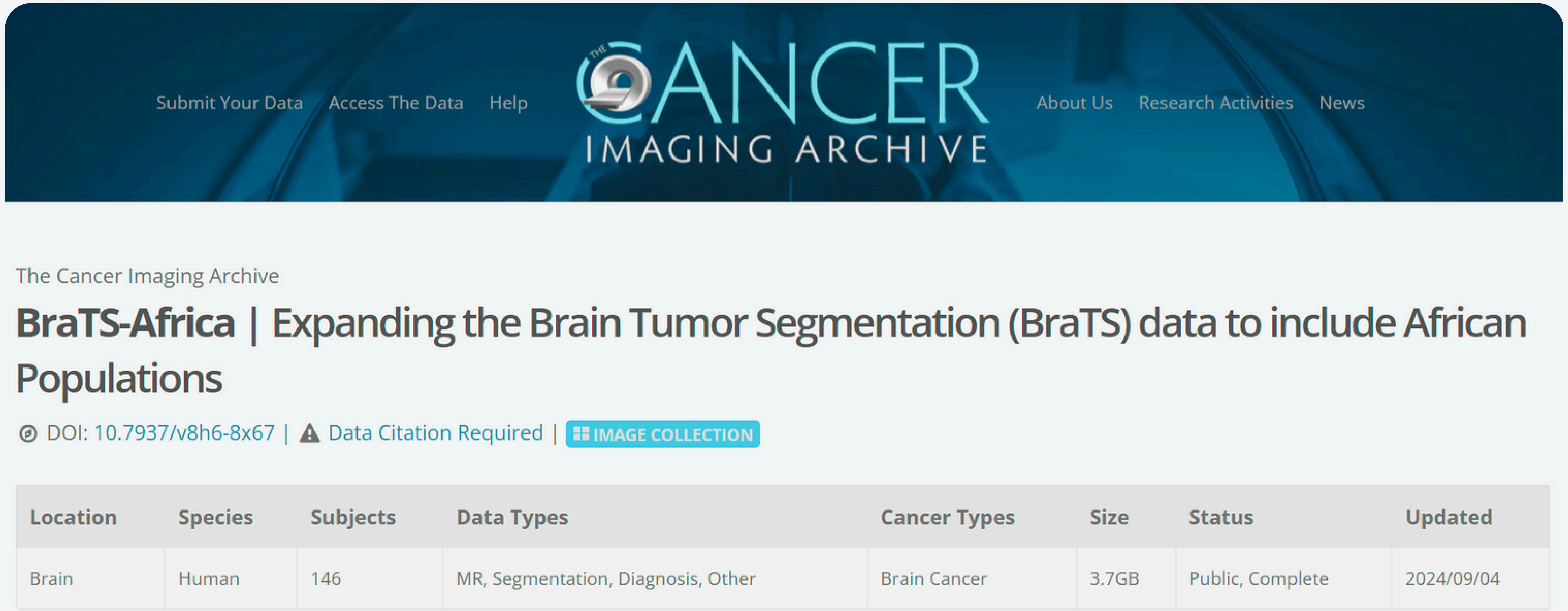
BRATS-AFRICA | EXPANDING THE BRAIN TUMOR SEGMENTATION (BRATS) DATA TO INCLUDE AFRICAN POPULATIONS

UPENN-GBM | MULTI-PARAMETRIC MAGNETIC RESONANCE IMAGING (MPMRI) SCANS FOR DE NOVO GLIOBLASTOMA (GBM) PATIENTS FROM THE UNIVERSITY OF PENNSYLVANIA HEALTH SYSTEM

REMIND | THE BRAIN RESECTION MULTIMODAL IMAGING DATABASE

DATASET - 2





Submit Your Data Access The Data Help THE CANCER IMAGING ARCHIVE About Us Research Activities News

The Cancer Imaging Archive

BraTS-Africa | Expanding the Brain Tumor Segmentation (BraTS) data to include African Populations

DOI: 10.7937/v8h6-8x67 | Data Citation Required | IMAGE COLLECTION

Location	Species	Subjects	Data Types	Cancer Types	Size	Status	Updated
Brain	Human	146	MR, Segmentation, Diagnosis, Other	Brain Cancer	3.7GB	Public, Complete	2024/09/04

Data Type

- MR
- DIAGNOSIS

Cancer Type

- CNS NEOPLASMS
- DIFFUSE GLIOMA
- LOW GLIOMA
- GLIOBLASTOMA

Patients

- 146

Public

- YES

Image Size

- 240, 240, 155

Tumor Size

- 240, 240, 155

BRATS-AFRICA | EXPANDING THE BRAIN TUMOR SEGMENTATION (BRATS) DATA TO INCLUDE AFRICAN POPULATIONS

MRI Images

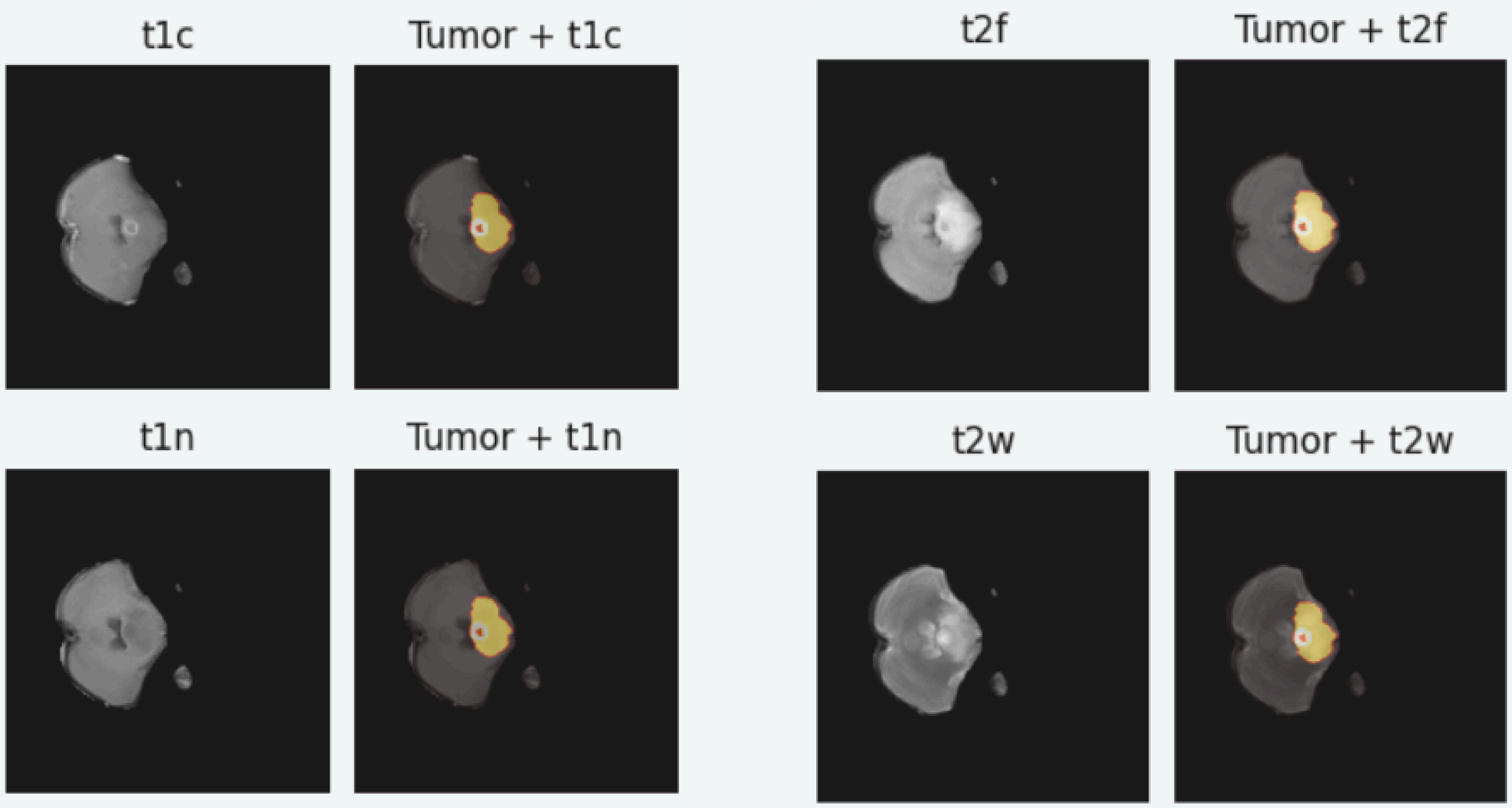
T1, T1-C, T2, FLAIR

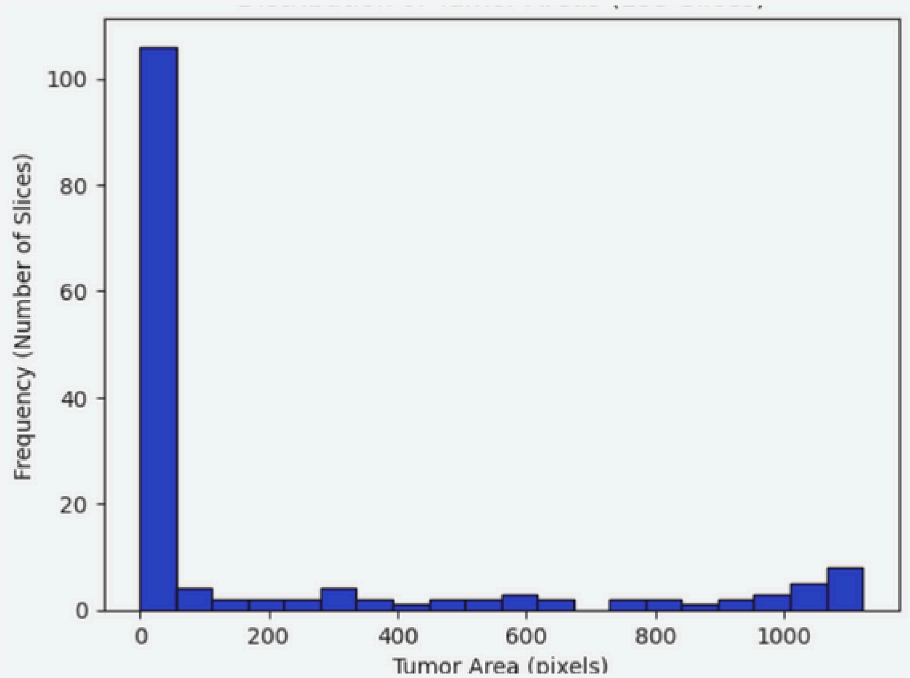
Planes

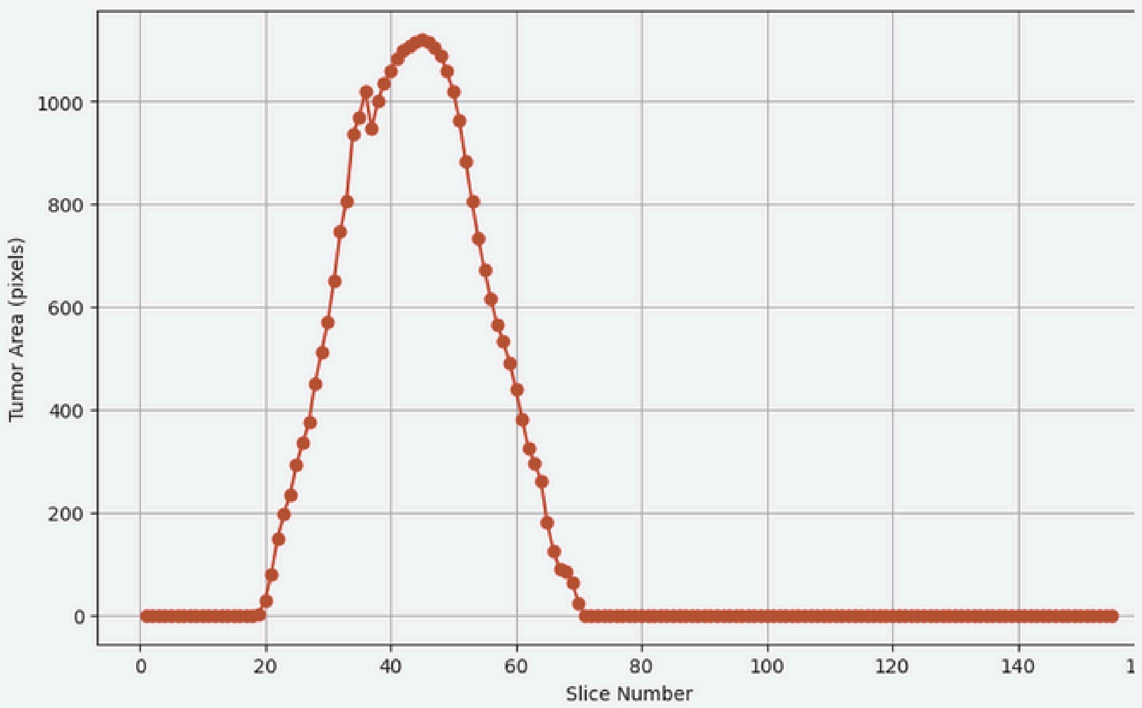
Axial

Distribution

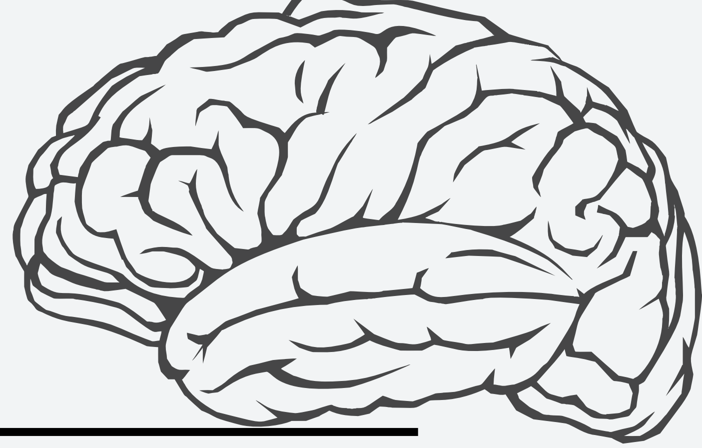
Right Skewed







DATASET - 3



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The Cancer Imaging Archive

UPENN-GBM | Multi-parametric magnetic resonance imaging (mpMRI) scans for de novo Glioblastoma (GBM) patients from the University of Pennsylvania Health System

DOI: 10.7937/TCIA.709X-DN49 | Data Citation Required | IMAGE COLLECTION

Location	Species	Subjects	Data Types	Cancer Types	Size	Supporting Data	Status	Updated
Brain	Human	630	MR, Molecular Test, Demographic, Radiomic Feature, Other, Histopathology, Segmentation	Glioblastoma	357.42GB	Clinical, Image Analyses	Public, Complete	2022/10/24

Data Type
- MR
- HISTOPATHOLOGY (NOT SEGMENTED

Cancer Type
- GLIOBLASTOMA

Patients
- 630

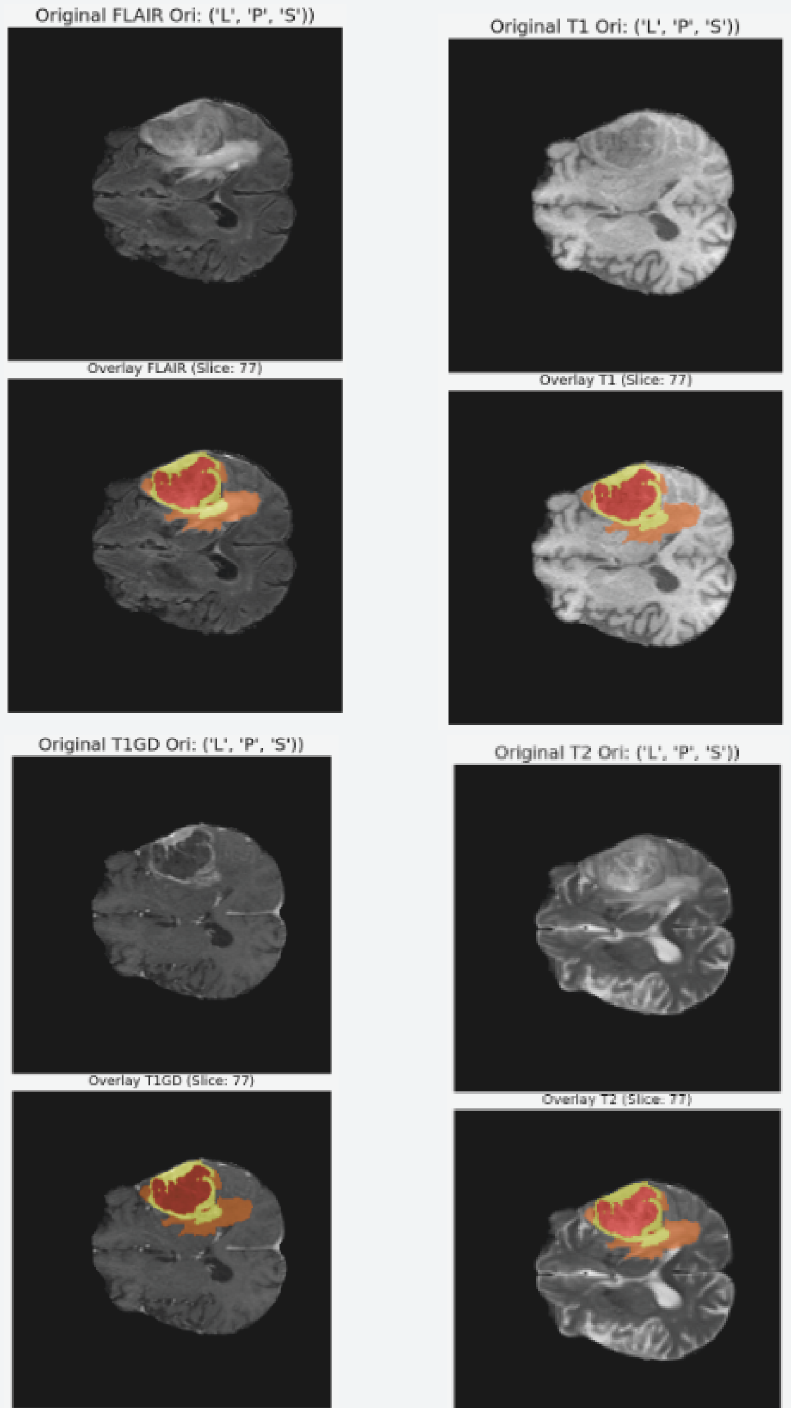
Public
- YES

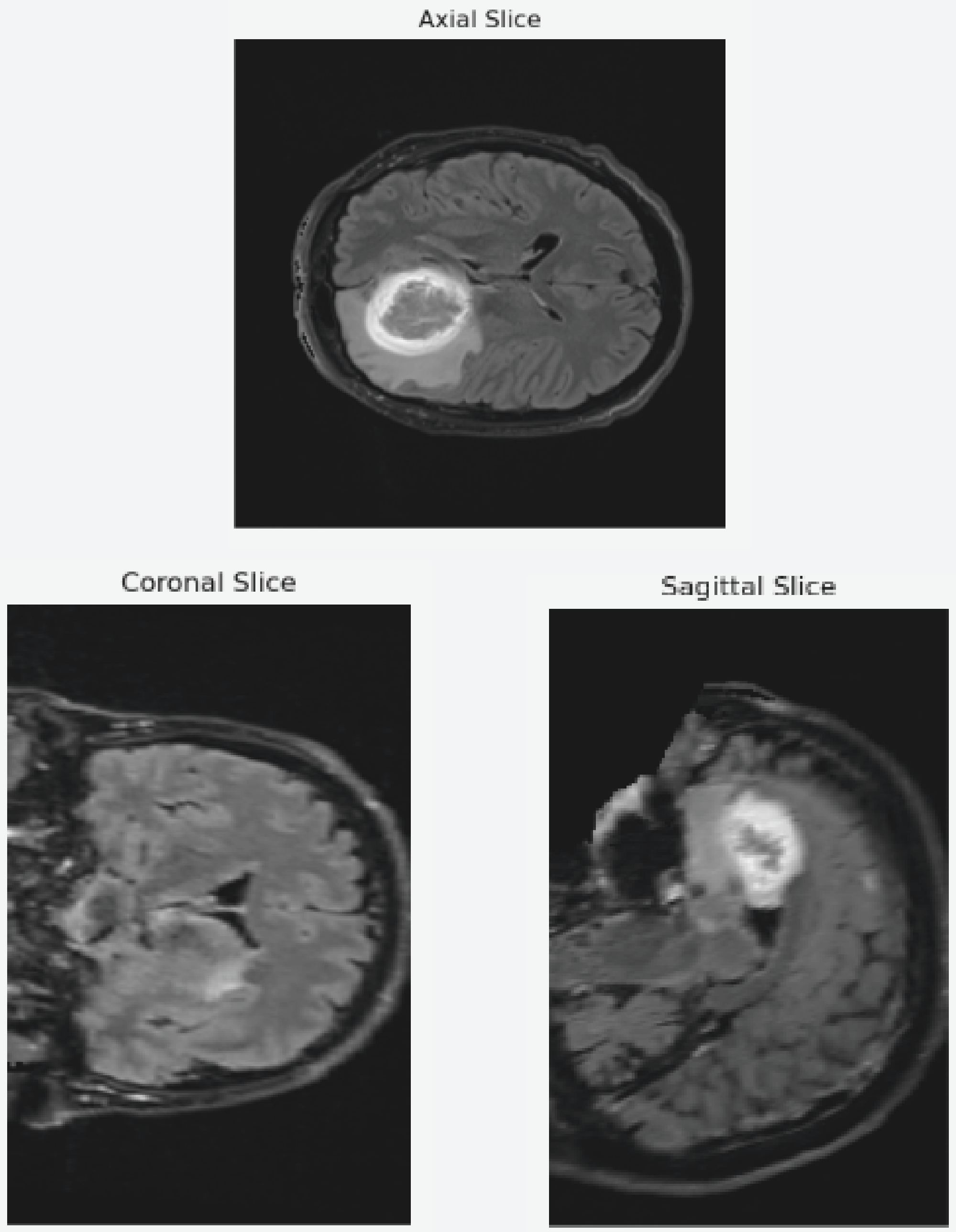
Image Size
- 240, 240, 155

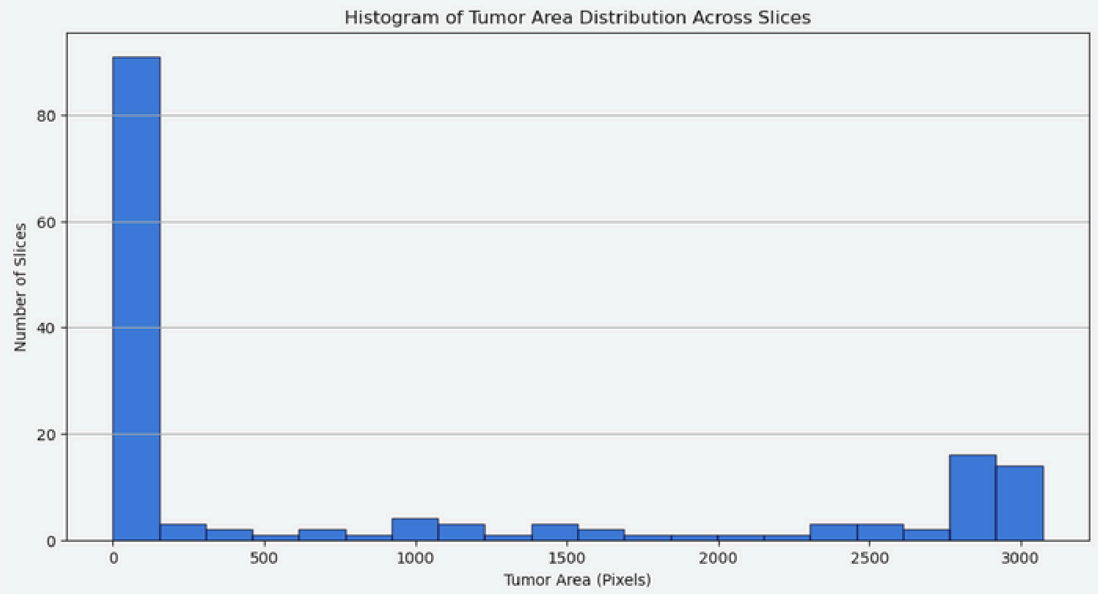
Tumor Size
- 240, 240, 155

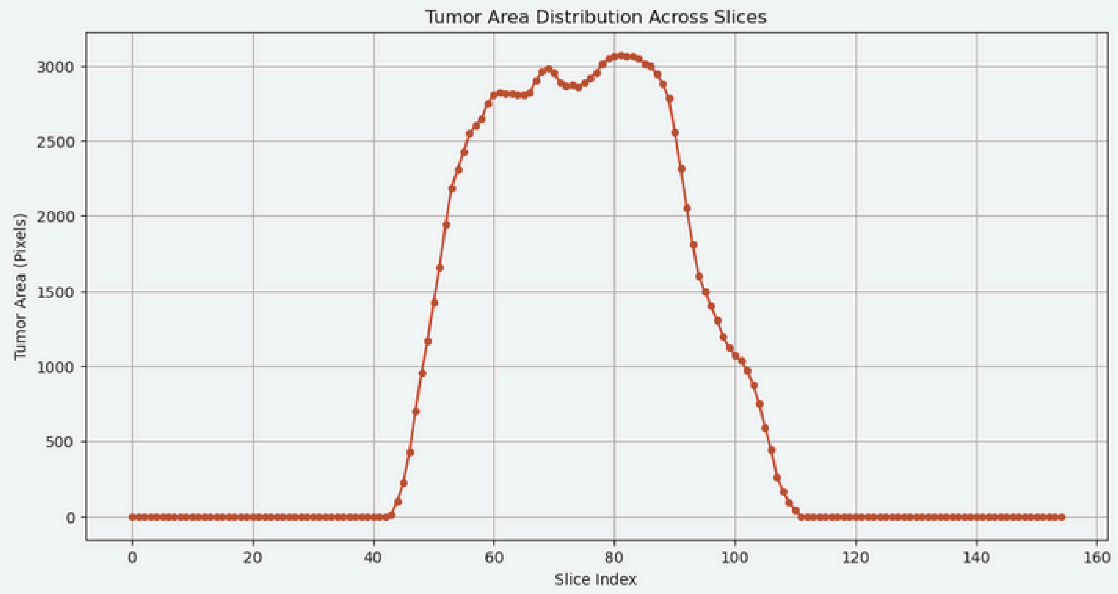
UPENN-GBM | MULTI-PARAMETRIC MAGNETIC RESONANCE IMAGING (MPMRI) SCANS FOR DE NOV GLIOBLASTOMA (GBM) PATIENTS FROM THE UNIVERSITY OF PENNSYLVANIA HEALTH SYSTEM

MRI Images	Planes	Distribution
Flair, T1, T1GD, T2	Axial, Coronal, Sagittal	Right Skewed

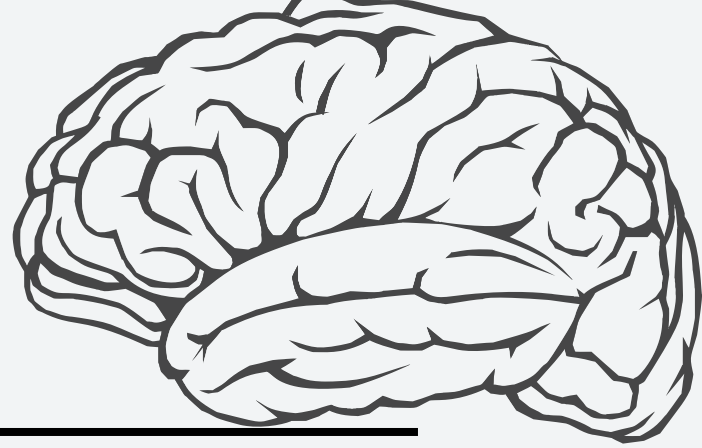


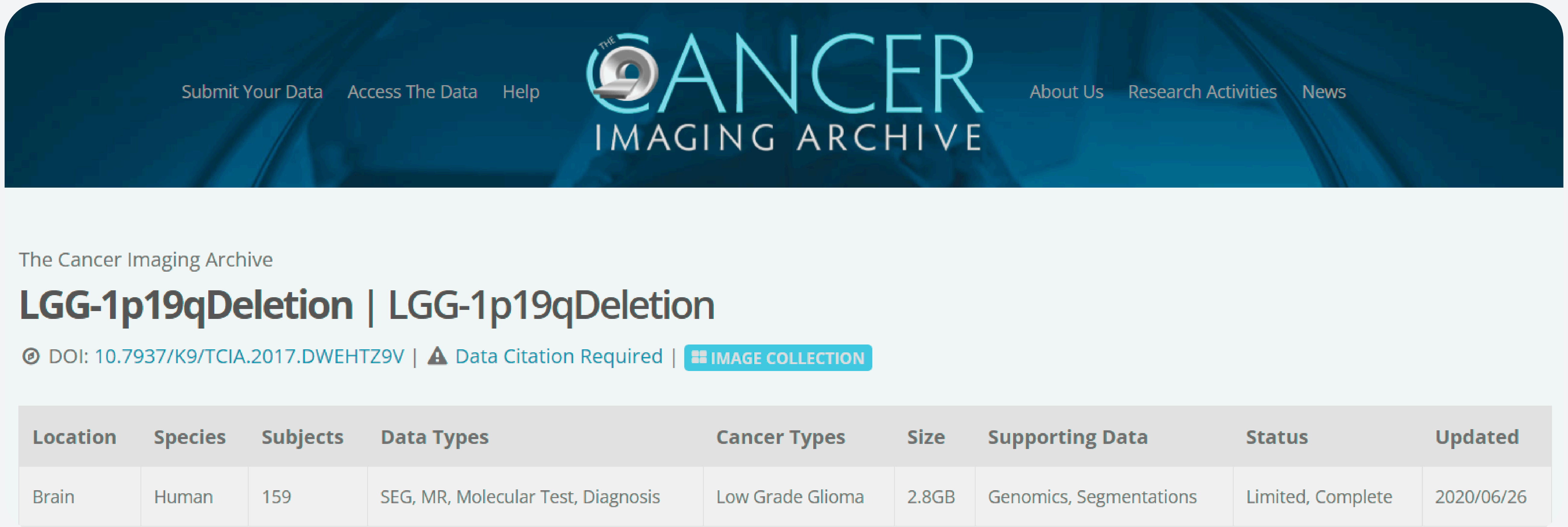






DATASET - 4





The Cancer Imaging Archive

LGG-1p19qDeletion | LGG-1p19qDeletion

DOI: 10.7937/K9/TCIA.2017.DWEHTZ9V | Data Citation Required | IMAGE COLLECTION

Location	Species	Subjects	Data Types	Cancer Types	Size	Supporting Data	Status	Updated
Brain	Human	159	SEG, MR, Molecular Test, Diagnosis	Low Grade Glioma	2.8GB	Genomics, Segmentations	Limited, Complete	2020/06/26

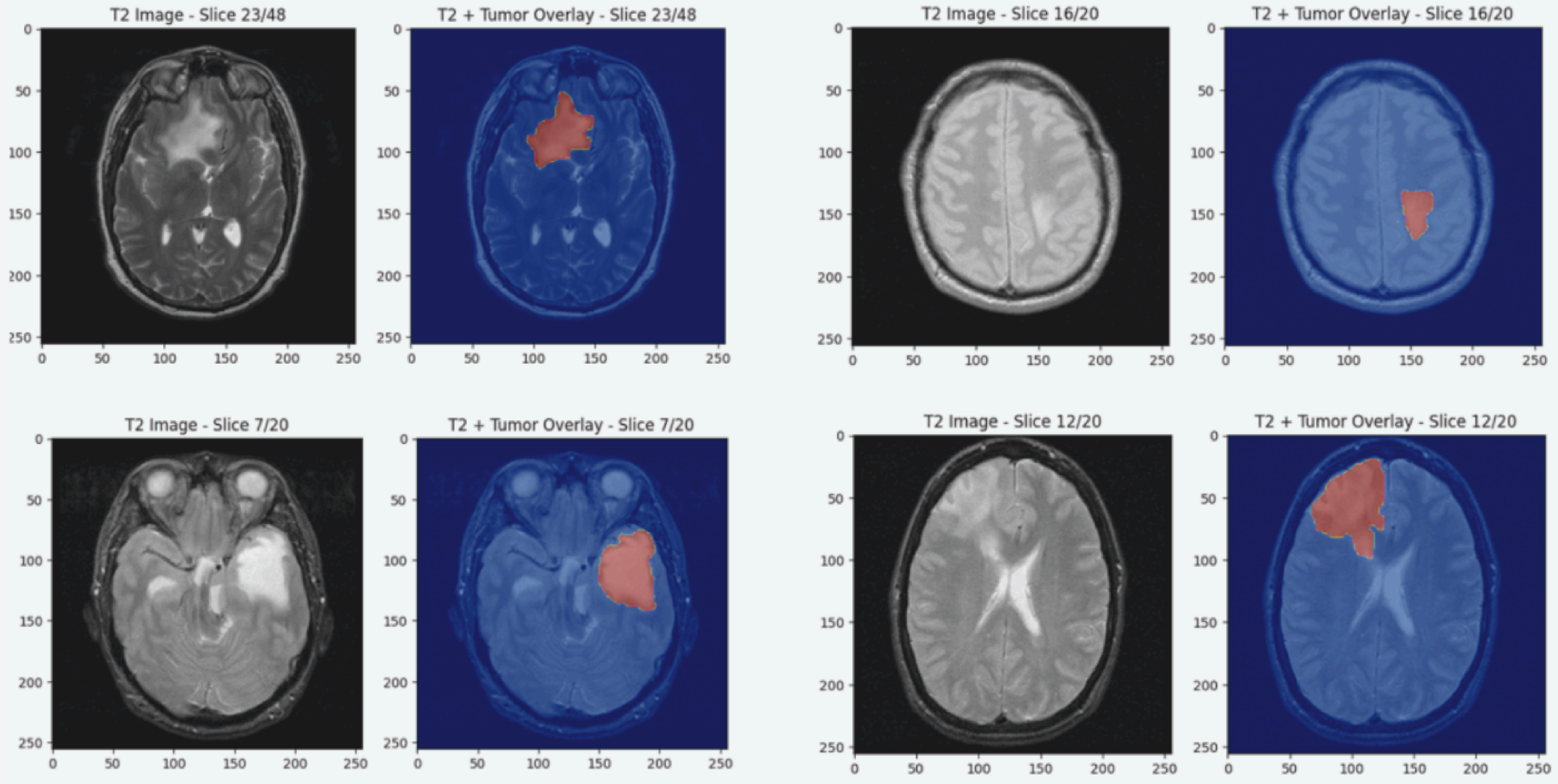
Data Type	Cancer Type	Patients	Public	Image Size	Tumor Size
• MR	• LOW GRADE GLIOMA	• 159	• NO	• M, 256, 256	• N, 256, 256

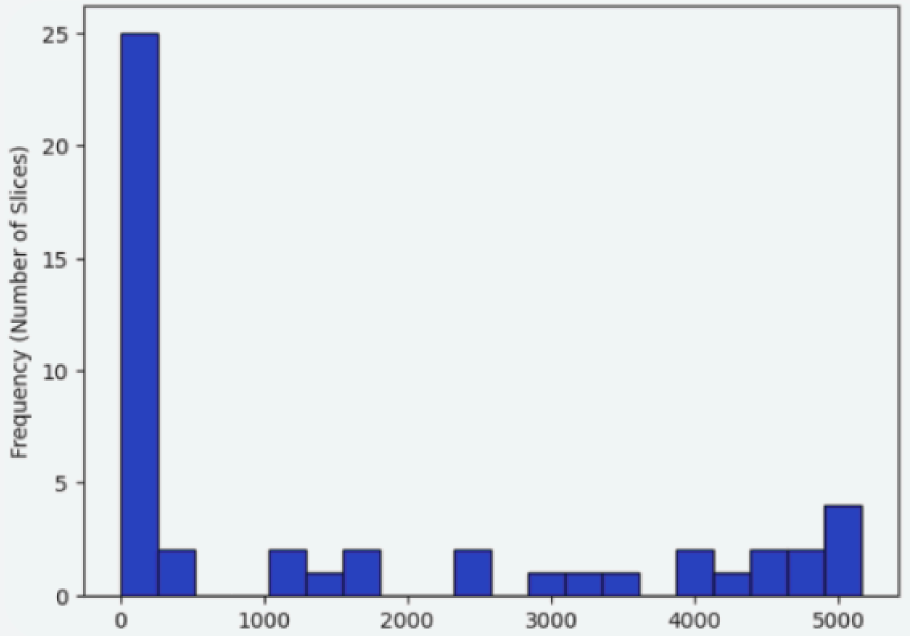
LGG-1P19QDELETION | LGG-1P19QDELETION

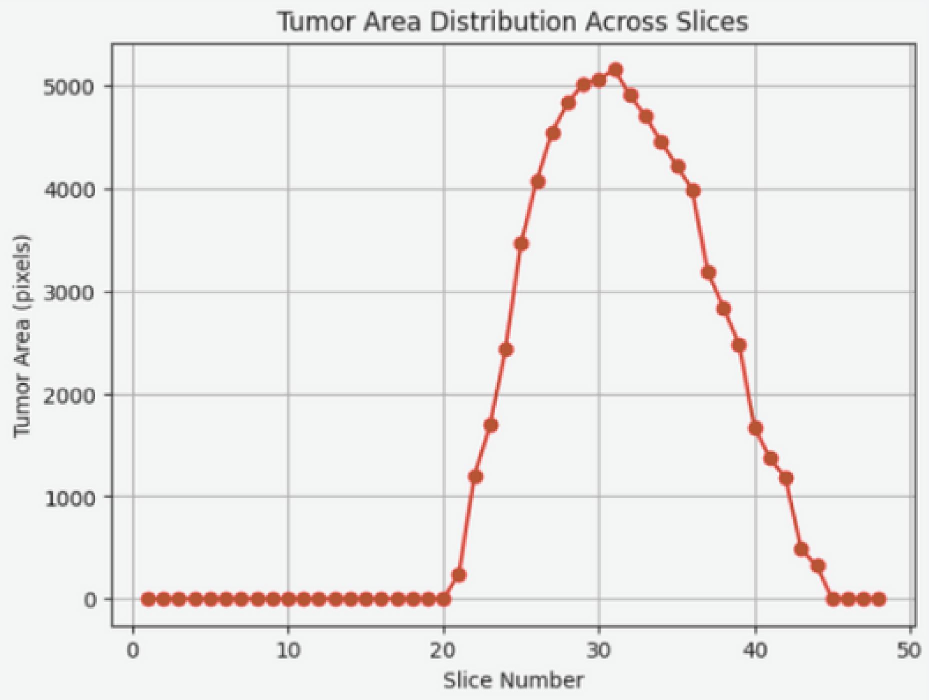
MRI Images
T2

Planes
Axial

Distribution
Right Skewed







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STRENGTHS

A GUIDE ON LOSS FUNCTIONS

- CLEAR AND ORGANIZED TAXONOMY OF EXISTING LOSS FUNCTIONS
- VALUABLE FOR BOTH RESEARCHERS AND PRACTITIONERS

WELL-DOCUMENTED AND PROCESSED DATASETS

- HIGH-QUALITY DATASETS THAT HAVE BEEN PROCESSED BY EXPERTS
- ENSURES ROBUST AND RELIABLE TRAINING

INNOVATIVE APPROACH

- STATISTICALLY-DRIVEN ADAPTIVE LOSS FUNCTION
- REGION-SPECIFIC ADAPTIVE LOSS FUNCTION

VERSATILITY

- CONFIGURABLE RATIOS OF SEGMENTED AND NON-SEGMENTED IMAGES
- ENSURES ROBUST TESTING ACROSS VARIOUS CONFIGURATIONS

CLINICAL RELEVANCE

- BRIDGES THE GAP BETWEEN RESEARCH ADVANCEMENTS AND PRACTICAL IMPLEMENTATIONS

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WEAKNESSES

LACK OF MEDICAL KNOWLEDGE IN THE TEAM

- TEAM OF COMPUTER SCIENCE STUDENTS
- LIMITS OUR UNDERSTANDING OF CLINICAL NUANCES

LIMITED TIMEFRAME

- SUBMIT OUR WORK TO MICCAI BY FEBRUARY
- RESTRICT THE DEPTH OF EXPLORATION AND THE EXTENT OF TESTING

GENERALIZABILITY CONCERNS

- WORKING ON BRAIN TUMOR DATASETS
- CANNOT COMMENT ON THE APPLICABILITY OF TO OTHER MEDICAL IMAGING DOMAINS

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OPPORTUNITIES

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EXPANDING APPLICATIONS

- EXPANSION TO OTHER CANCER TYPES
- INTEGRATION WITH NEW ARCHITECTURES

COLLABORATION WITH CLINICIANS

- ENGAGE WITH MEDICAL PROFESSIONALS TO IMPROVE OUR SOLUTION

PUBLICATIONS AND COLLABORATION OPPORTUNITIES

- PUBLICATION CAN LEAD TO RECOGNITION IN THE ACADEMIC AND MEDICAL IMAGING COMMUNITIES.
- CAN FOSTER COLLABORATION WITH OTHER RESEARCHERS AND INSTITUTIONS

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THREATS

SUBJECTIVITY AND ERROR IN CANCER ANNOTATIONS

- SUBJECTIVE INTERPRETATIONS BY RADIOLOGISTS
- CAN INTRODUCE INCONSISTENCIES AND ERRORS INTO THE DATA

DATA AVAILABILITY

- THE DATA FOR 1410 PATIENTS MAY NOT BE ENOUGH TO ENSURE THE RELIABILITY

OVERFITTING DUE TO HOMOGENEOUS DATASETS

- MOST OF THE DATASETS HAVE SIMILAR TUMOR DISTRIBUTIONS
- RISK OF OVERFITTING TO SPECIFIC PATTERNS IN THE DATA.

REGULATORY AND ETHICAL CONCERNS

- CHALLENGES RELATED TO REGULATIONS AND ETHICAL GUIDELINES
- NEED TO MEET STANDARDS LIKE FDA APPROVAL IN THE UNITED STATES OR CE CERTIFICATION IN EUROPE

THEORY

SKEWNESS

DATA WITH EITHER A +1 OR MORE, OR -1 OR LESS, IS SAID TO BE HIGHLY POSITIVELY/NEGATIVELY SKEWED

A MORE MODERATE POSITIVE OR NEGATIVE SKEWNESS LIES BETWEEN +0.5 AND +1, OR -0.5 AND -1 RESPECTIVELY

KURTOSIS

NORMAL DISTRIBUTION HAS KURTOSIS 3 BUT IN THE CODE FISHER ALGORITHM IS USED TO MOVE IT TO 0

A DISTRIBUTION WITH A KURTOSIS OF APPROXIMATELY 0 WOULD BE SAID TO BE MESOKURTIC.

A DISTRIBUTION WITH A KURTOSIS OF LESS THAN 0 (AND THEREFORE A NEGATIVE EXCESS KURTOSIS) IS PLATYKURTIC.

A DISTRIBUTION WITH A KURTOSIS GREATER THAN 0 (AND THEREFORE A POSITIVE EXCESS KURTOSIS) IS LEPTOKURTIC. THESE KINDS OF DISTRIBUTIONS ARE MORE PRONE TO THE PRESENCE OF OUTLIERS BECAUSE THE MAJORITY OF POINTS CLOSE TO THE MEAN RESULT IN A SMALLER STANDARD DEVIATION.

GUIDE TO PLANES

1. AXIAL (AX) MRI

REFERS TO A SCAN TAKEN IN THE AXIAL PLANE, WHICH SLICES THE BODY HORIZONTALLY, FROM TOP TO BOTTOM (PARALLEL TO THE GROUND). THIS PLANE DIVIDES THE BODY INTO SUPERIOR (UPPER) AND INFERIOR (LOWER) PARTS.

2. CORONAL (COR) MRI

SLICES THE BODY FROM FRONT TO BACK (LIKE A HEADBAND), DIVIDING IT INTO ANTERIOR (FRONT) AND POSTERIOR (BACK) SECTIONS.

3. SAGITTAL (SAG) MRI

SLICES THE BODY FROM SIDE TO SIDE, DIVIDING IT INTO LEFT AND RIGHT PARTS.

4. OBLIQUE MRI

SCAN IS TAKEN IN AN ANGLED PLANE

GUIDE TO MRI SCAN TYPES

T1-WEIGHTED IMAGING (T1WI)

DESCRIPTION: PROVIDES HIGH CONTRAST BETWEEN DIFFERENT SOFT TISSUES.

USE CASES:

ANATOMICAL DETAIL: GREAT FOR VISUALIZING THE BRAIN'S ANATOMY, FAT TISSUES, AND NORMAL STRUCTURAL DETAIL.

POST-CONTRAST ENHANCEMENT: T1WI IS OFTEN USED AFTER ADMINISTERING GADOLINIUM CONTRAST AGENTS TO VISUALIZE ENHANCED AREAS LIKE TUMORS OR INFLAMMATION.

2. T2-WEIGHTED IMAGING (T2WI)

DESCRIPTION: FLUIDS APPEAR BRIGHT, WHILE TISSUES LIKE FAT APPEAR DARKER COMPARED TO T1WI.

USE CASES:

DETECTING EDEMA, INFLAMMATION, AND PATHOLOGICAL CHANGES.

IDENTIFYING BRAIN LESIONS, TUMORS, OR ABNORMALITIES INVOLVING INCREASED WATER CONTENT.

DIFFERENTIATING BETWEEN VARIOUS TYPES OF TISSUES BASED ON WATER CONTENT.

3. FLAIR (FLUID-ATTENUATED INVERSION RECOVERY)

DESCRIPTION: SIMILAR TO T2-WEIGHTED IMAGING, BUT SUPPRESSES SIGNALS FROM FLUIDS LIKE CEREBROSPINAL FLUID (CSF), MAKING LESIONS NEAR FLUID-FILLED AREAS MORE VISIBLE.

USE CASES:

DETECTING LESIONS IN CONDITIONS LIKE MULTIPLE SCLEROSIS OR BRAIN INJURIES.

VISUALIZING BRAIN ABNORMALITIES NEAR VENTRICLES AND SULCI.

FUTURE WORK

A GENERAL AND ROBUST LOSS FUNCTION

- A **SINGLE LOSS FUNCTION** THAT IS A **SUPERSET** OF MANY **COMMON ROBUST LOSS FUNCTIONS**
- A **SINGLE** CONTINUOUS-VALUED **PARAMETER** IN THE GENERAL LOSS FUNCTION CAN BE SET SUCH THAT IT IS EQUAL TO SEVERAL TRADITIONAL LOSSES, AND CAN BE ADJUSTED TO **MODEL A WIDER FAMILY OF FUNCTIONS**
- OUR **CURRENT LOSS** FUNCTION HAS **NO HYPERPARAMETERS**
- **ROBUSTNESS PARAMETER** IS A **LEARNABLE** PARAMETER - **NO MANUAL TUNING**
- **TWO-PARAMETER** LOSS FUNCTION THAT **GENERALIZES** MANY EXISTING **ONE-PARAMETER ROBUST LOSS FUNCTIONS**

FUTURE WORK

A GENERAL AND ROBUST LOSS FUNCTION

$$f(x,\alpha,c) = \frac{|\alpha-2|}{\alpha}\left(\left(\frac{(x/c)^2}{|\alpha-2|}+1\right)^{\alpha/2}-1\right)$$

- Α ∈ R IS A **SHAPE PARAMETER** THAT CONTROLS THE **ROBUSTNESS** OF THE LOSS
- C > 0 IS A **SCALE PARAMETER** THAT CONTROLS THE SIZE OF THE LOSS'S QUADRATIC BOWL NEAR X = 0
- Α IS USUALLY IN **(0, 3)**, WHICH ALLOWS FUNCTION DISTRIBUTION TO GENERALIZE **CAUCHY** (Α = 0) AND **NORMAL** (Α = 2) **DISTRIBUTIONS** AND ANYTHING IN BETWEEN, ALSO FOR **NUMERICAL STABILITY**
- C IS FIXED TO MATCH THE FIXED SCALE ASSUMPTION OF THE BASELINE MODELS AND ROUGHLY MATCHE THE SHAPE OF ITS L1 LOSS

FUTURE WORK

A GENERAL AND ROBUST LOSS FUNCTION

$$\lim_{\alpha \to 2} f(x, \alpha, c) = \frac{1}{2} \left({}^{x}/_{c} \right)^2$$

A -> 2 = L2 LOSS

$$\lim_{\alpha \to 0} f(x, \alpha, c) = \log \left(\frac{1}{2} \left({}^{x}/_{c} \right)^2 + 1 \right)$$

A -> 0 = CAUCHY (AKA LORENTZIAN) LOSS

$$f(x, -2, c) = \frac{2 \left({}^{x}/_{c} \right)^2}{\left({}^{x}/_{c} \right)^2 + 4}$$

A = -2 = GEMAN-MCCLURE LOSS

$$f(x, 1, c) = \sqrt{\left({}^{x}/_{c} \right)^2 + 1} - 1$$

A = 1 = SMOOTHED L1 LOSS

$$\lim_{\alpha \to -\infty} f(x, \alpha, c) = 1 - \exp \left(-\frac{1}{2} \left({}^{x}/_{c} \right)^2 \right)$$

A -> -INF = WELSCH (AKA LECLERC) LOSS

FUTURE WORK

A GENERAL AND ROBUST LOSS FUNCTION

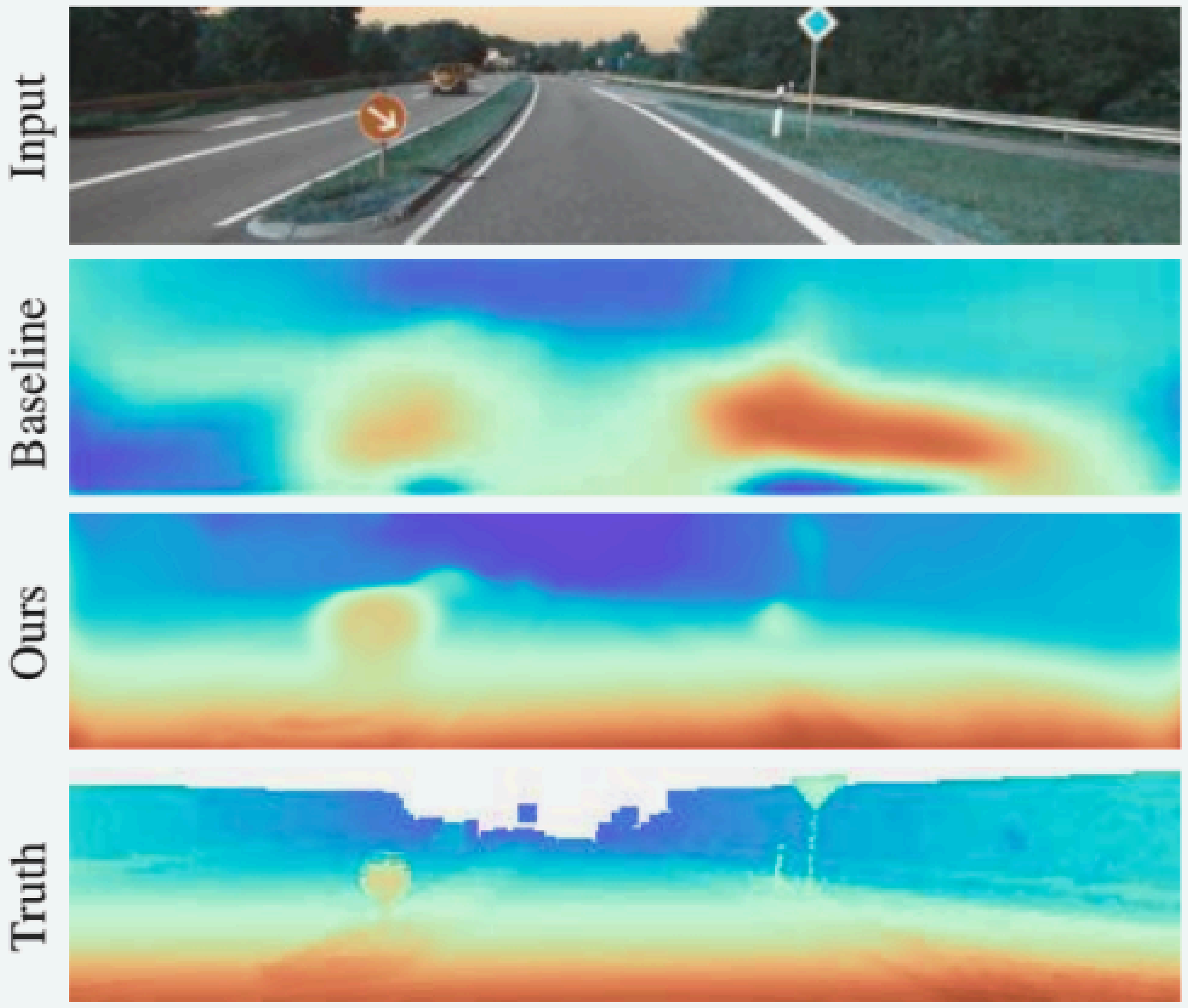
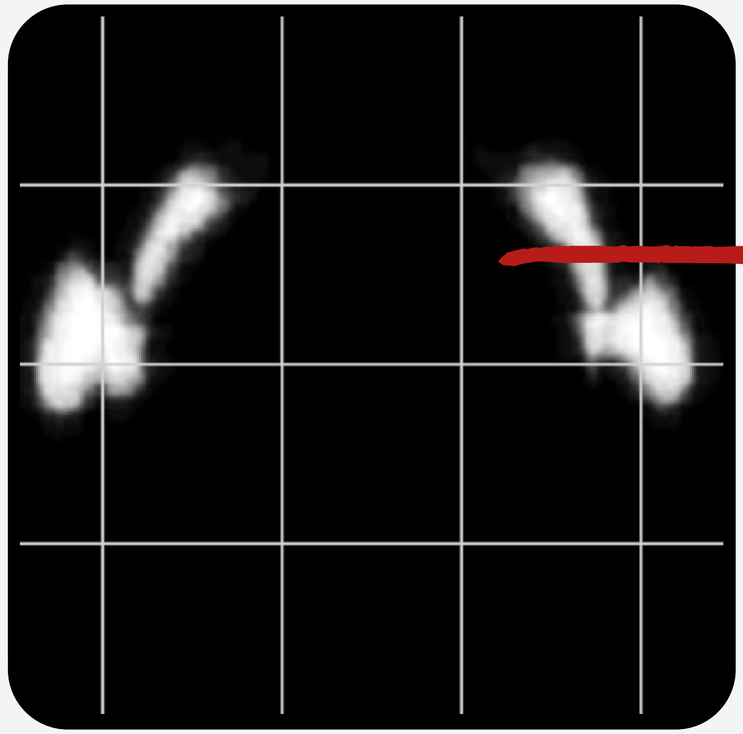


Figure 4. Monocular depth estimation results on the KITTI benchmark using the "Baseline" network of [41]. Replacing only the network's loss function with our "adaptive" loss over wavelet coefficients results in significantly improved depth estimates.

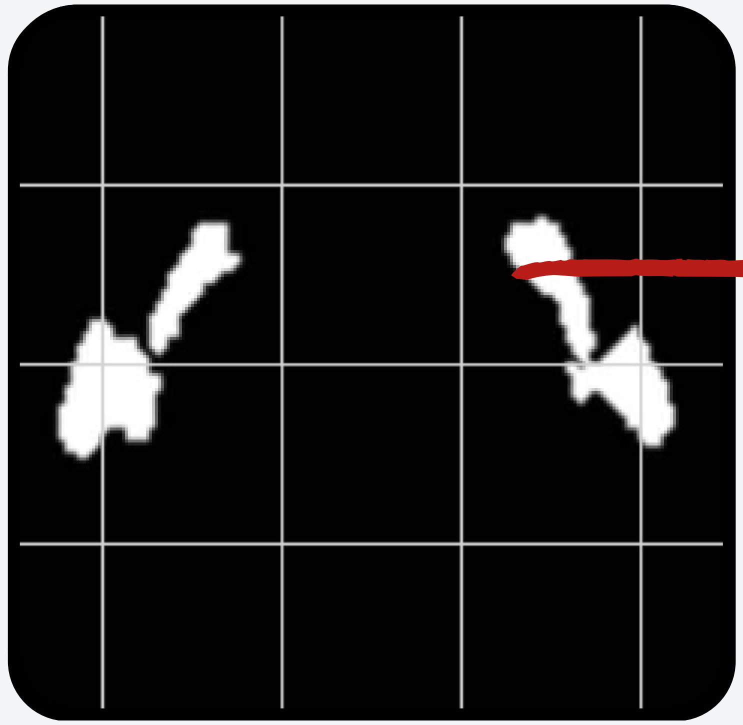
- IN THE ADAPTIVE A ∈ (0, 2) MODEL THEY ASSIGN **EACH WAVELET COEFFICIENT** ITS **OWN SHAPE PARAMETER** AS A **FREE VARIABLE**, WHICI ARE **OPTIMIZED** ALONGSIDE THEIR NETWORK WEIGHTS **DURING TRAINING**
- NO **SINGLE SETTING** OF A IS **OPTIMAL** FOR ALL WAVELET COEFFICIENTS. OVERALL, JUST **REPLACING THE LOSS FUNCTION** OF **BASELINE MODEL** WITH THIS ADAPTIVE LOSS ON WAVELET COEFFICIENTS **REDUCES AVERAGE ERROR** BY 17%.

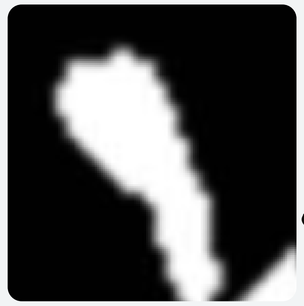
FUTURE WORK

REGION SPECIFIC ADAPTIVE LOSS FUNCTION



Local Output in a sub-region ‘k’





Local Label in a sub-region ‘k’

ADJUSTING PENALTY

BASED ON FP & FN ERRORS

$$\alpha_{\text{Adaptive}} = \mathrm{A} + \mathrm{B} \cdot \frac{FP}{FP + FN}$$

$$\beta_{\text{Adaptive}} = \mathrm{A} + \mathrm{B} \cdot \frac{FN}{FP + FN}$$

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