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

GROUP-1


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AGENDA

01 Introduction

02 Loss Functions Overview

03 Our approach

04 Datasets

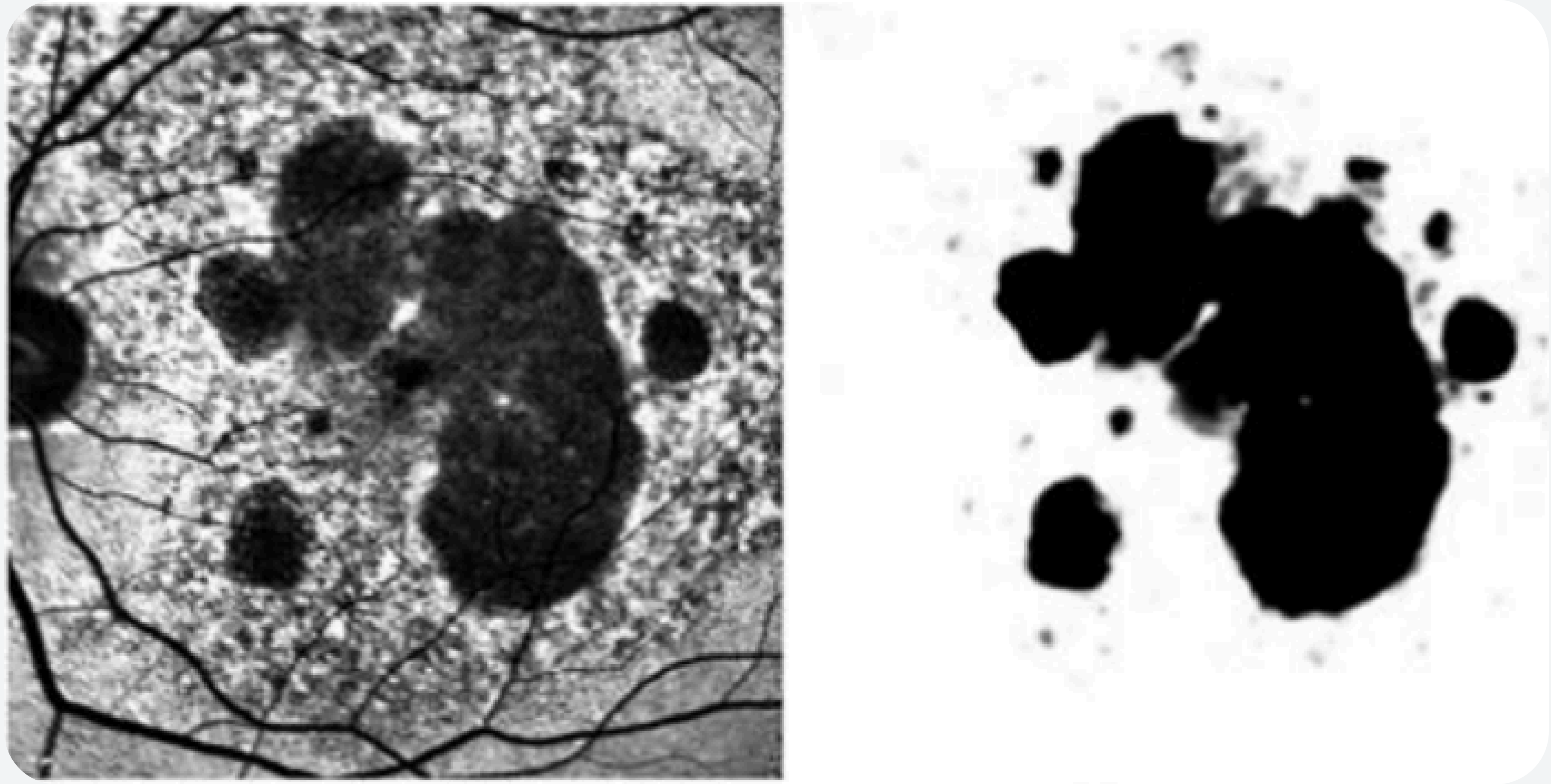
05 Future Work

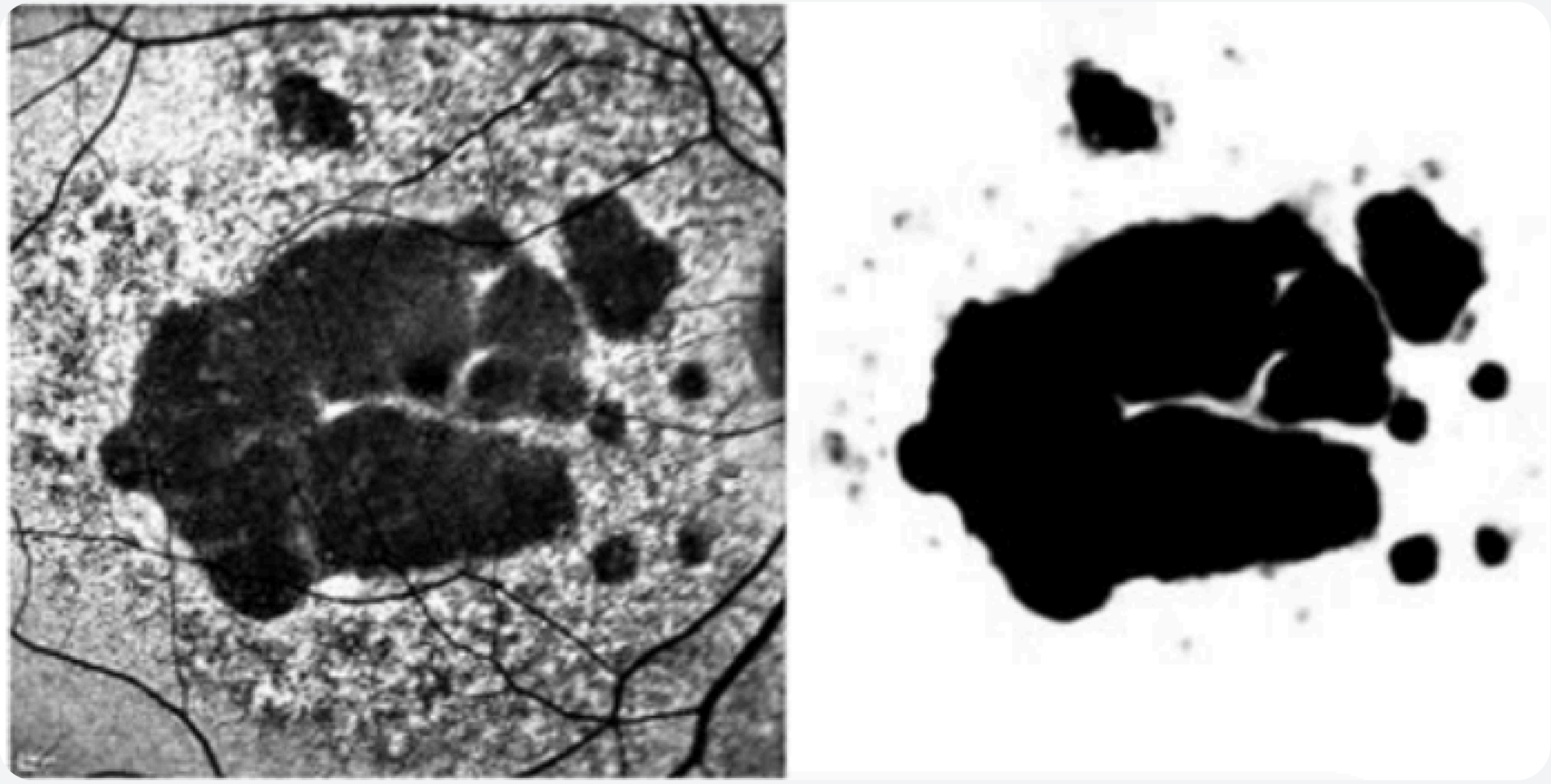
06 Limitations

07 Roadmap

INTRODUCTION

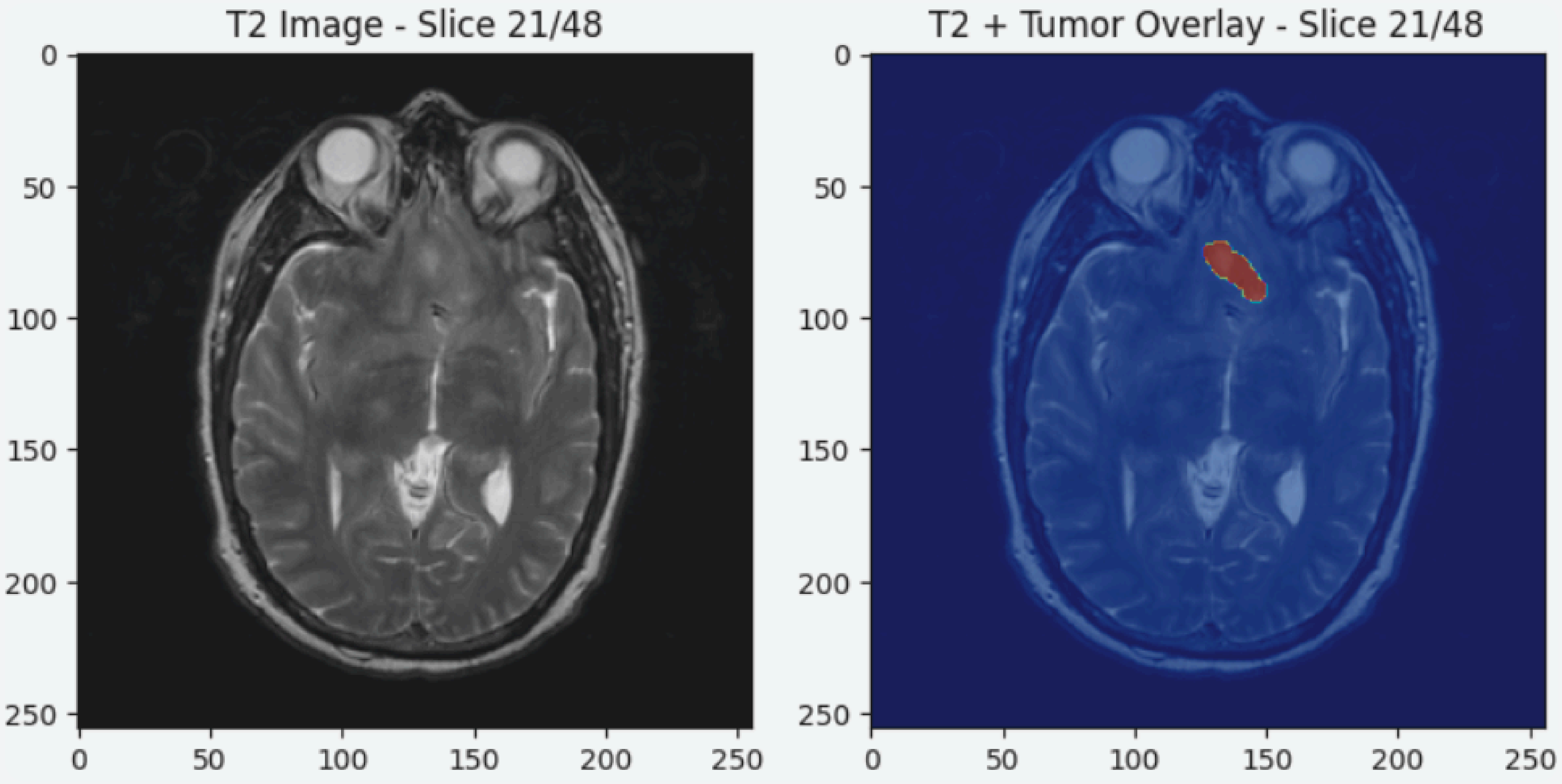
- **ARTIFICIAL INTELLIGENCE** (AI) AND **DEEP LEARNING** (DL) METHODS - TRANSFORMING THE **HIGH-RISK** AND **HIGH-STAKE** WORLD OF **MEDICAL APPLICATIONS**
- INCREASING INTEREST IN THE EXPLORATION OF **MEDICAL IMAGES**
- IDENTIFYING **DISEASE-RELEVANT BIOMARKERS** FOR INFORMATION DISCOVERY AND PREDICTIVE ANALYTICS





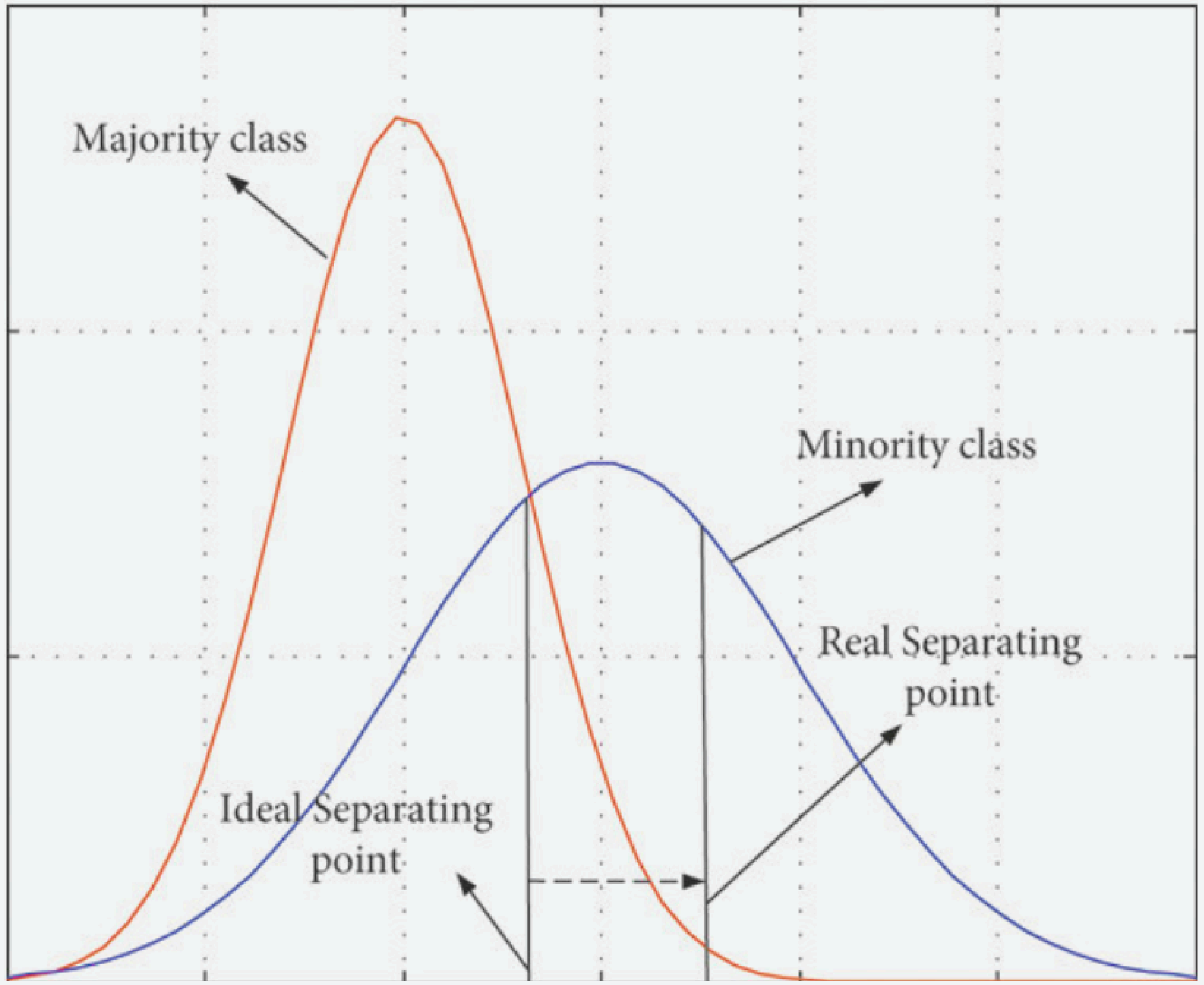
INTRODUCTION

- **MANUAL SEGMENTATION** FOR MEDICAL IMAGES IS **TIME-CONSUMING**
- **AUTOMATED TOOLS** RELY ON **TRAINING DATA** IN ORDER TO **GENERATE CORRECT ANNOTATIONS**
- **TRAINING DATA** IS OFTEN **IMBALANCED**, WITH **ANNOTATIONS NOT** BEING **VERY PRECISE**
- DIFFERENT WAYS EXIST TO TRY AND ACCOUNT FOR THESE IMBALANCES



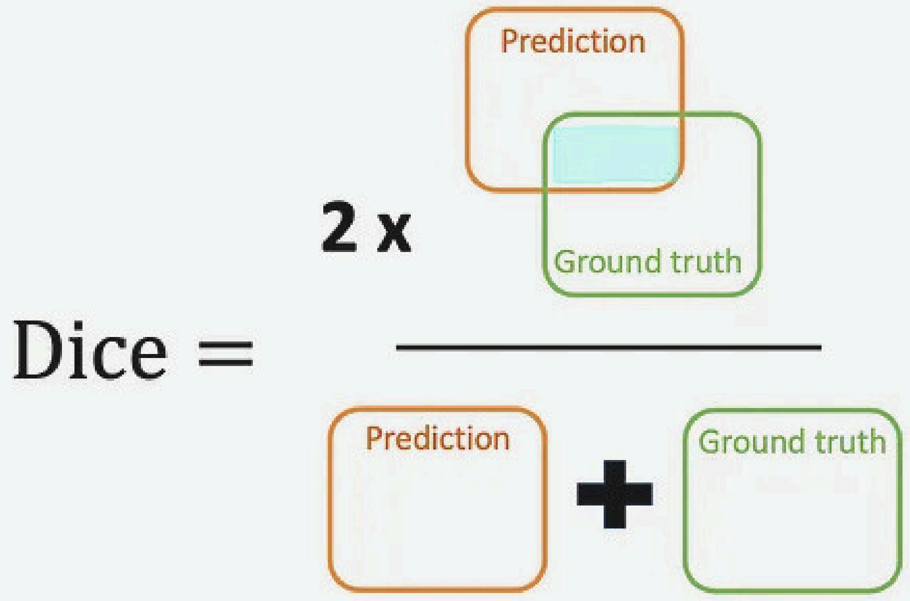
INTRODUCTION

- **USE OF LOSS FUNCTIONS** TO BETTER **IMPROVE** DL PARAMETER ESTIMATION
- DIFFERENT LOSS FUNCTIONS DO DIFFERENT THINGS TO OVERCOME IMBALANCED DATASETS:
  - ASSIGN **HIGHER WEIGHTS** TO **MINORITY CLASSES** *(WBCE)*
  - **FOCUS** ON **HARD-TO-CLASSIFY** EXAMPLES, **REDUCE** THE **WEIGHT** FOR **WELL-CLASSIFIED EXAMPLES** *(FOCAL LOSS)*
  - USE **OVERLAPPING METRICS** SUCH AS **DICE SIMILARITY COEFFICIENT** *(DICE LOSS)*
  - USE ADJUSTABLE PARAMETERS TO **CONTROL** THE **BALANCE** BETWEEN **FALSE POSITIVES** VS **FALSE NEGATIVES** *(TVERSKY LOSS)*



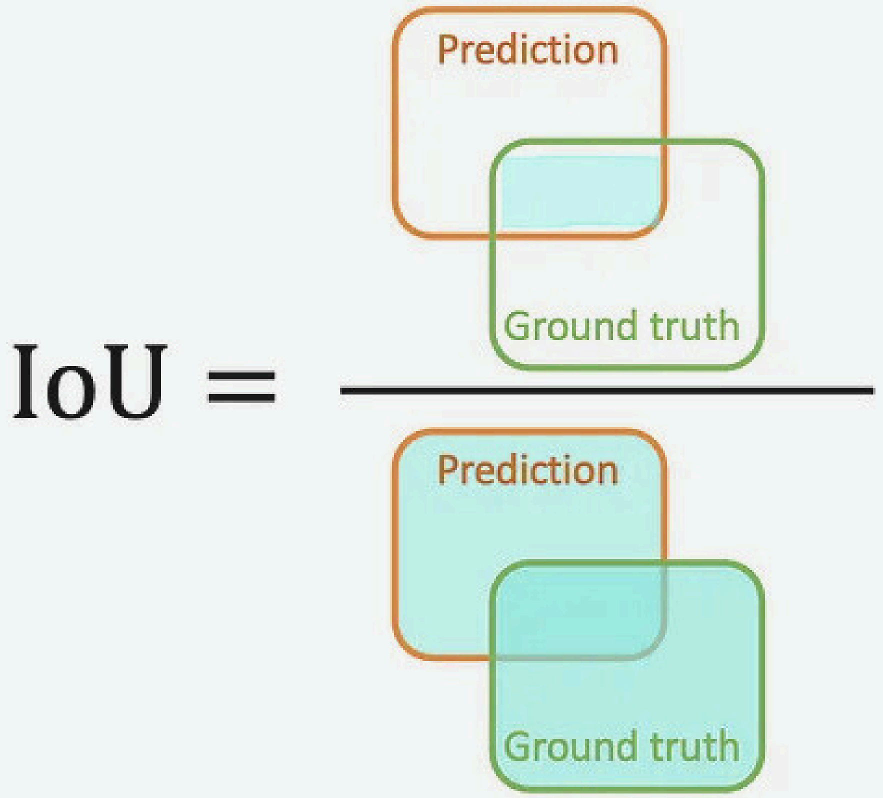
STATE-OF-THE-ART ~ LOSS FUNCTIONS

DEFINITION: A **MATHEMATICAL MEASURE** THAT EVALUATES THE **DIFFERENCE** BETWEEN A **MODEL'S PREDICTED SEGMENTATION** AND THE **TRUE SEGMENTATION** LABELS IN AN IMAGE

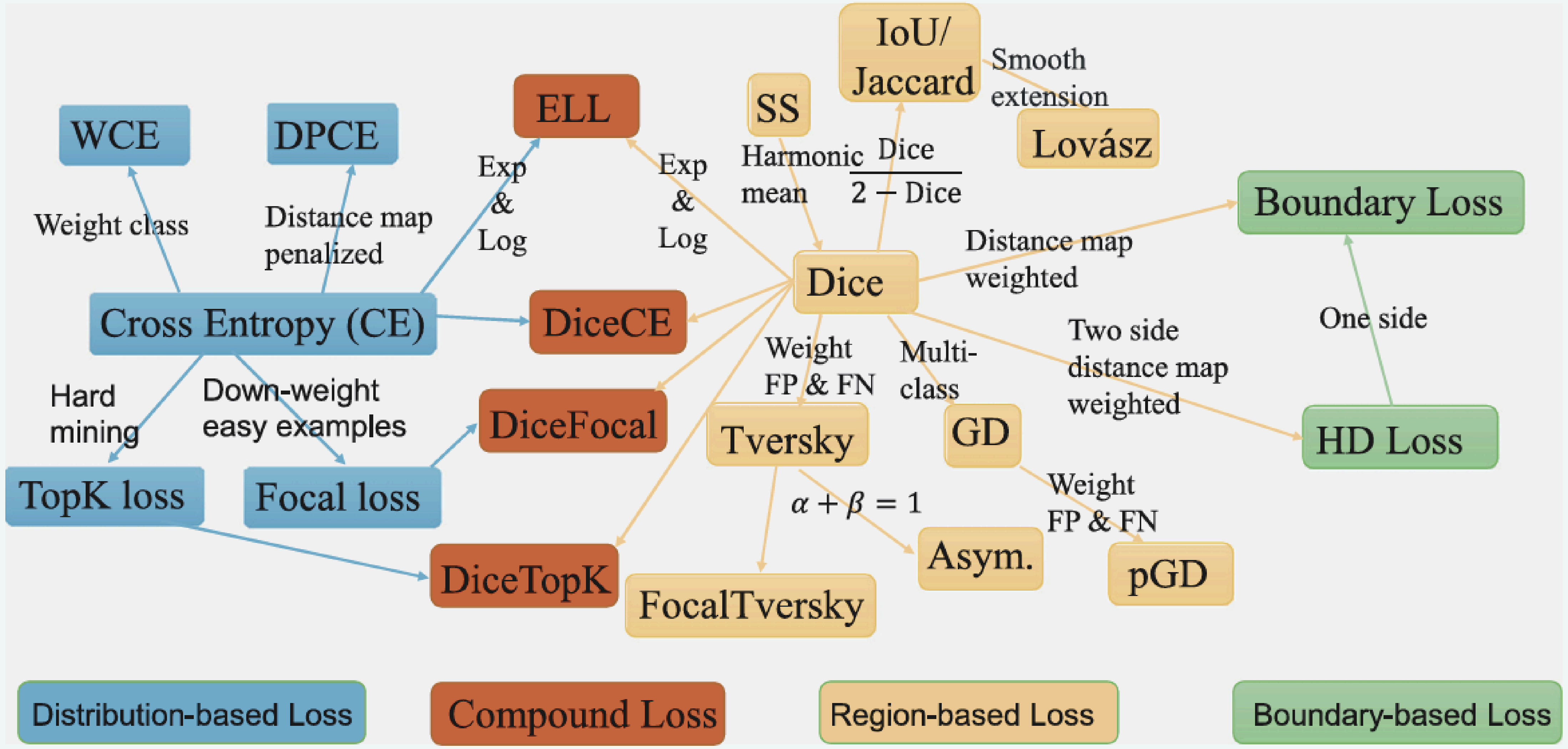


OUR CONTEXT: IT **QUANTIFIES** HOW **ACCURATELY** THE MODEL IDENTIFIES **TUMORS** FROM THE **BACKGROUND** IN A **MEDICAL IMAGE**

PURPOSE: DURING TRAINING, THE MODEL TRIES TO **MINIMIZE** THE **LOSS** BY **ADJUSTING ITS PARAMETERS**, WITH THE GOAL OF **IMPROVING** ITS PREDICTIVE **ACCURACY**



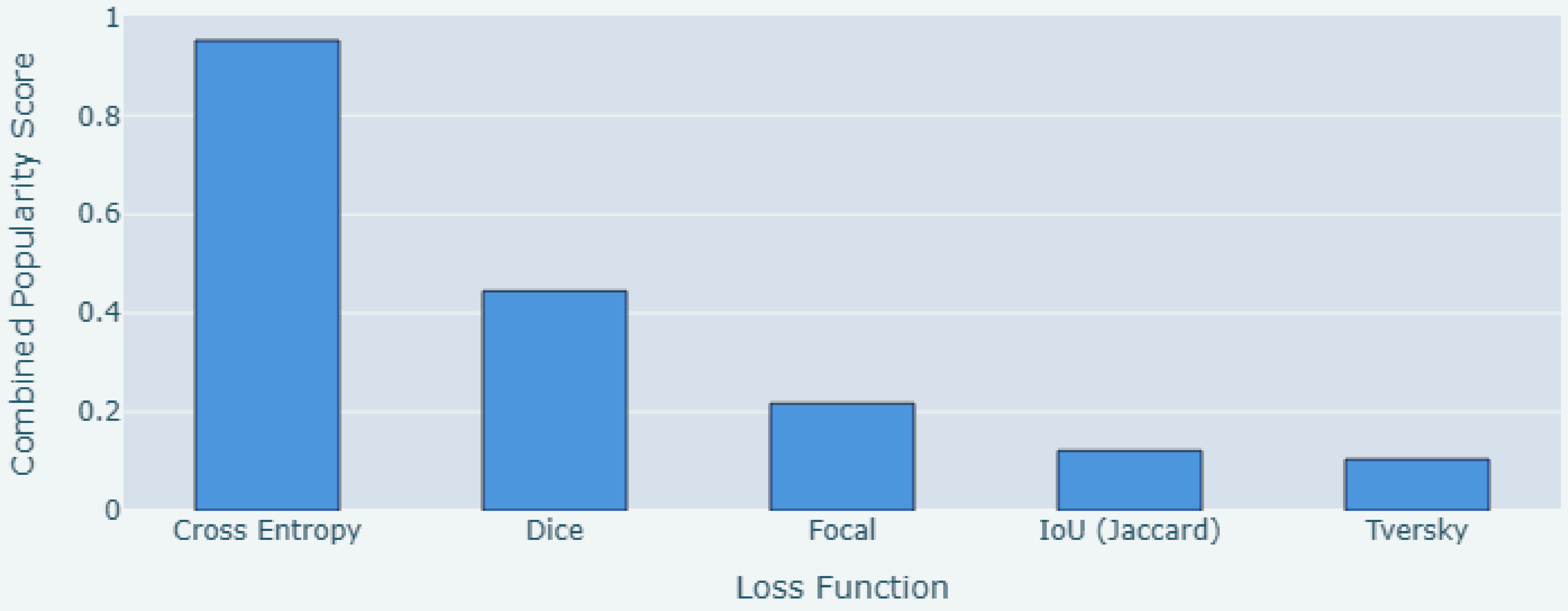
STATE-OF-THE-ART ~ LOSS FUNCTIONS



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

POPULAR LOSS FUNCTIONS

TOP 5 LOSS FUNCTION BY COMBINED POPULARITY SCORE



POPULAR LOSS FUNCTIONS

DICE SIMILARITY COEFFICIENT

- SMALL REGION OF INTERSET ✓
- WELL CALIBRATED ✗

CROSS ENTROPY

- WELL CALIBRATED ✓
- IMBALANCED DATA ✗

FOCAL LOSS

- IMBALANCED DATA ✓
- SENSITIVITY TO MISLABELED OR NOISY DATA ✓

Calibrating the Dice loss to handle neural network overconfidence for biomedical image segmentation

October 2021
DOI: 10.48550/arXiv.2111.00528

ELSEVIER
Medical Image Analysis
Volume 71, July 2021, 102035

Loss odyssey in medical image segmentation

A Comprehensive Survey of Loss Functions in Machine Learning

April 2022 · Annals of Data Science · 9(5500)
DOI: 10.1007/s40745-020-00253-5

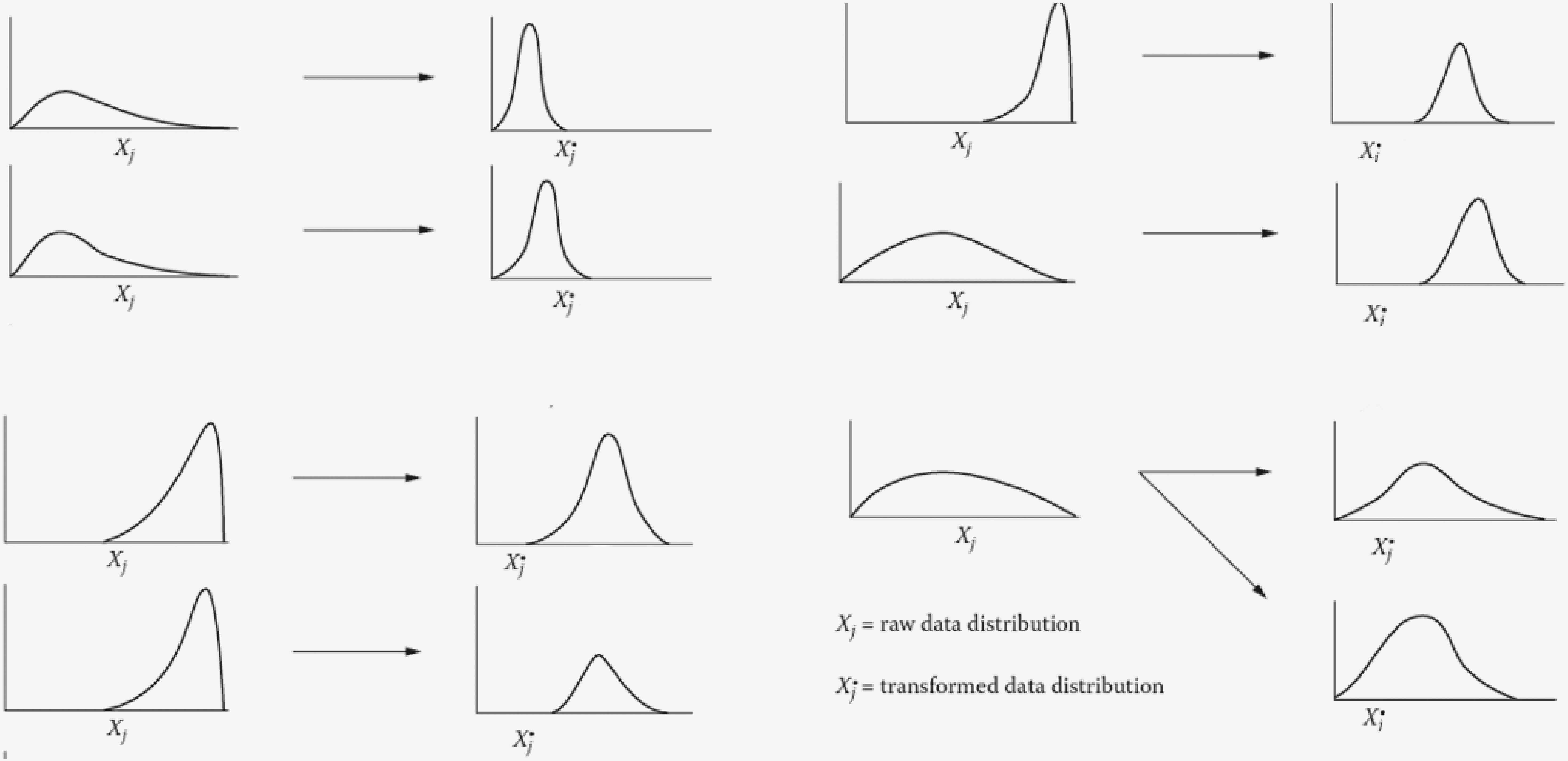
OUR APPROACH

- PROPOSED APPROACH **- ADAPTIVE LOSS FUNCTION** DERIVES ITS FORM BASED ON THE **DATA DISTRIBUTION**
- **SKEWNESS AND KURTOSIS** ARE EXPLORED
- TRANSFORMATIONS LIKE **ARCSIN, LN, LOG10** ARE USED TO **NORMALIZE THE DATA DISTRIBUTION**

BENEFITS

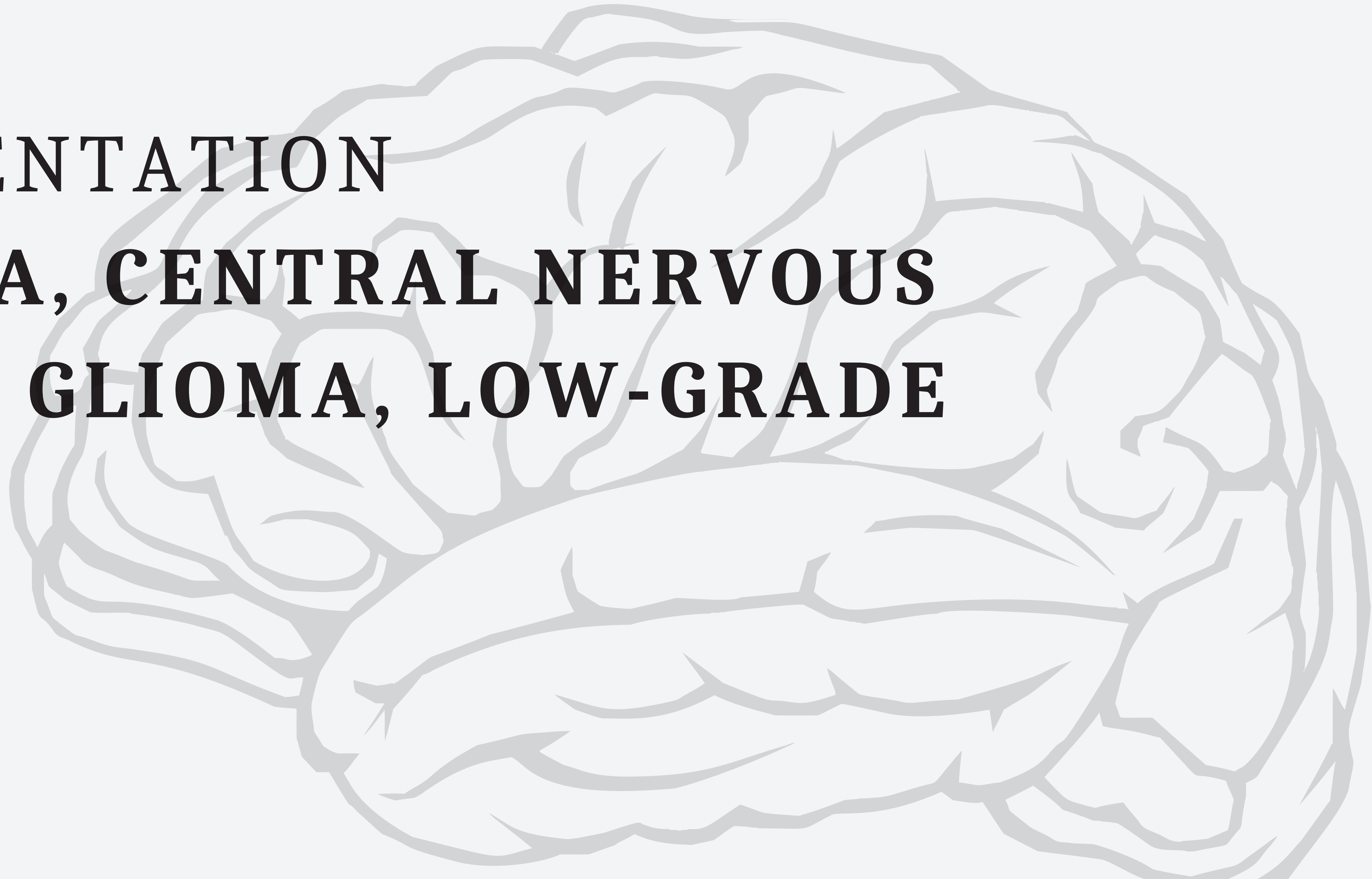
- **STABILIZING VARIANCE**
- **MAKING THE DISTRIBUTION MORE GAUSSIAN**
- **HANDLING OUTLIERS**
- **IMPROVING CONVERGENCE FOR GRADIENT-BASED ALGORITHMS**

OUR APPROACH

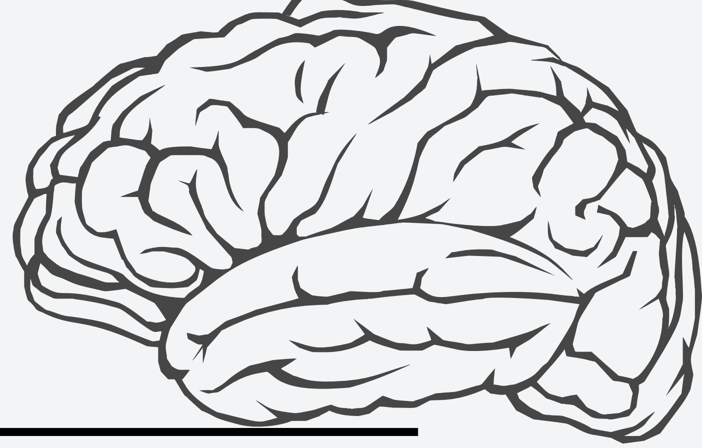


DATASETS

- **5** DATASETS FROM THE CANCER IMAGING ARCHIVE
- **4** PUBLIC AND **1** PRIVATE
- **1531 PATIENTS** IN TOTAL
- **MR** IMAGES
- **BINARY** OR **GRAYSCALE** SEGMENTATION
- CANCER TYPES: **GLIOBLASTOMA, CENTRAL NERVOUS SYSTEM NEOPLASMS, DIFFUSE GLIOMA, LOW-GRADE GLIOMA**



DATASET - 1



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

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

- MR

Cancer Type

- LOW GRADE GLIOMA

Patients

- 159

Public

- NO

Image Size

- 256, 256, N

Tumor Size

- N, 256, 256

LGG-1P19QDELETION | LGG-1P19QDELETION

MRI Images

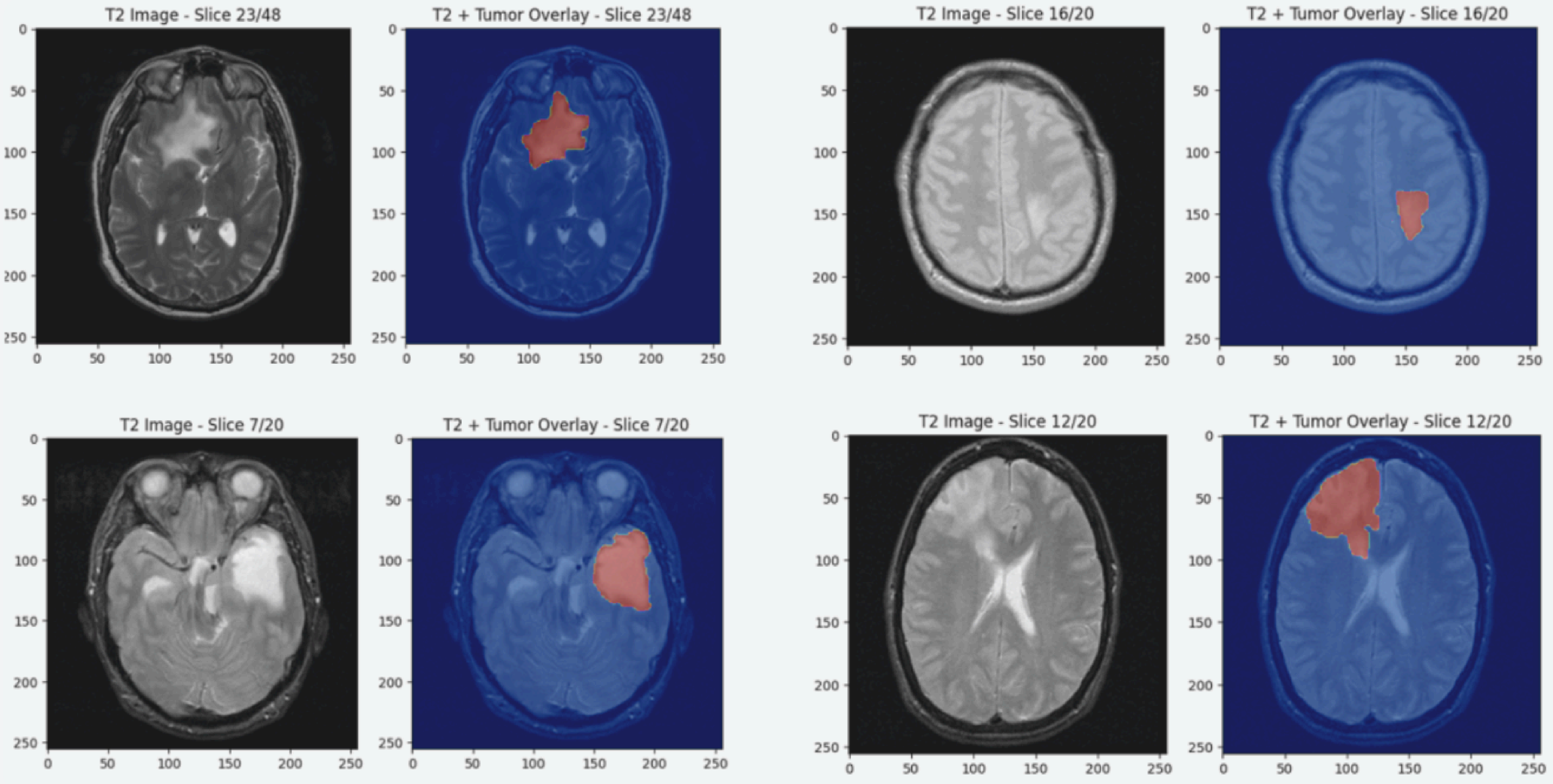
T2

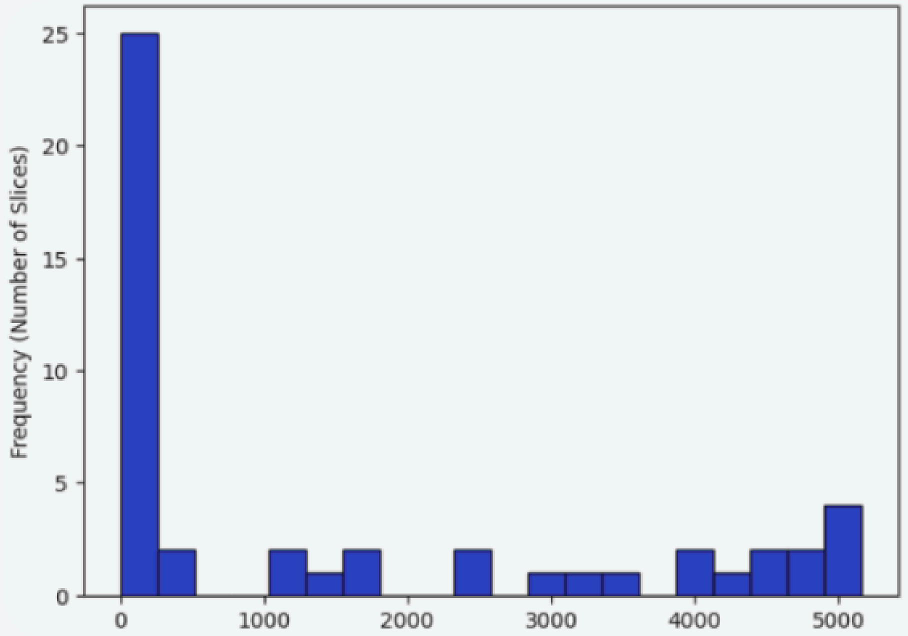
Planes

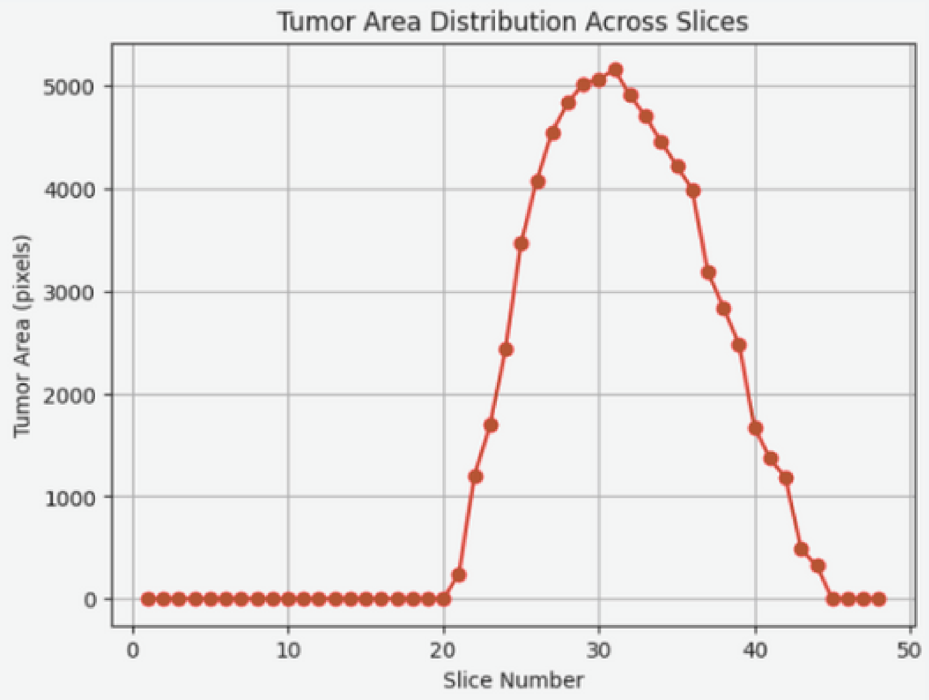
Axial

Distribution

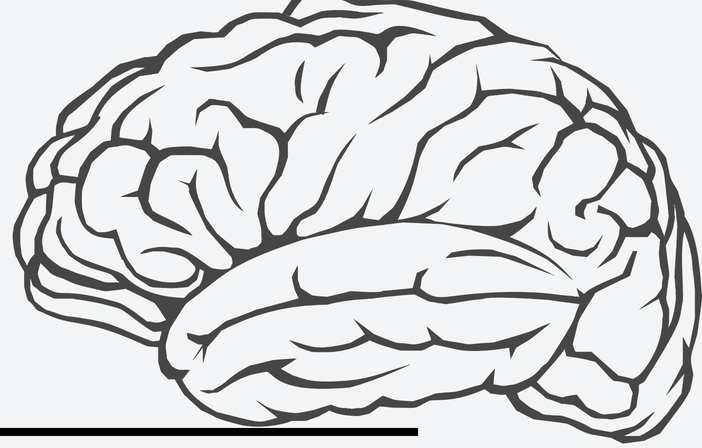
Right Skewed







DATASET - 2



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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

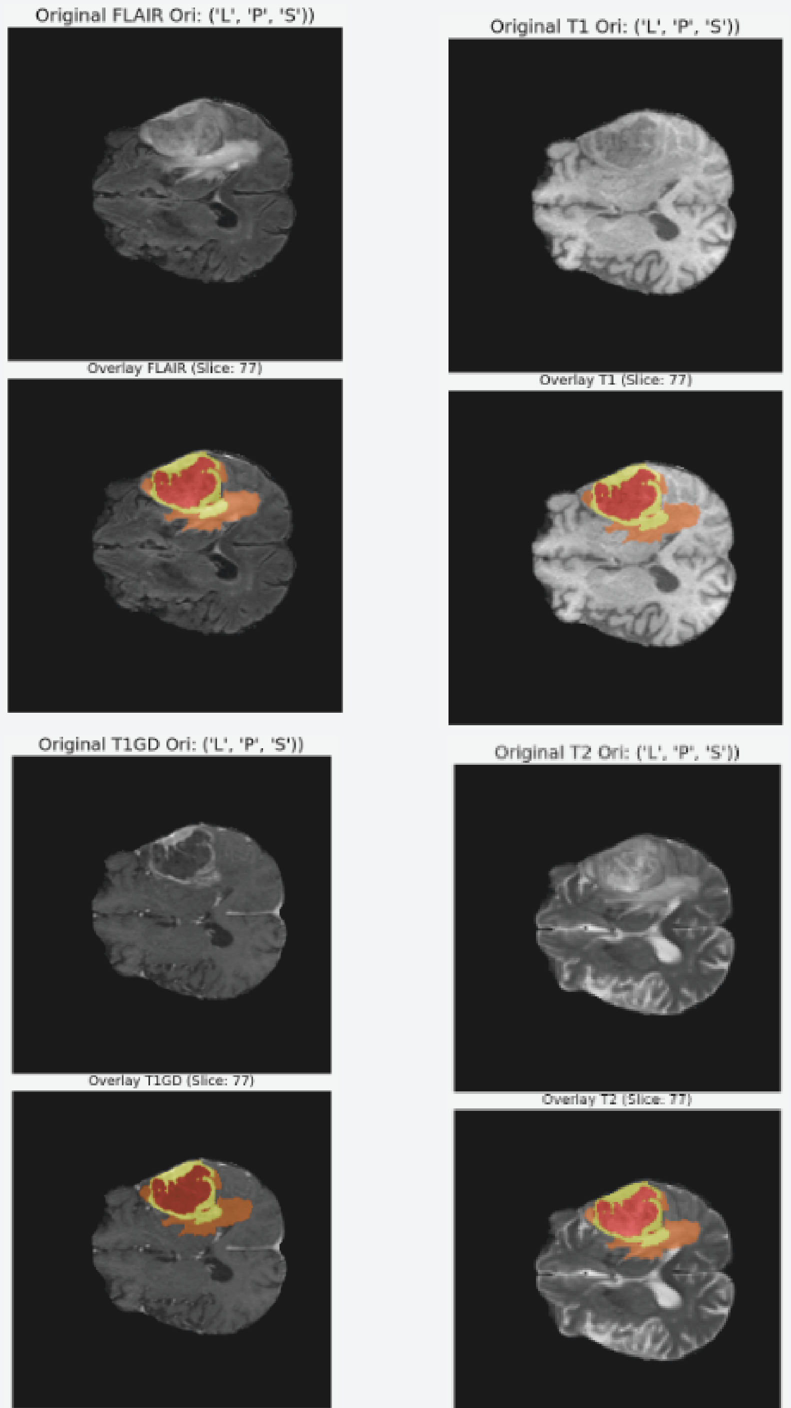
Flair, T1, T1GD, T2

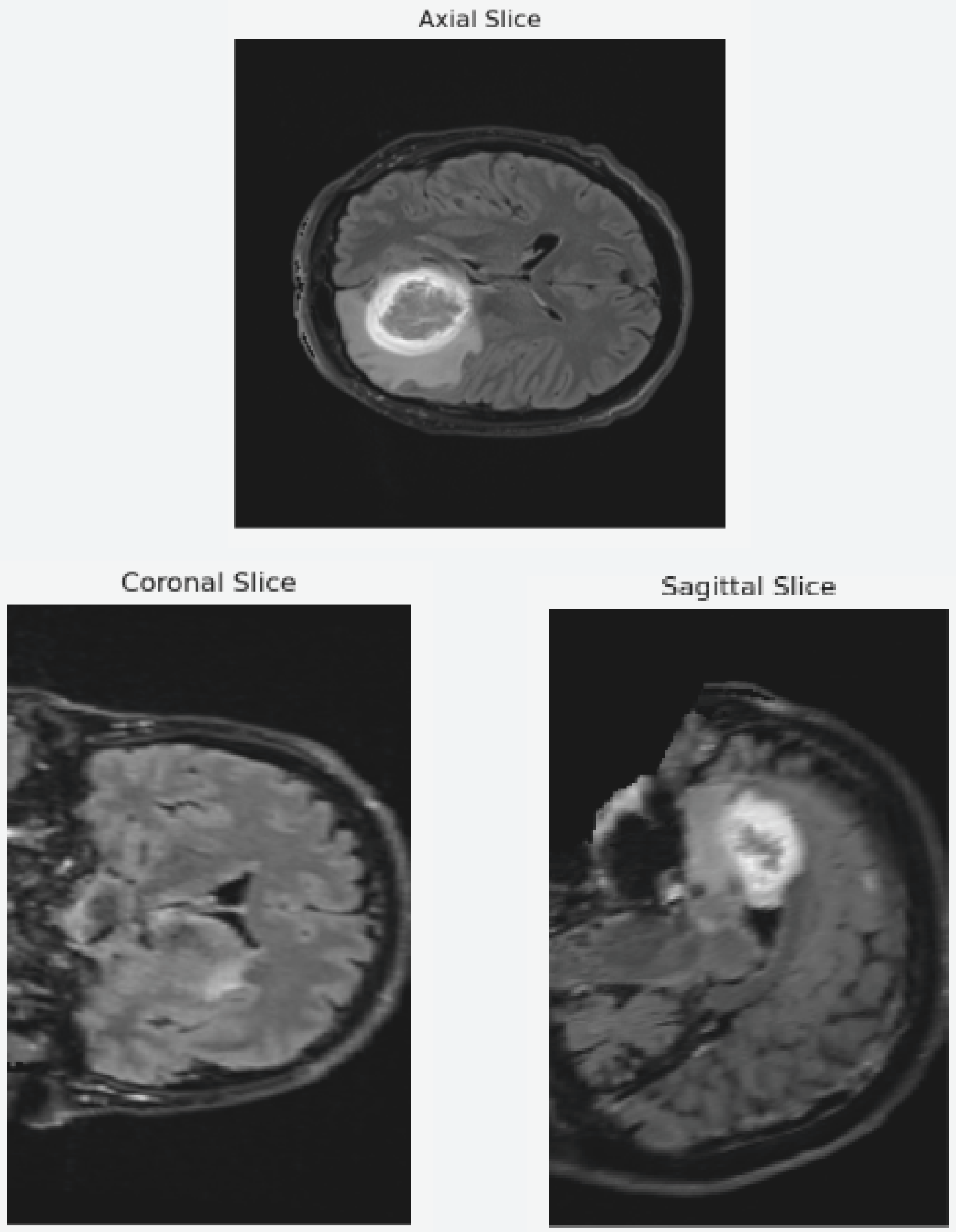
Planes

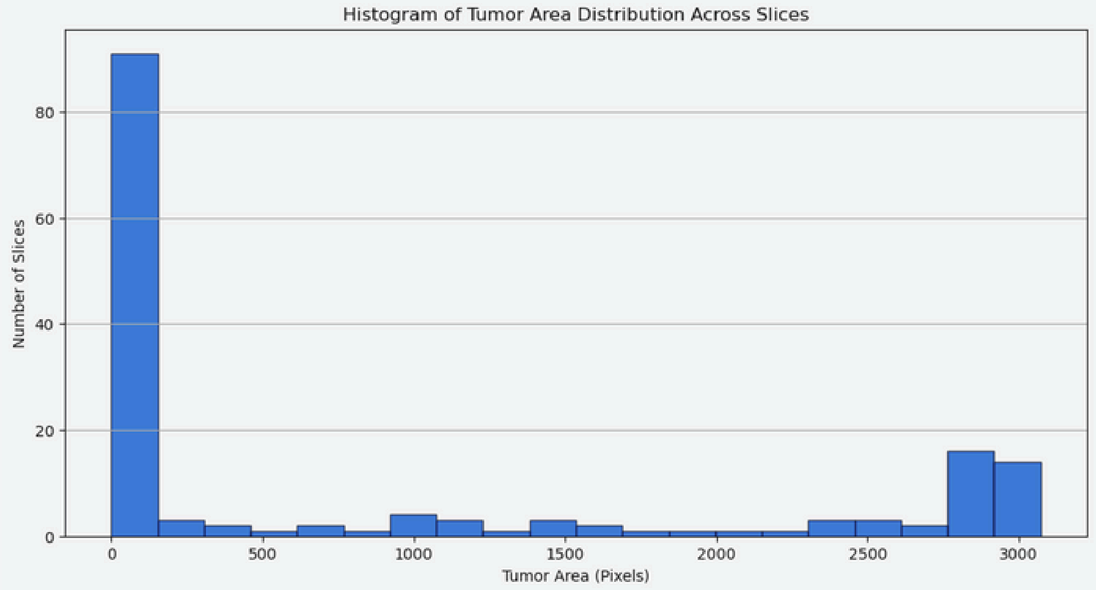
Axial, Coronal, Sagittal

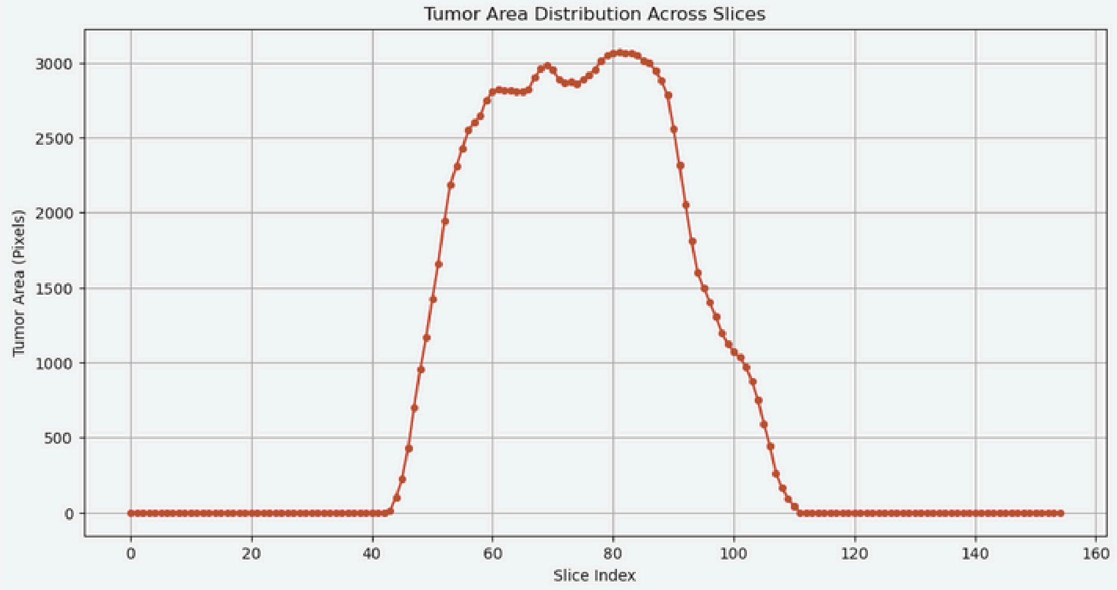
Distribution

Right Skewed

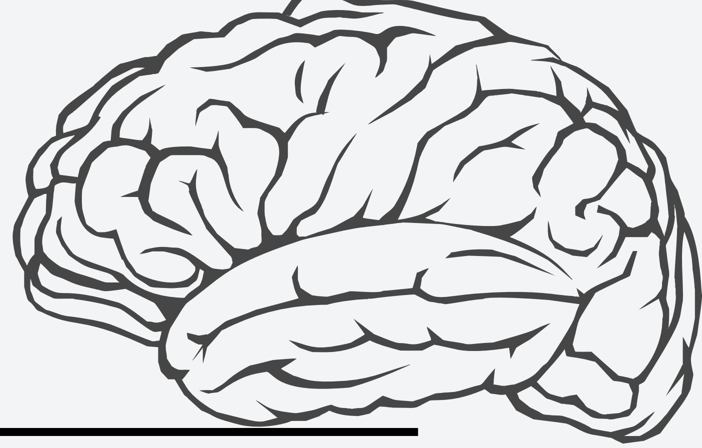








DATASET - 3

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THE CANCER IMAGING ARCHIVE

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The Cancer Imaging Archive

UCSF-PDGM | The University of California San Francisco Preoperative Diffuse Glioma MRI

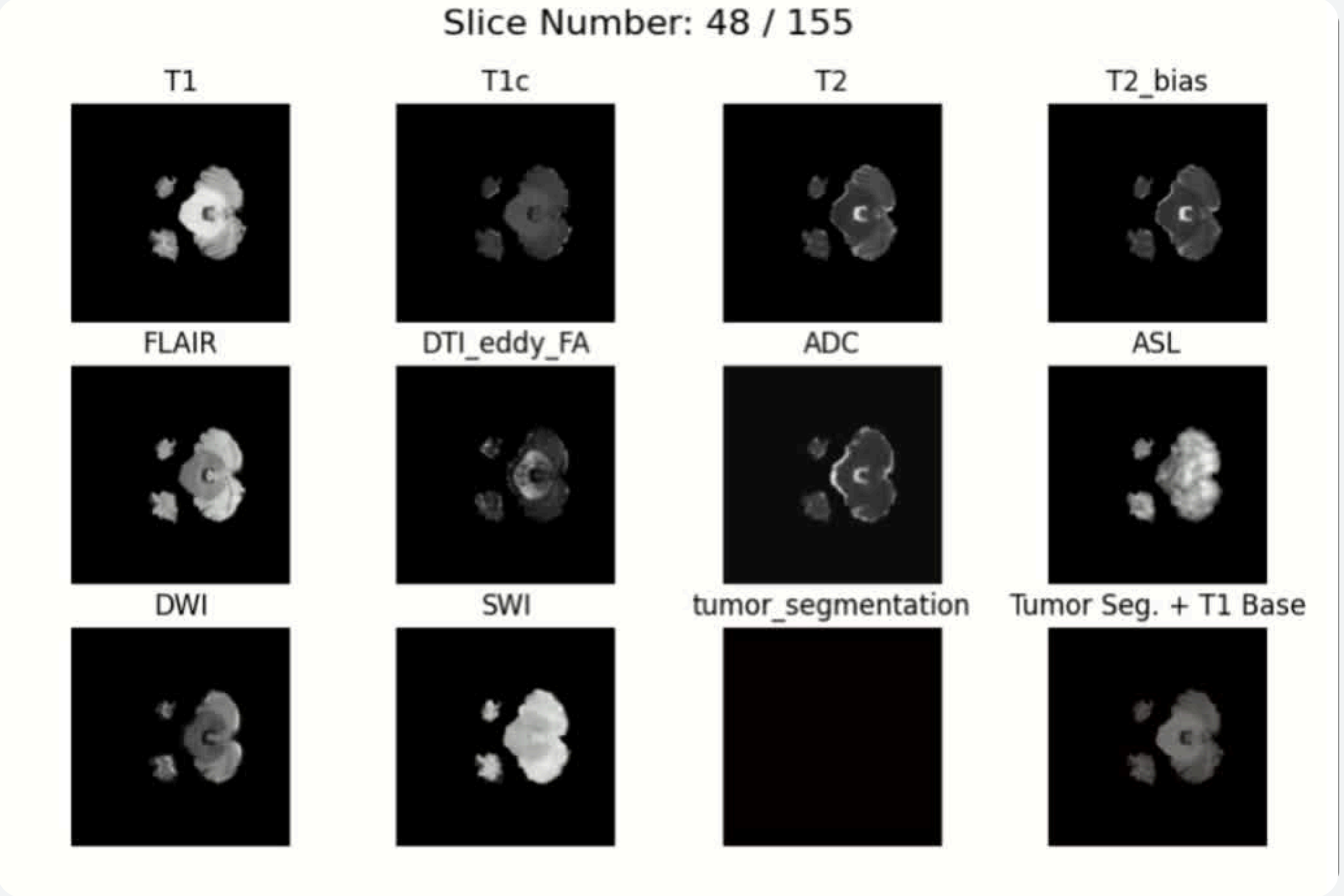
DOI: 10.7937/tcia.bdgf-8v37 | Data Citation Required | IMAGE COLLECTION

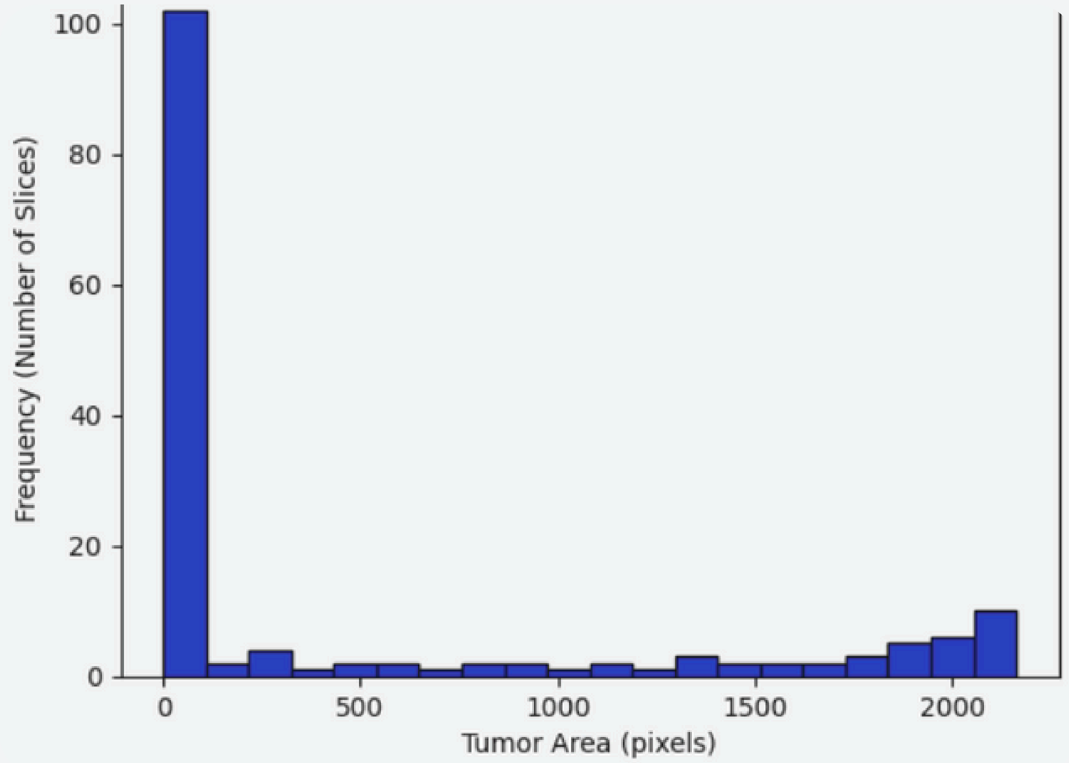
Location	Species	Subjects	Data Types	Cancer Types	Size	Supporting Data	Status	Updated
Brain	Human	495	MR, Measurement	Diffuse Glioma	156GB	Clinical, Genomics, Image Analyses, Software/Source Code	Public, Complete	2023/04/07

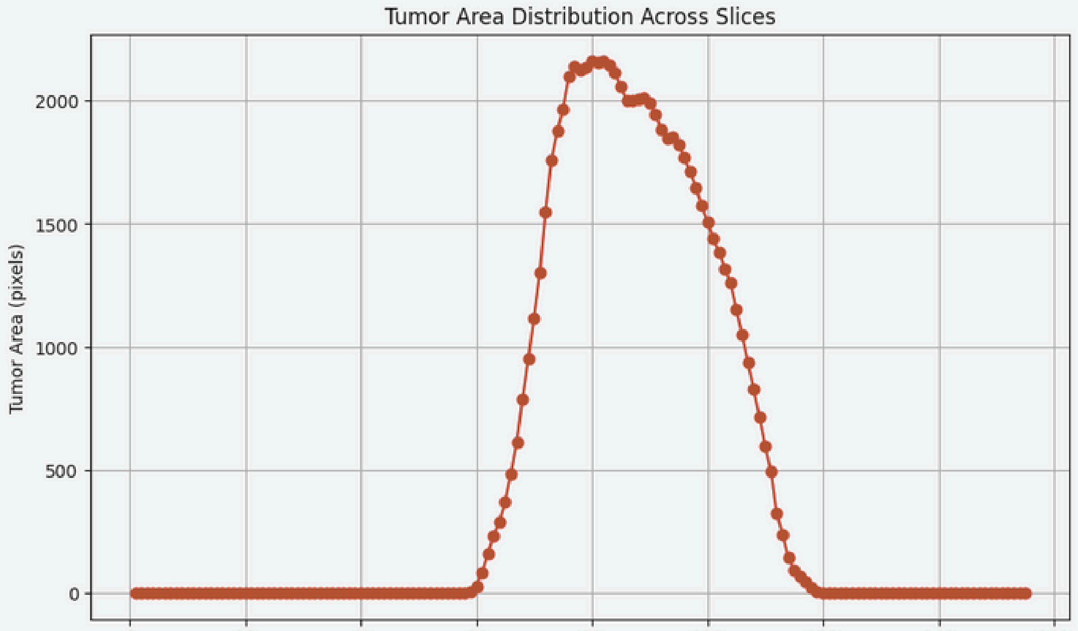
Data Type	Cancer Type	Patients	Public	Image Size	Tumor Size
• MR • MEASUREMENT	• DIFFUSE GLIOMA	• 501	• YES	• 240, 240, 155	• 240, 240, 155

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

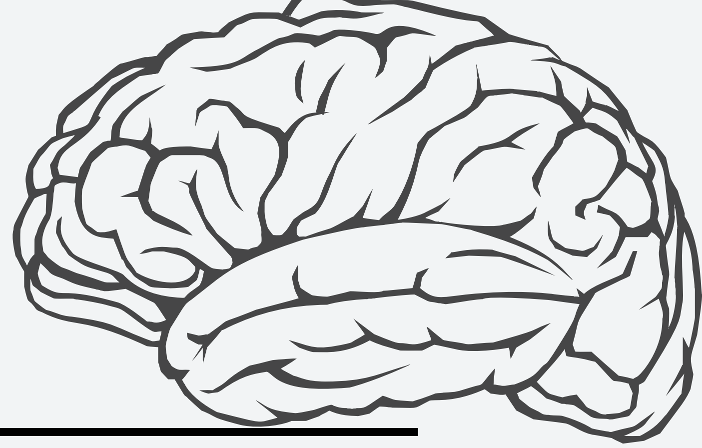
MRI Images	Planes	Distribution
T1, T2, FLAIR, HARDI (FA), ADC, ASL, DWI, SWI	Axial	Right Skewed







DATASET - 4



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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

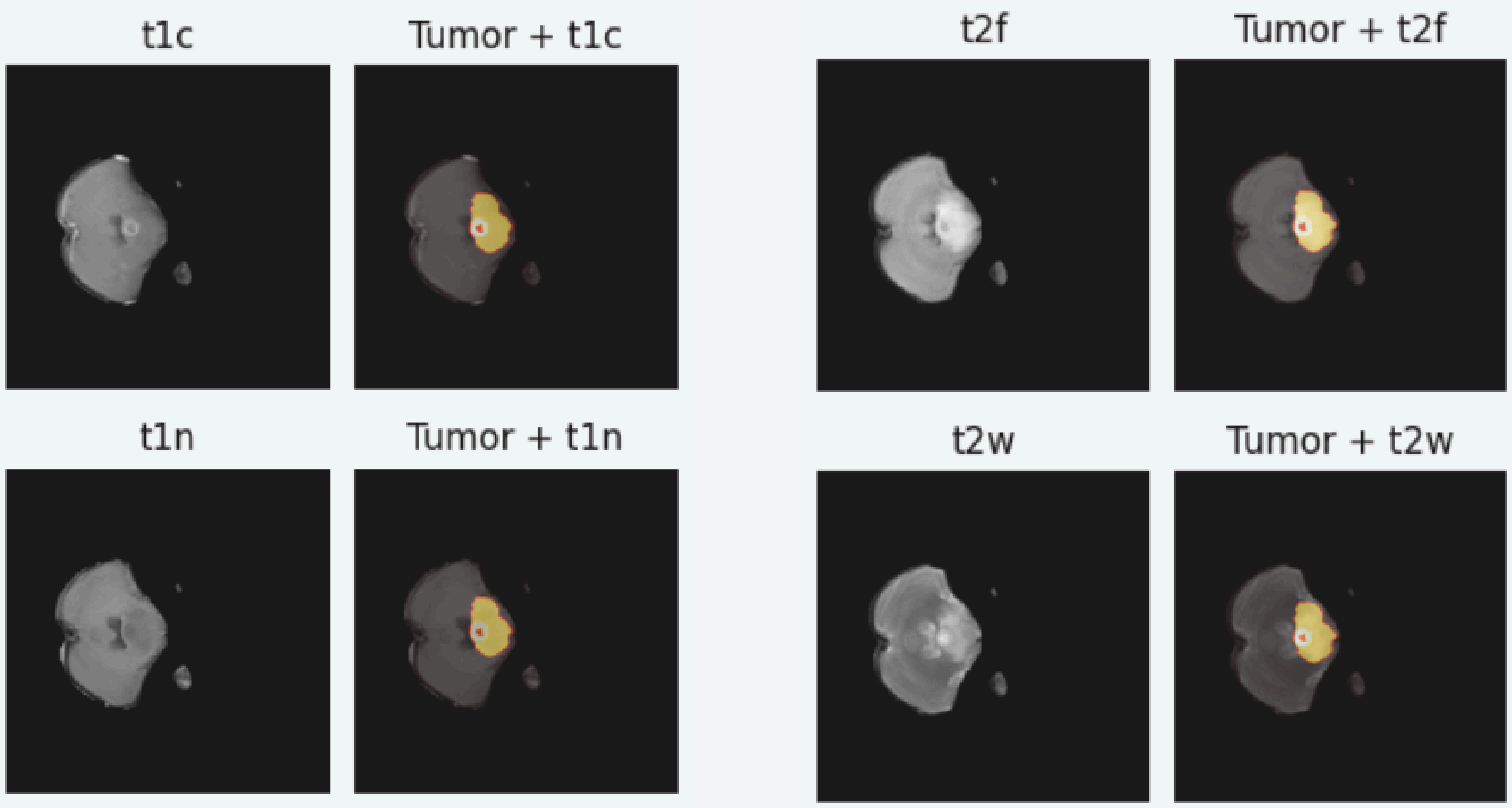
- 240, 240, 155

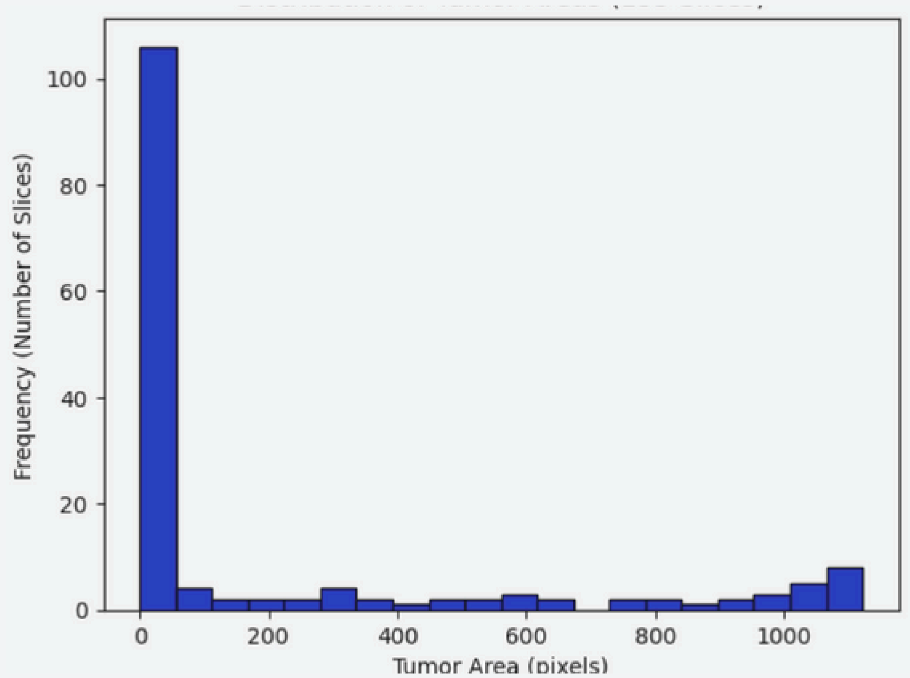
Tumor Size

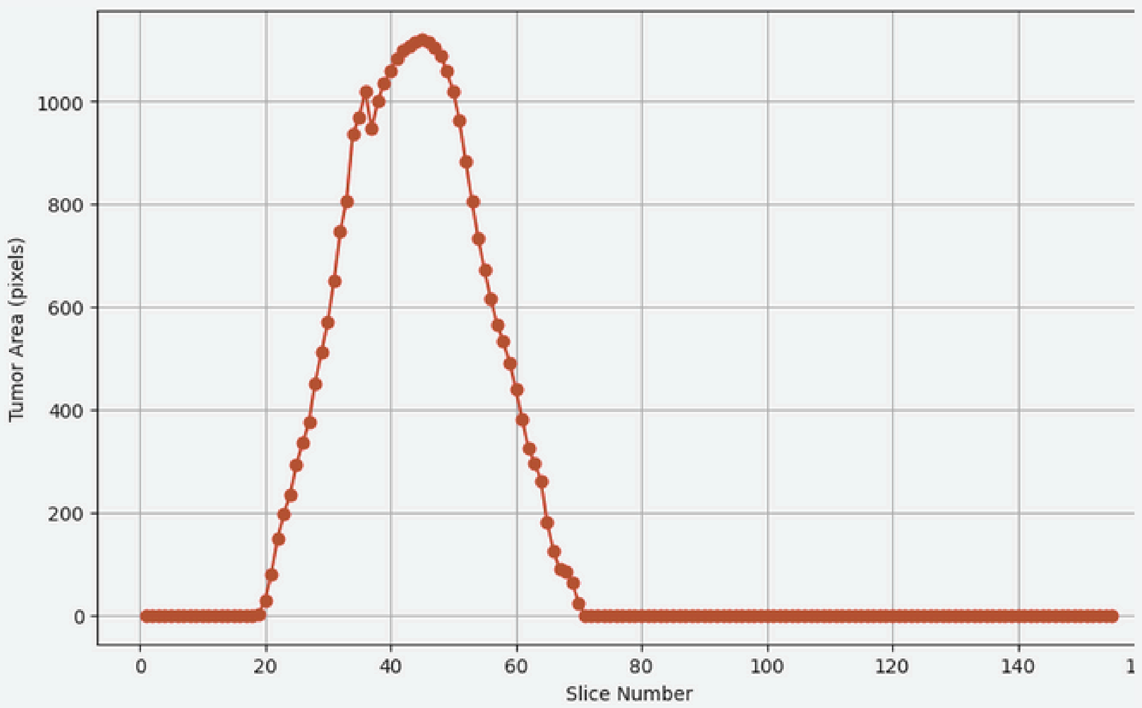
- 240, 240, 155

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

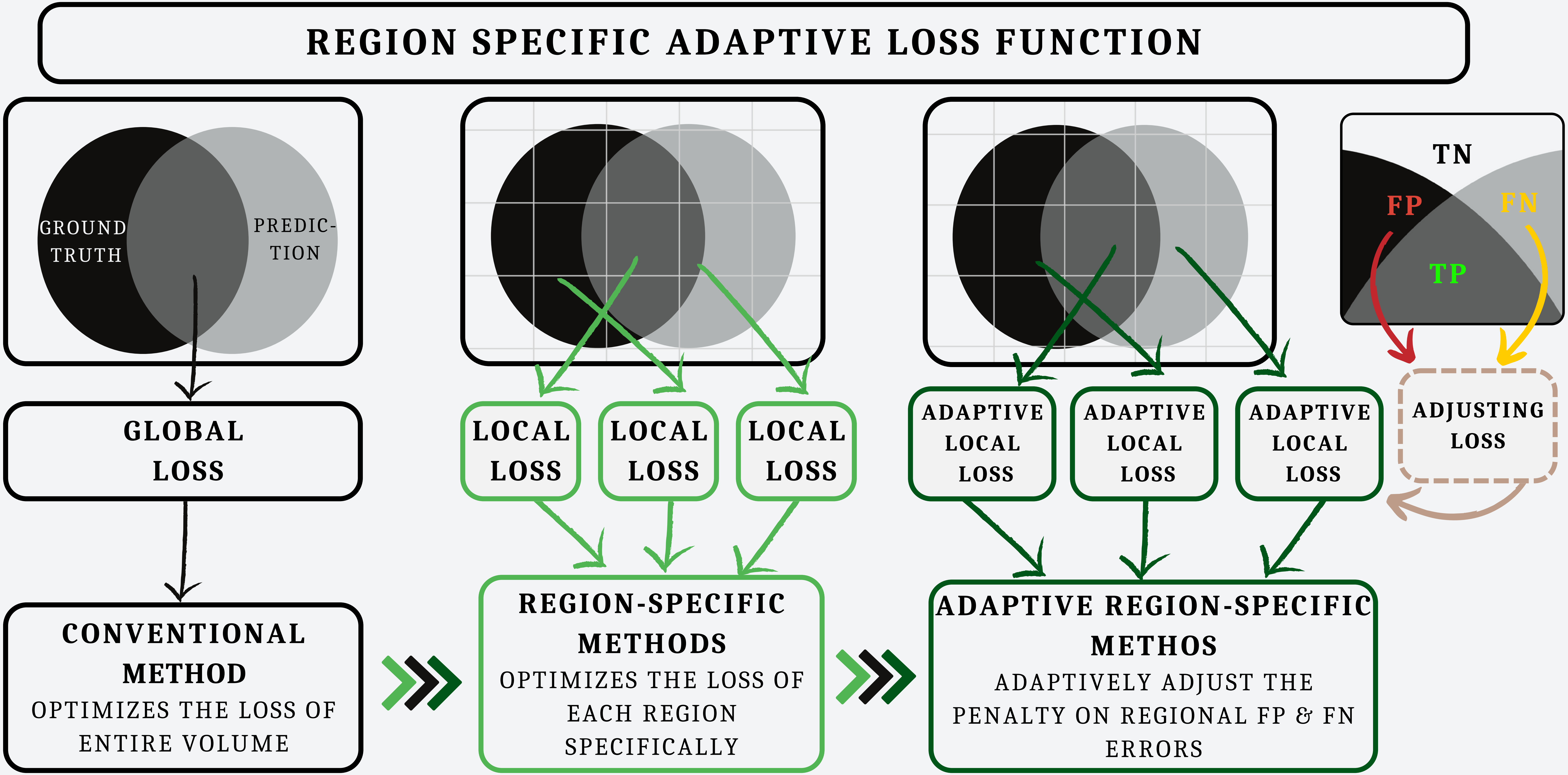
MRI Images	Planes	Distribution
T1, T1-C, T2, FLAIR	Axial	Right Skewed





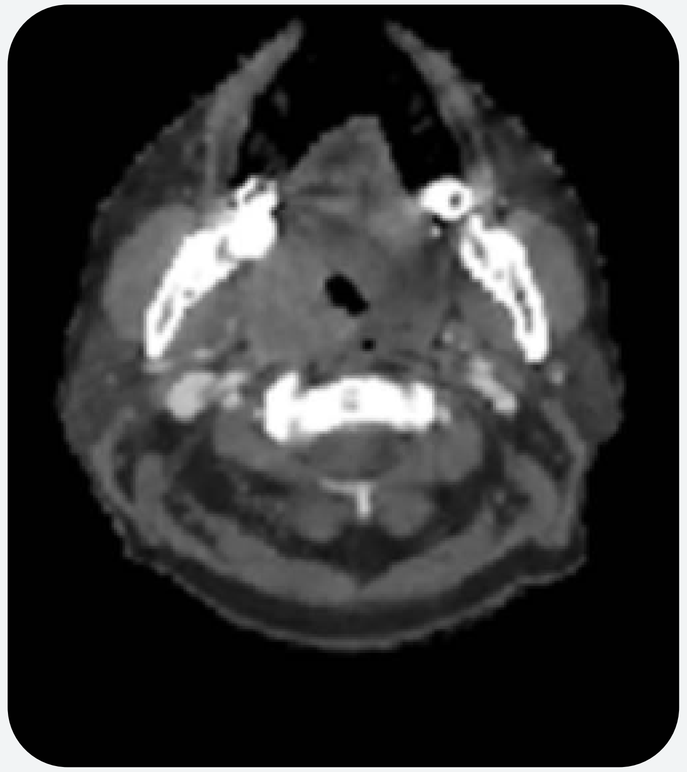


FUTURE WORK

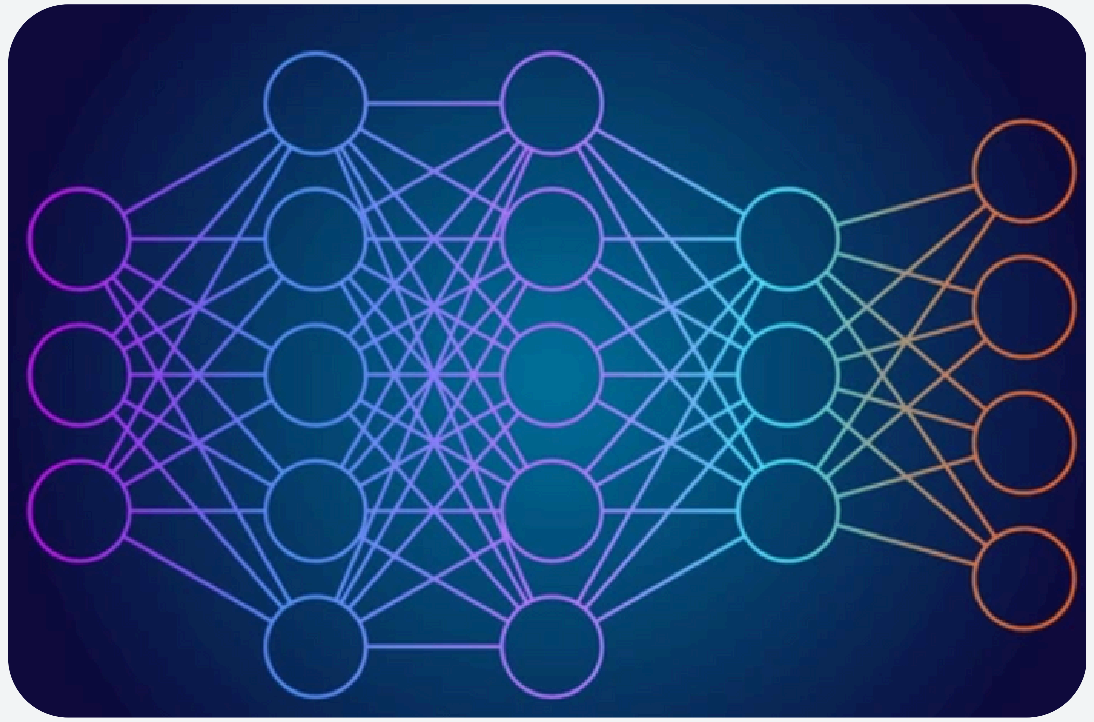

REGION SPECIFIC ADAPTIVE LOSS FUNCTION
GROUND TRUTH
PREDIC-TION
TN
FP
FN
TP
GLOBAL LOSS
LOCAL LOSS
LOCAL LOSS
LOCAL LOSS
ADAPTIVE LOCAL LOSS
ADAPTIVE LOCAL LOSS
ADAPTIVE LOCAL LOSS
ADJUSTING LOSS
CONVENTIONAL METHOD
OPTIMIZES THE LOSS OF ENTIRE VOLUME
REGION-SPECIFIC METHODS
OPTIMIZES THE LOSS OF EACH REGION SPECIFICALLY
ADAPTIVE REGION-SPECIFIC METHOS
ADAPTIVELY ADJUST THE PENALTY ON REGIONAL FP & FN ERRORS

FUTURE WORK

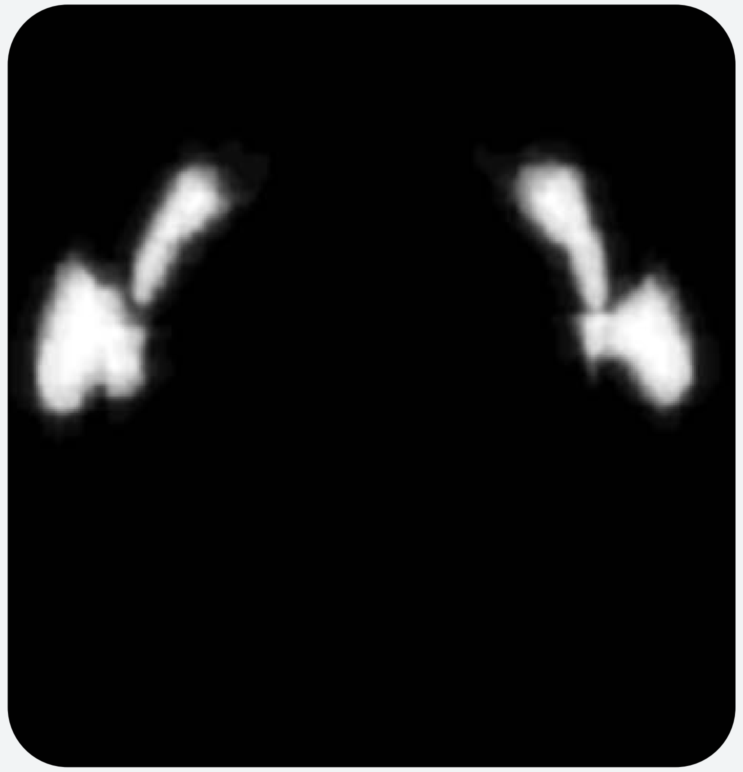
REGION SPECIFIC ADAPTIVE LOSS FUNCTION



INPUT IMAGE



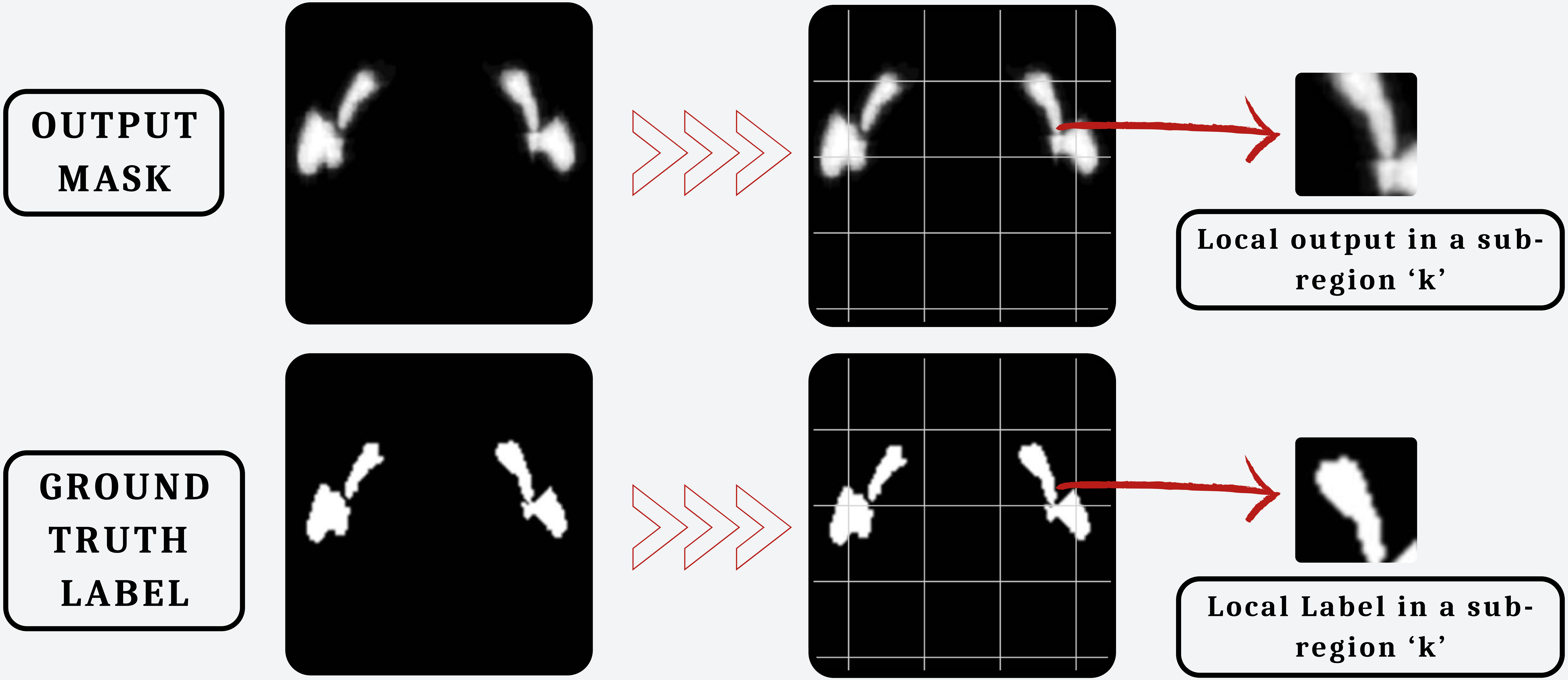
NETWORK



OUTPUT MASK

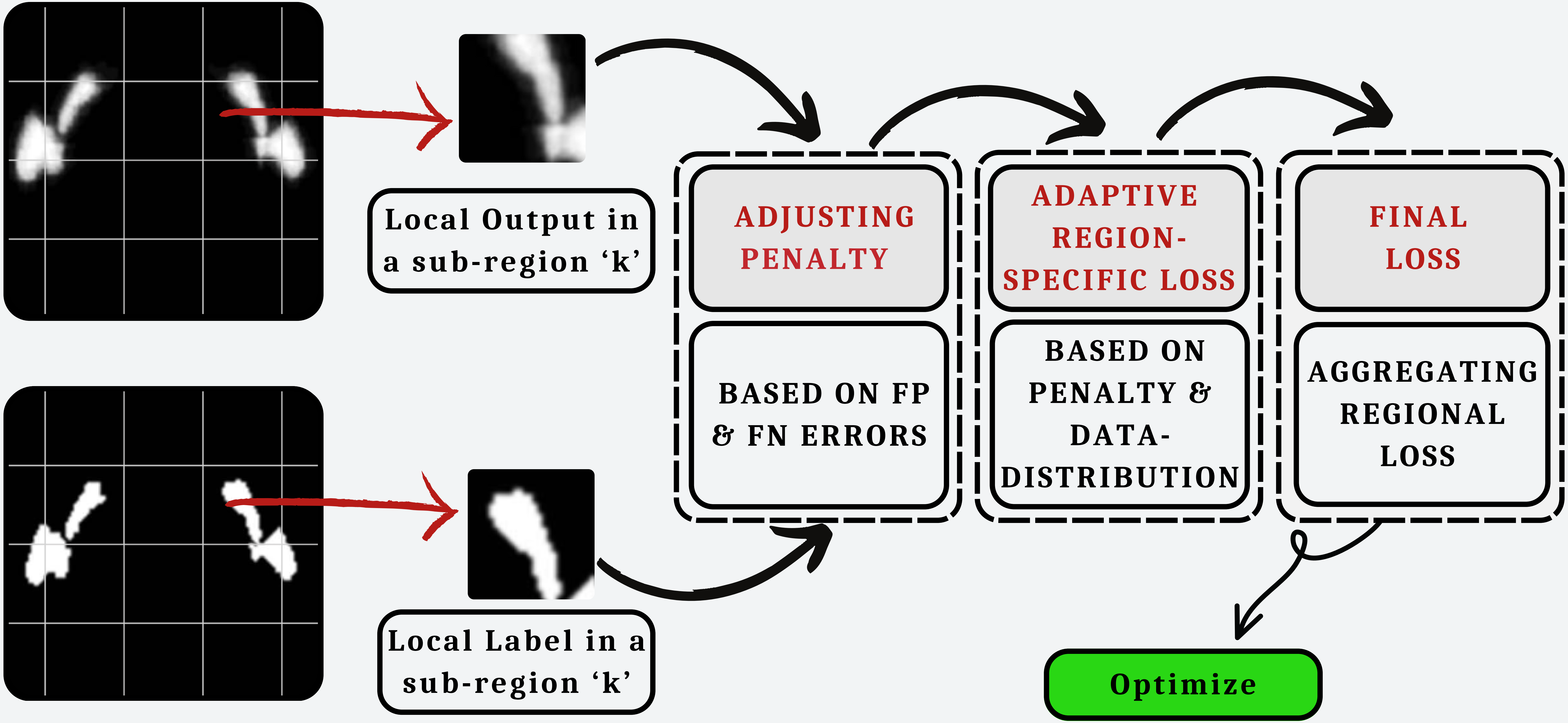
FUTURE WORK

REGION SPECIFIC ADAPTIVE LOSS FUNCTION



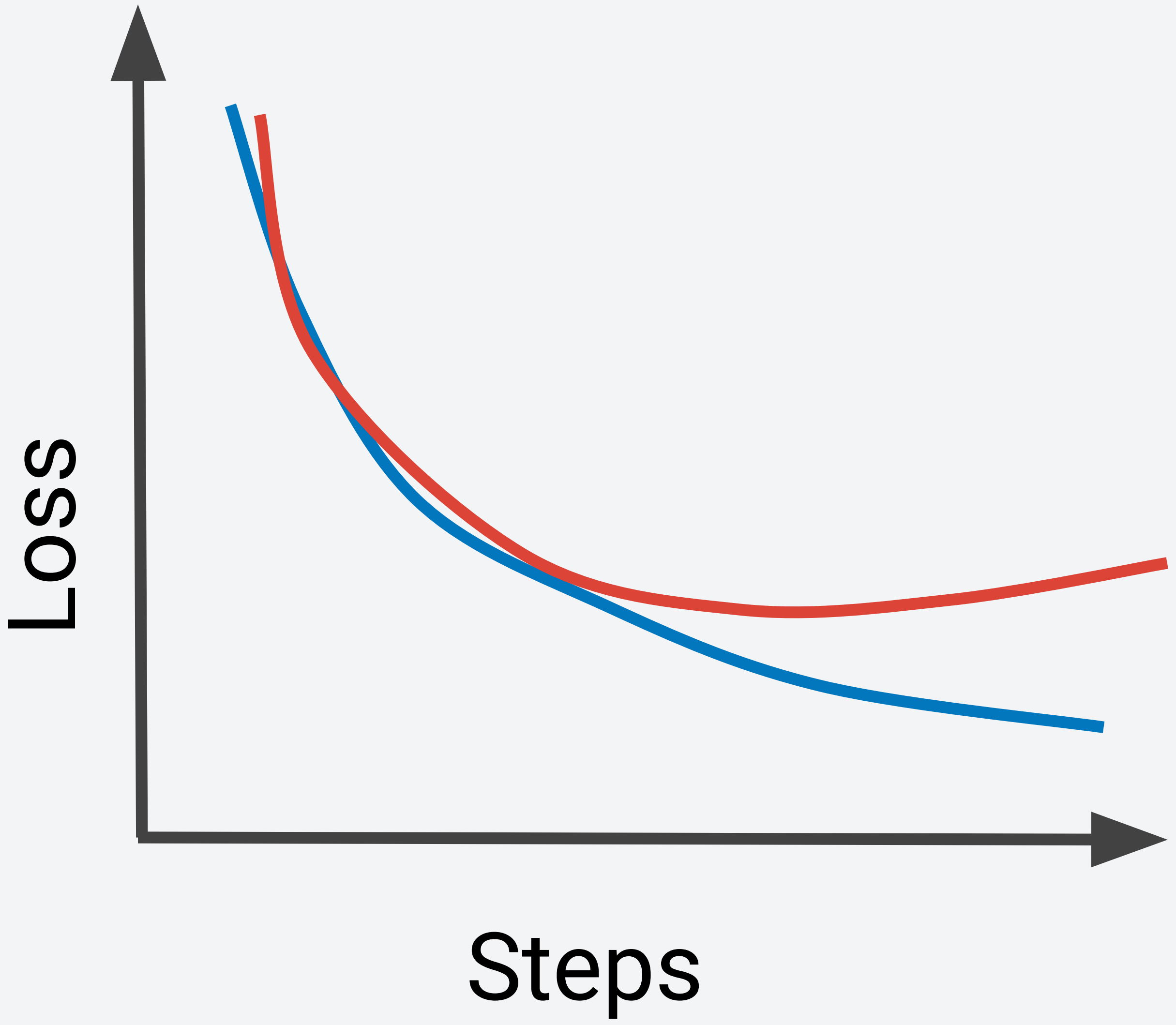
FUTURE WORK

REGION SPECIFIC ADAPTIVE LOSS FUNCTION



FUTURE WORK

REGION SPECIFIC ADAPTIVE LOSS FUNCTION



LOSS FUNCTION

ADAPTIVE

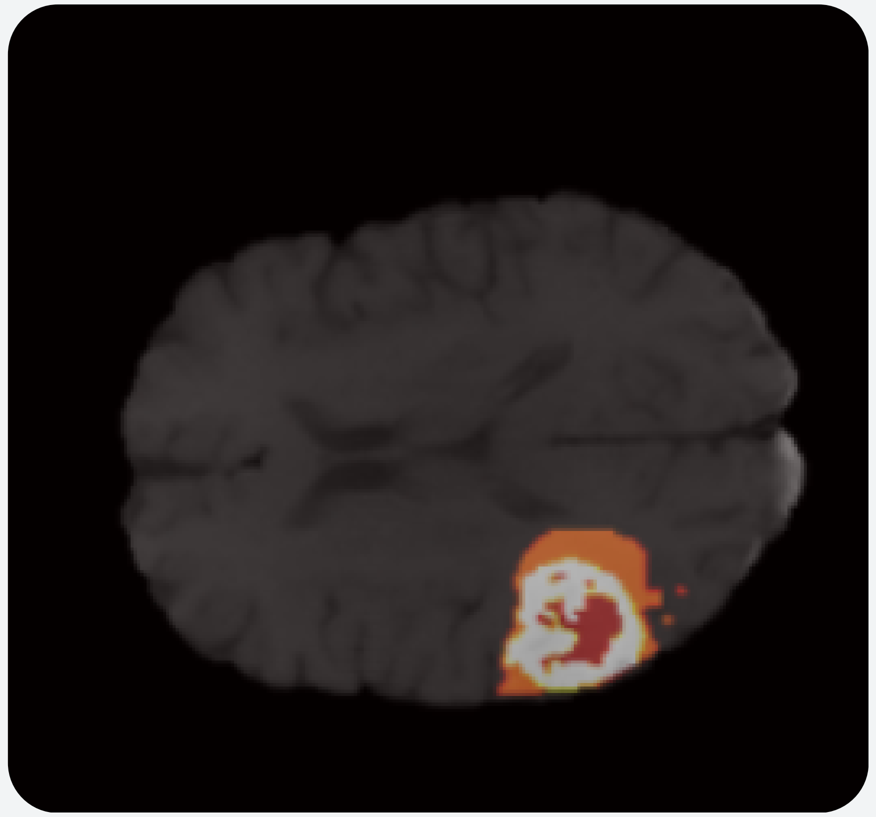
DATA DISTRIBUTION

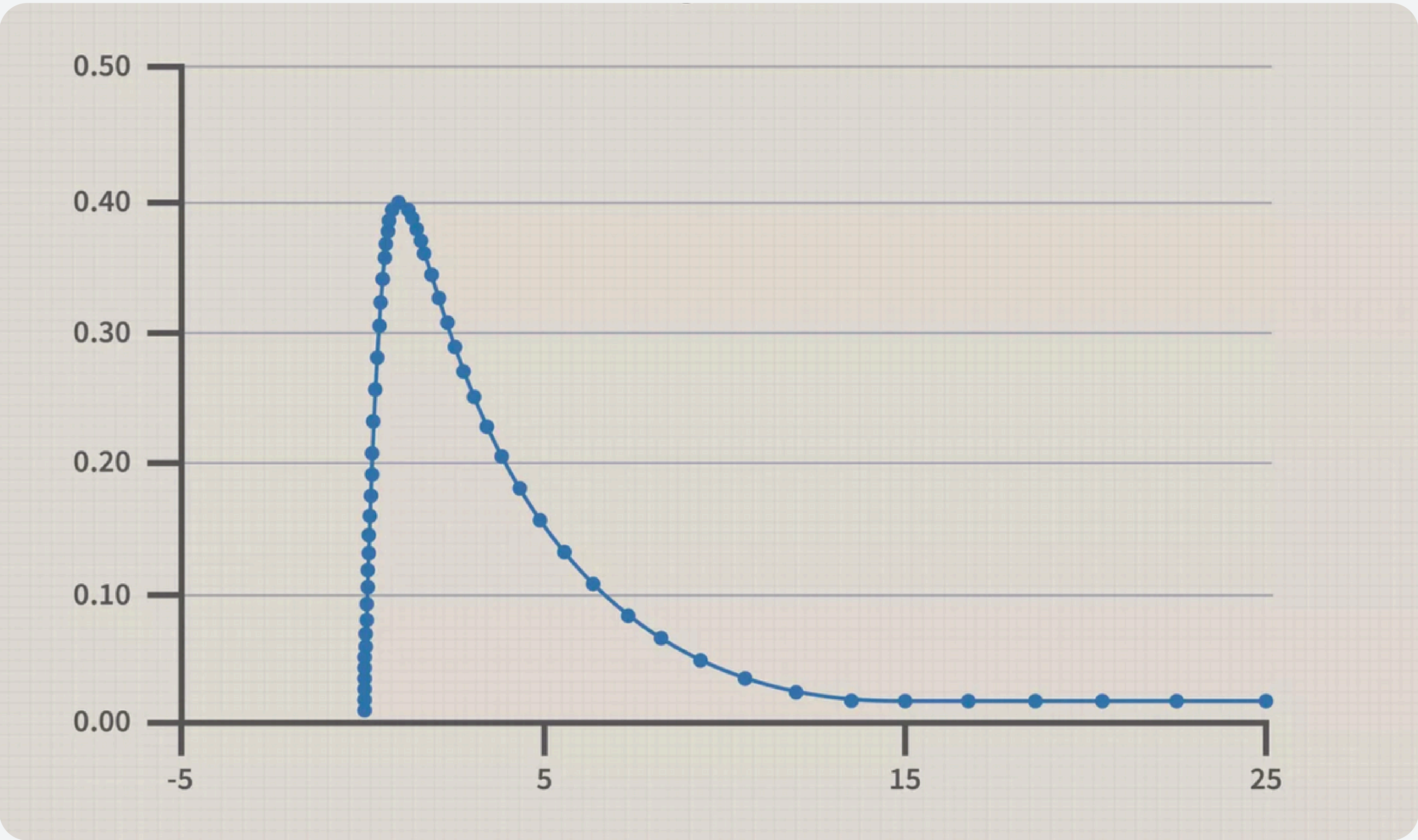
SPECIFIC TO REGION

LIMITATIONS

RIGHT SKEWED DATA

- **When the region of interest is much smaller than the background**

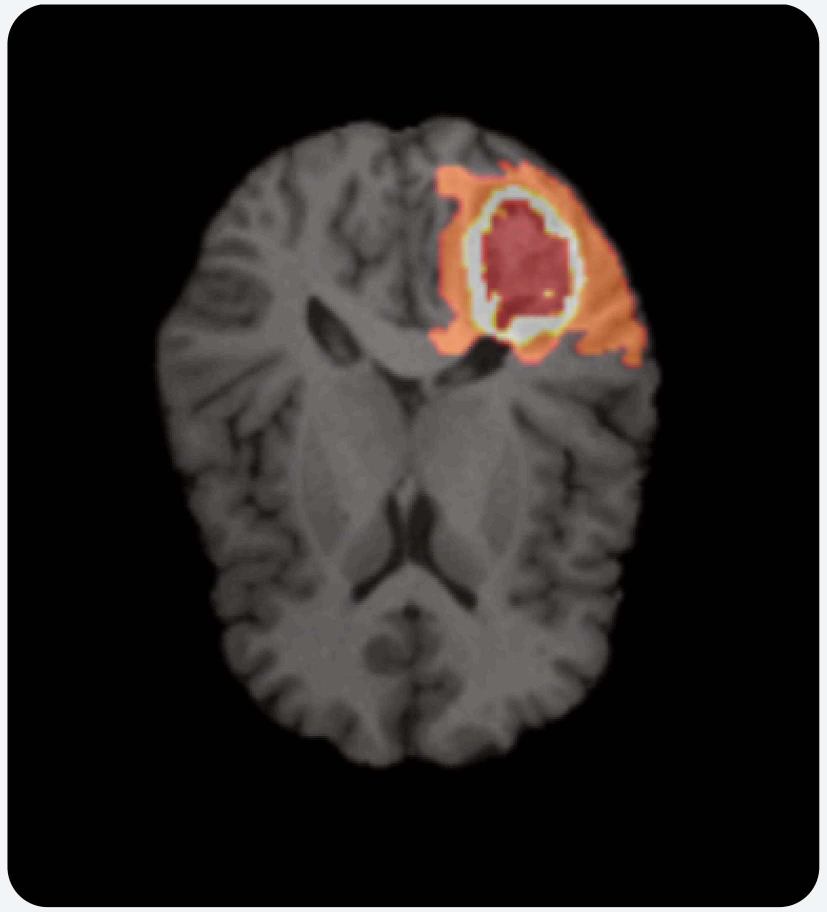




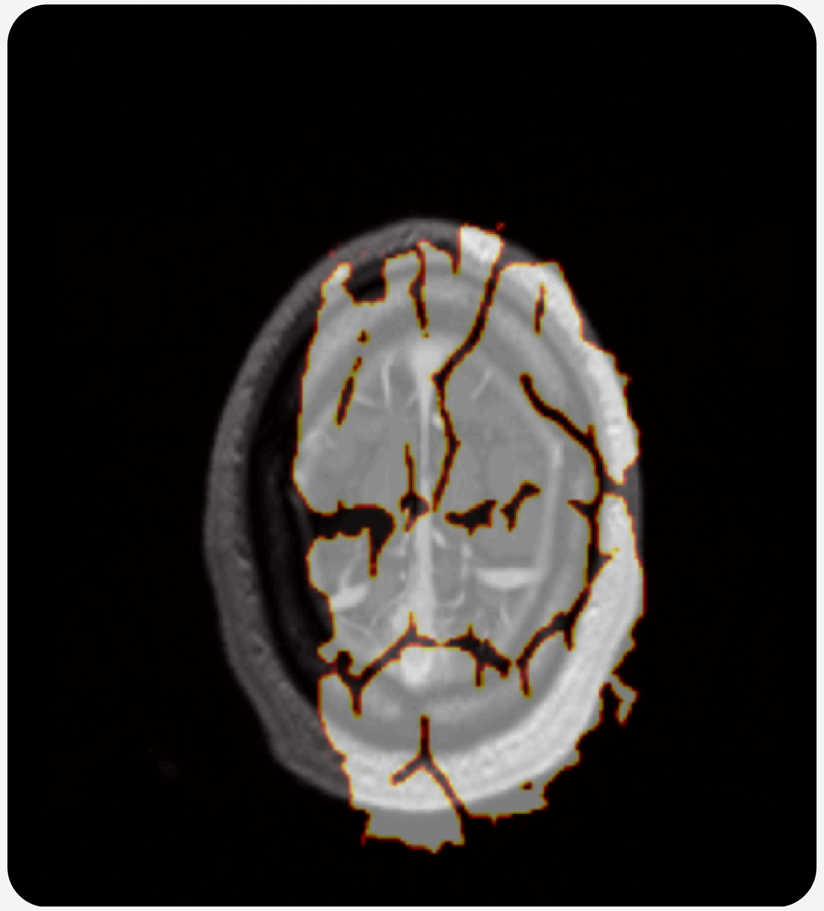
LIMITATIONS

NON-STANDARDIZED DATA

- The segmentation image appears larger than it should be

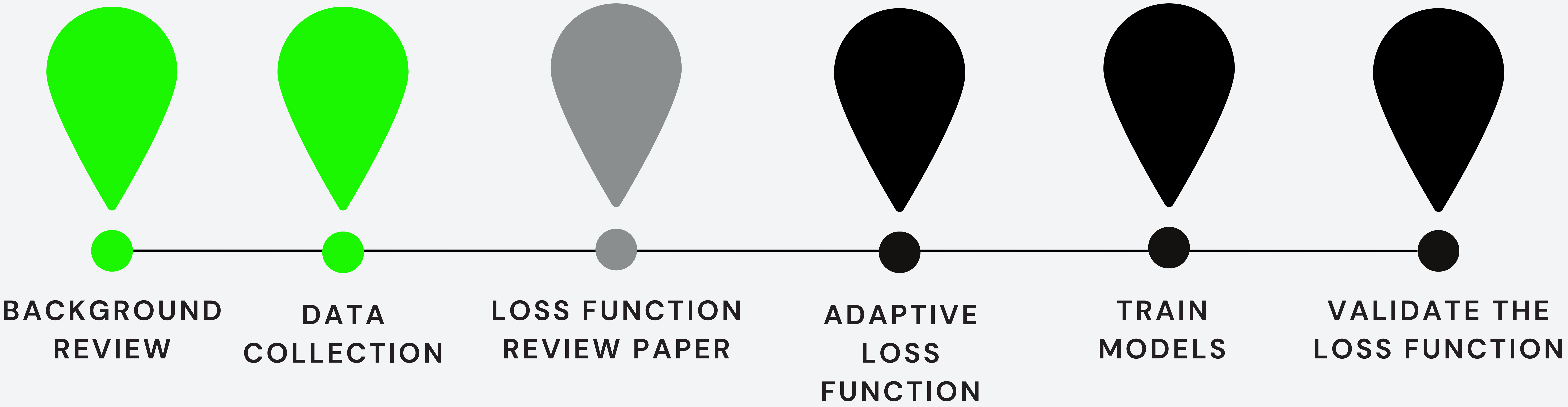


STANDARDIZED



NON-STANDARDIZED

MILESTONES



BACKGROUND REVIEW
DATA COLLECTION
LOSS FUNCTION REVIEW PAPER
ADAPTIVE LOSS FUNCTION
TRAIN MODELS
VALIDATE THE LOSS FUNCTION

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

THANK YOU!

QUESTIONS

LOSS FUNCTIONS TABLE

Name	Class	Year	Citations to Original Paper	Publications	Citations in total	Purpose	Use Cases - Pros/Cons
CE	Distribution	2015	94542	477	100000	Minimize cross entropy H(P,Q)	works best in equal data distribution among classes
WCE	Distribution	2015	94542	66	96000	Minimize CE, penalize majority weights	widely used in skewed datasets
TopK	Distribution	2016	187	4	343	Force networks to focus on hard samples during training	used in imbalanced data
Focal	Distribution	2017	199	336	5000	Adapts 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 examples
DPCE	Distribution	2019	104	22	215	Guide the network's focus towards hard-to-segment boundary regions	used for hard-to-segment boundaries
Sensitivity-specificity	Region	2015	52	26	164	Addresses the class imbalance problem by weighting specificity higher	used when there is more focus on True Positives
Dice	Region	2016	10882	557	22000	Optimize the Dice Similarity Coefficient (DSC)	does not require class re-weighting for imbalanced segmentation tasks
IoU (Jaccard)	Region	2016	1033	183	3000	Optimize the object category segmentation metric	highly effective for tasks where boundary precision is crucial
Lovász	Region	2018	613	37	1000	Optimize the Jaccard index	Optimizing with cross entropy first is needed
Tversky	Region	2017	1056	154	3000	achieve a better trade-off between precision and recall	used where the cost of false positives and false negatives differs significantly and it is wanted to adjust the model's behavior accordingly.
Generalized Dice	Region	2017	2688	37	5000	Multi-class extension of Dice loss	used in multi-class segmentation
Focal Tversky	Region	2018	930	46	2000	Focus on hard cases with low probabilities	focus on hard examples
Asymmetric similarity	Region	2018	206	10	463	Make a better adjustment of the weights of FPs and FNs	used in imbalanced data
Penalty	Region	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	2018	558	63	1000	Use integral framework to compute distance between two boundaries	time-consuming, Should be coupled with region-based loss
Hausdorff Distance Loss	Boundary	2019	503	6	845	Avoid unstable training	time-consuming, Should be coupled with region-based loss
Combo	Compound	2018	388	6	701	handle input and output imbalance in multi-organ segmentation	used for lightly class imbalanced
ELL	Compound	2018	251	3	441	Address the issues of highly unbalanced object sizes	focuses on less accurately predicted cases
Dice - Focal	Compound	2018	514	18	566	learn from poorly segmented voxels better	good in multi-class segmentation
Dice - TopK	Compound	2020	29	4	89	Used for automated volumetric assessment of multiple sclerosis	good in multi-class segmentation
G. Wasserstein Dice loss	Tailored	2018	184	4	296	To improve multi-class segmentation	used in multi-class segmentation, tackles hierarchical classes and can take advantage of known relationships between classes

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

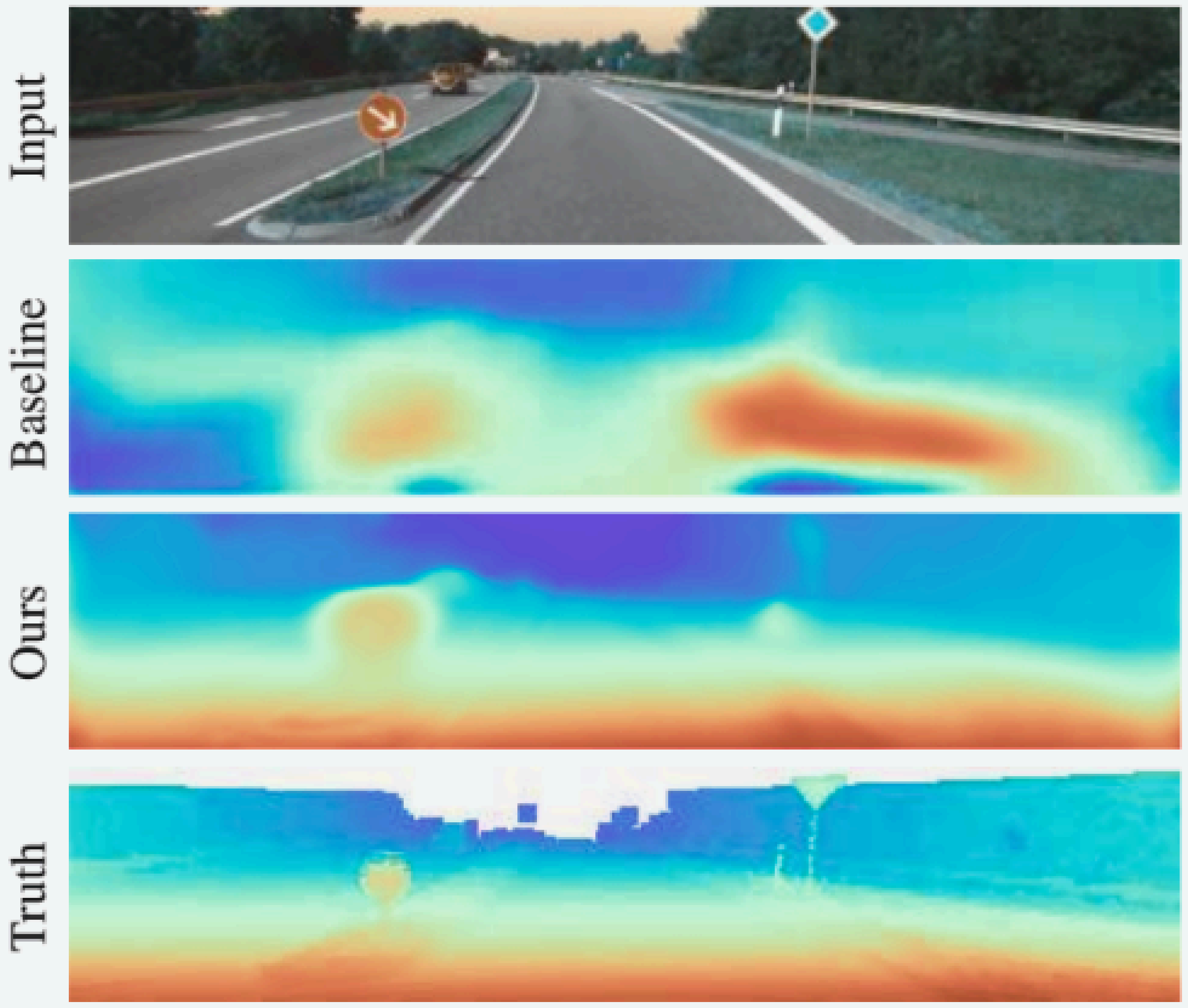
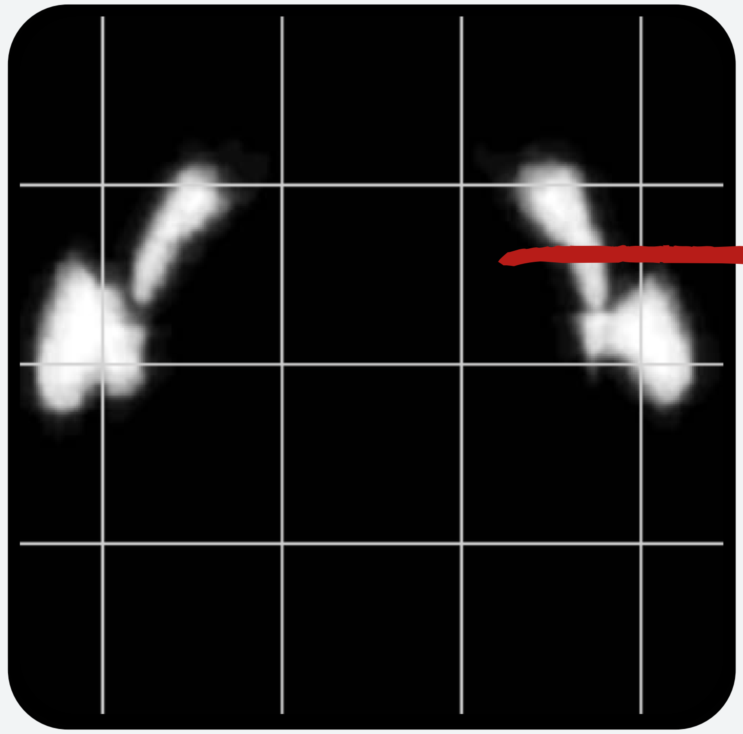


Figure 4. Monocular depth estimation results on the KITTI benchmark using the "Baseline" network of [41]. Replacing only the network's loss function with our "adaptive" loss over wavelet coefficients results in significantly improved depth estimates.

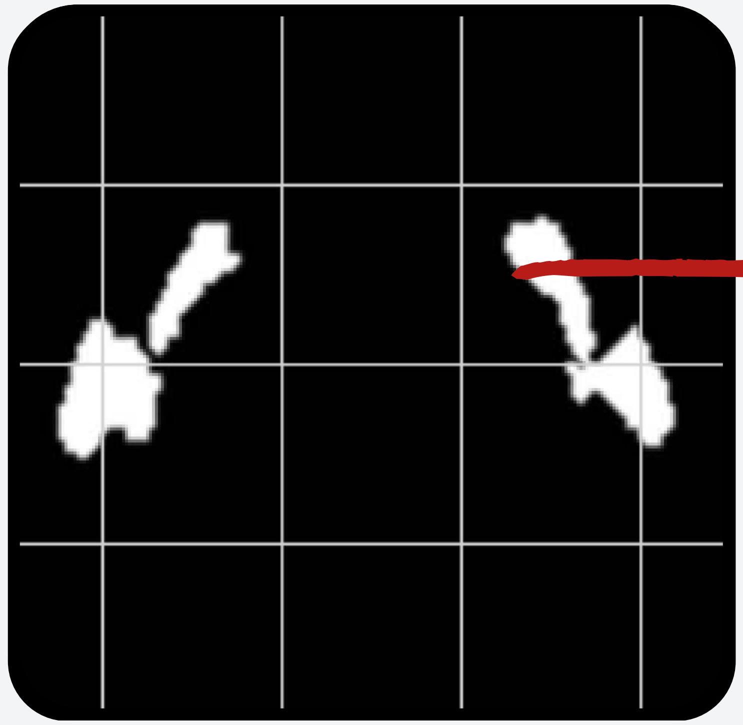
- IN THE ADAPTIVE A ∈ (0, 2) MODEL THEY ASSIGN **EACH WAVELET COEFFICIENT** ITS **OWN SHAPE PARAMETER** AS A **FREE VARIABLE**, WHICI ARE **OPTIMIZED** ALONGSIDE THEIR NETWORK WEIGHTS **DURING TRAINING**
- NO **SINGLE SETTING** OF A IS **OPTIMAL** FOR ALL WAVELET COEFFICIENTS. OVERALL, JUST **REPLACING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

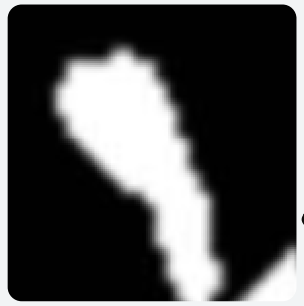
FUTURE WORK

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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