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

GROUP-1



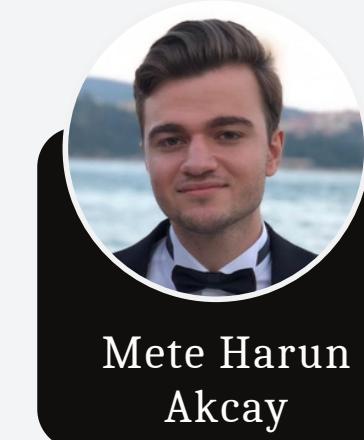
Masa
Cirkovic



Bashir
Alam



Md Kaf
Shahrier



Mete Harun
Akcay

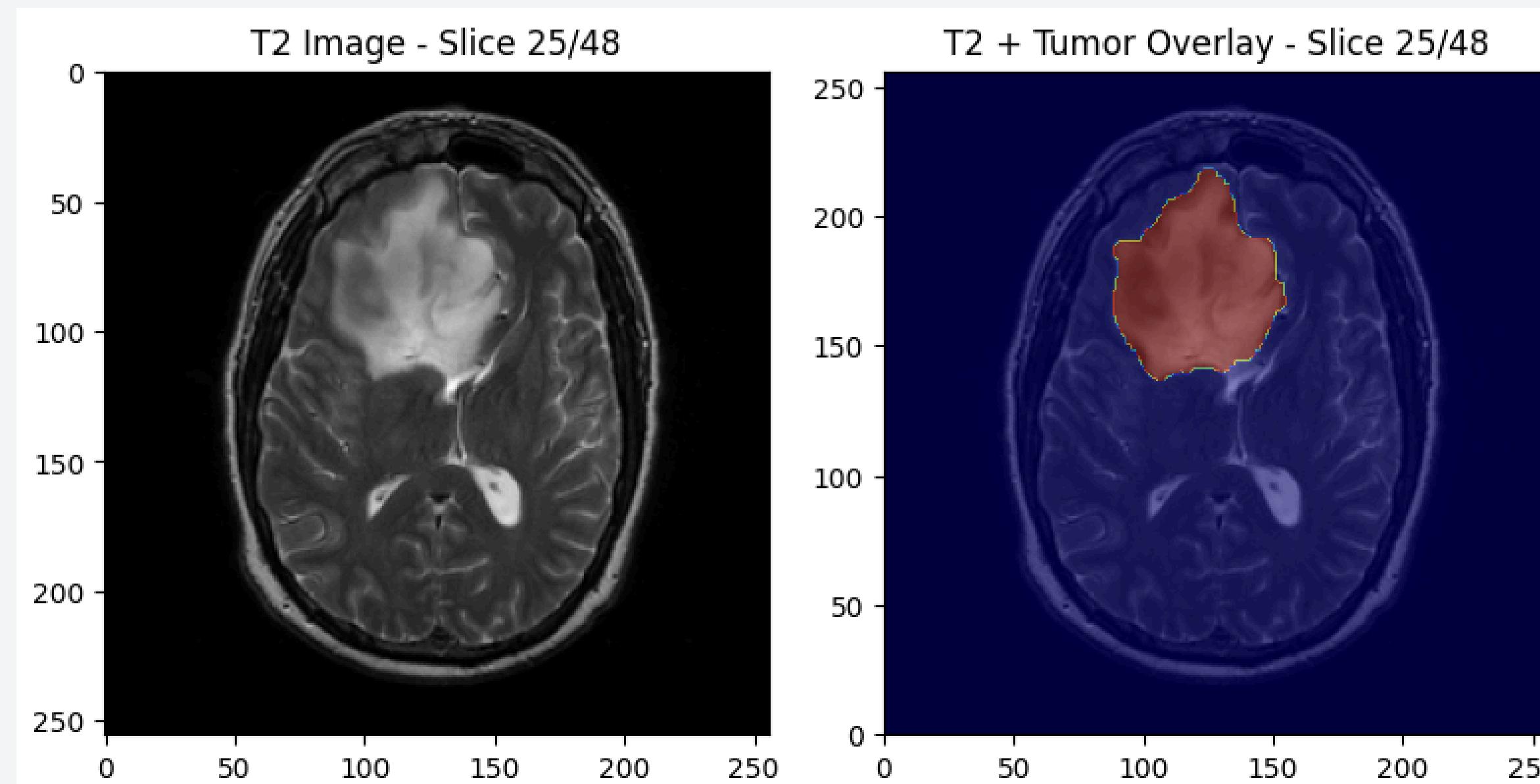
AGENDA

- 01 Problem Statement
- 02 State of the Art
- 03 Data Report
- 04 SWOT
- 05 Planned Pipeline
- 06 Milestones

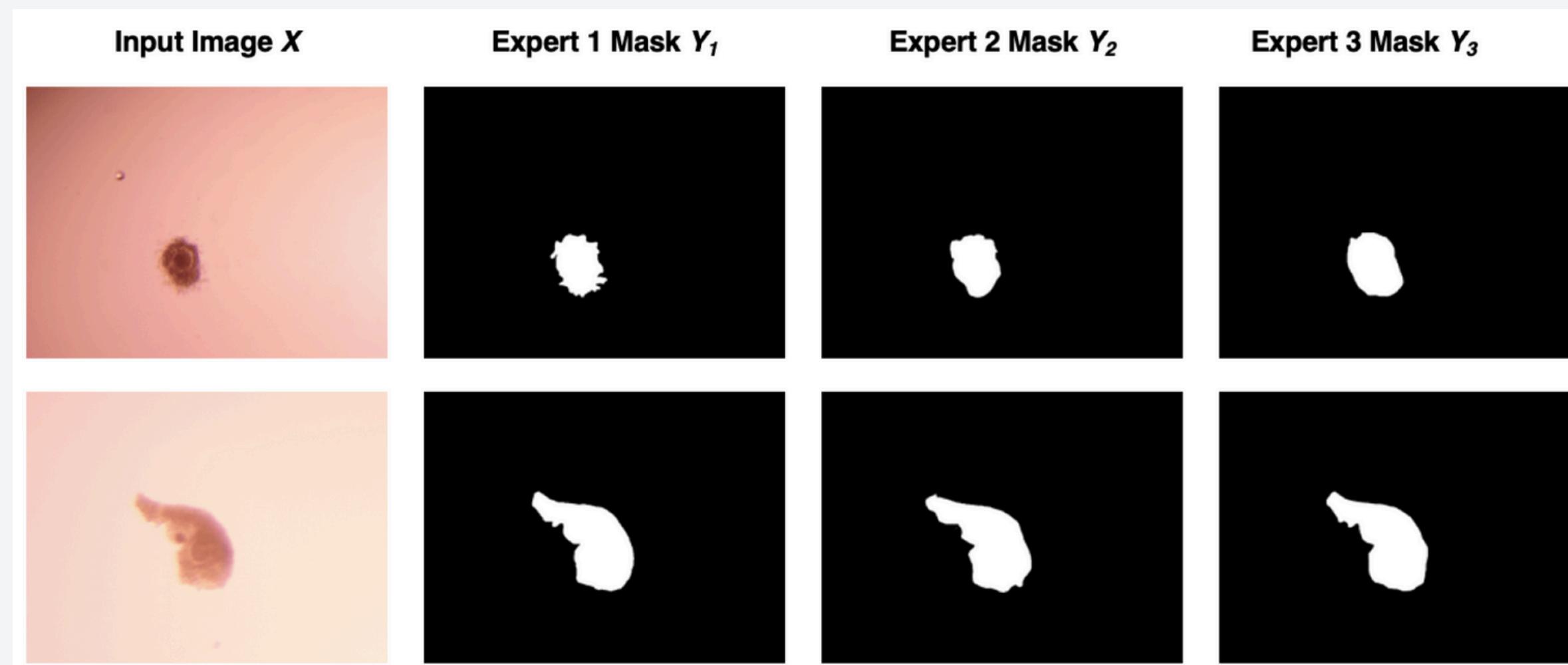
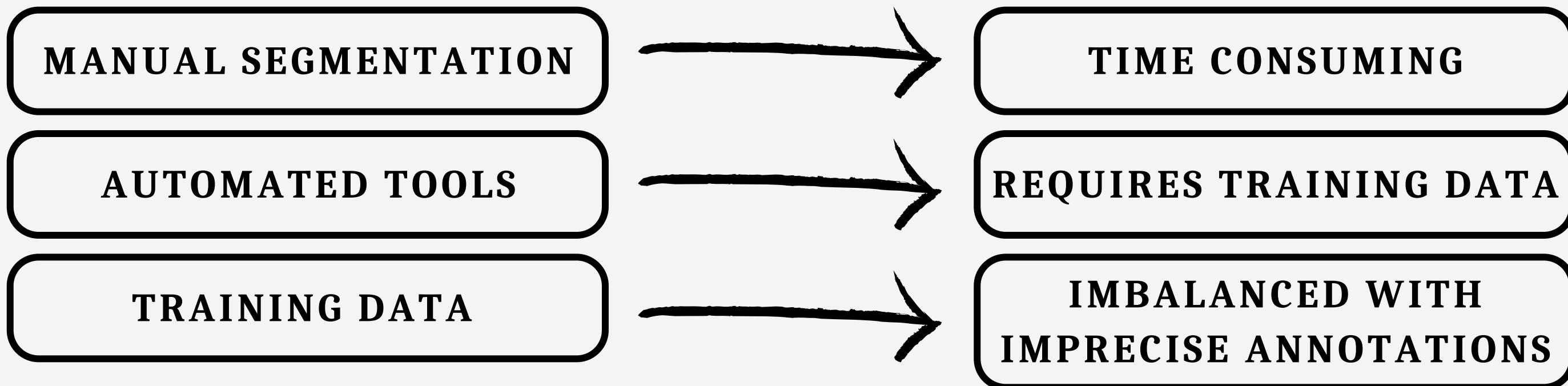


PROBLEM STATEMENT

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

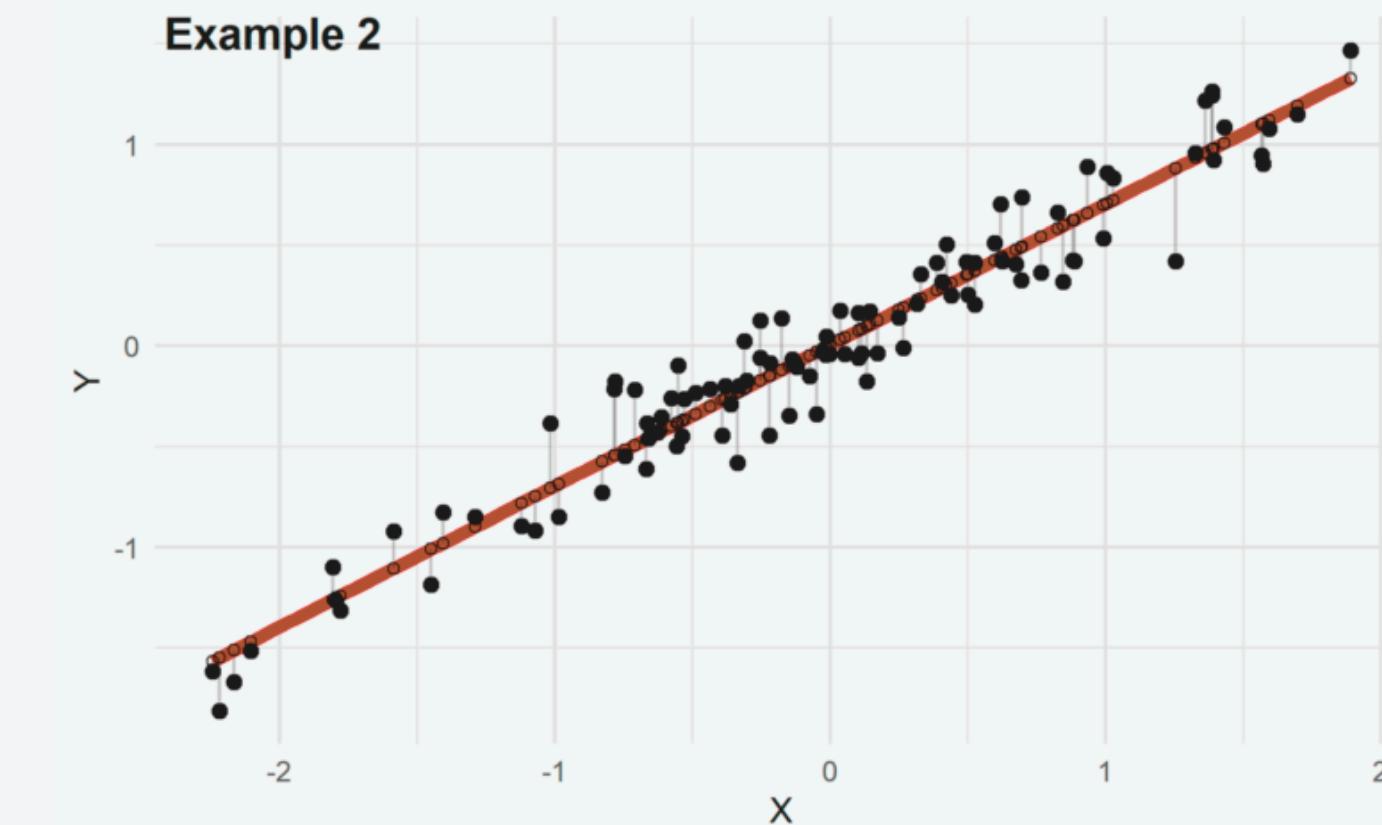
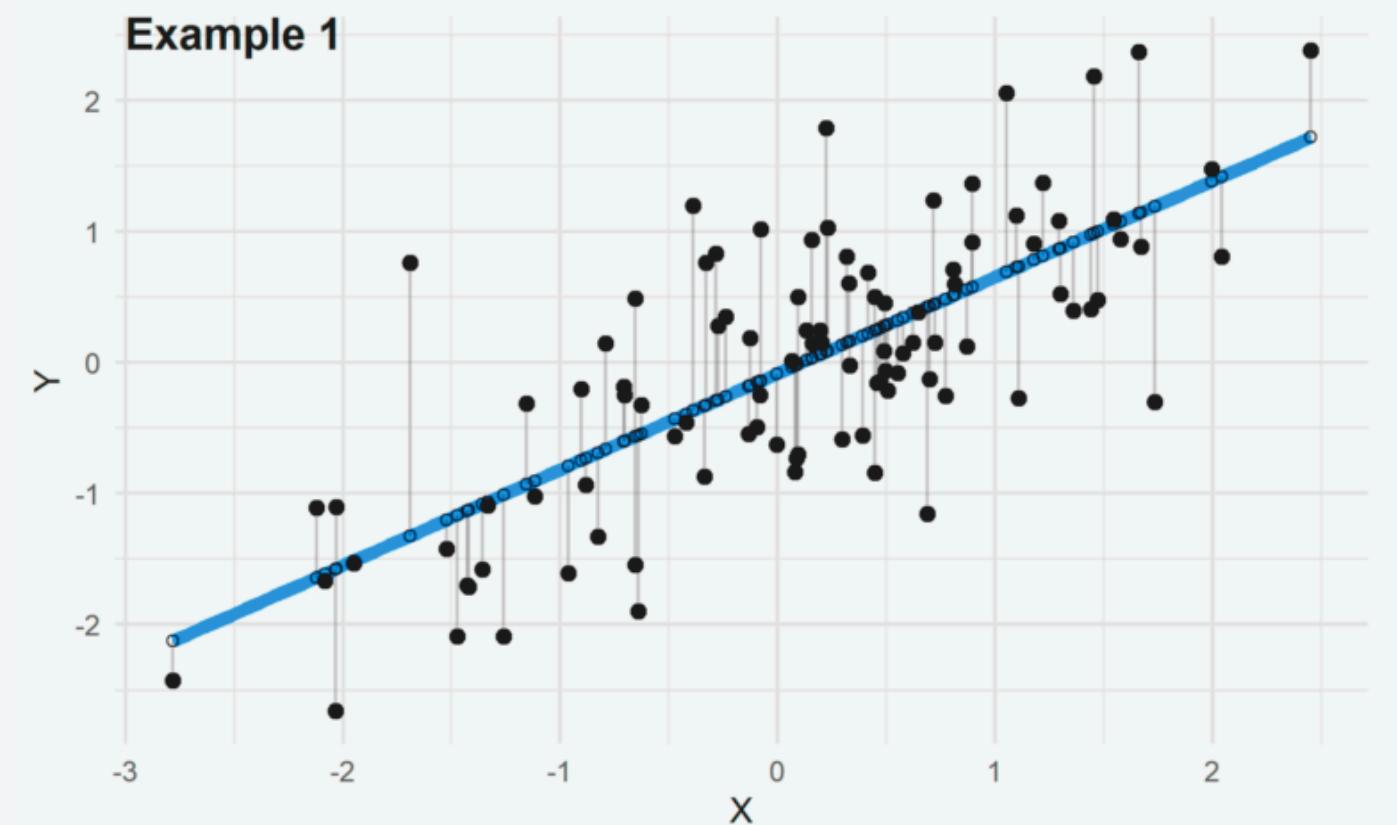


PROBLEM STATEMENT



LOSS FUNCTION

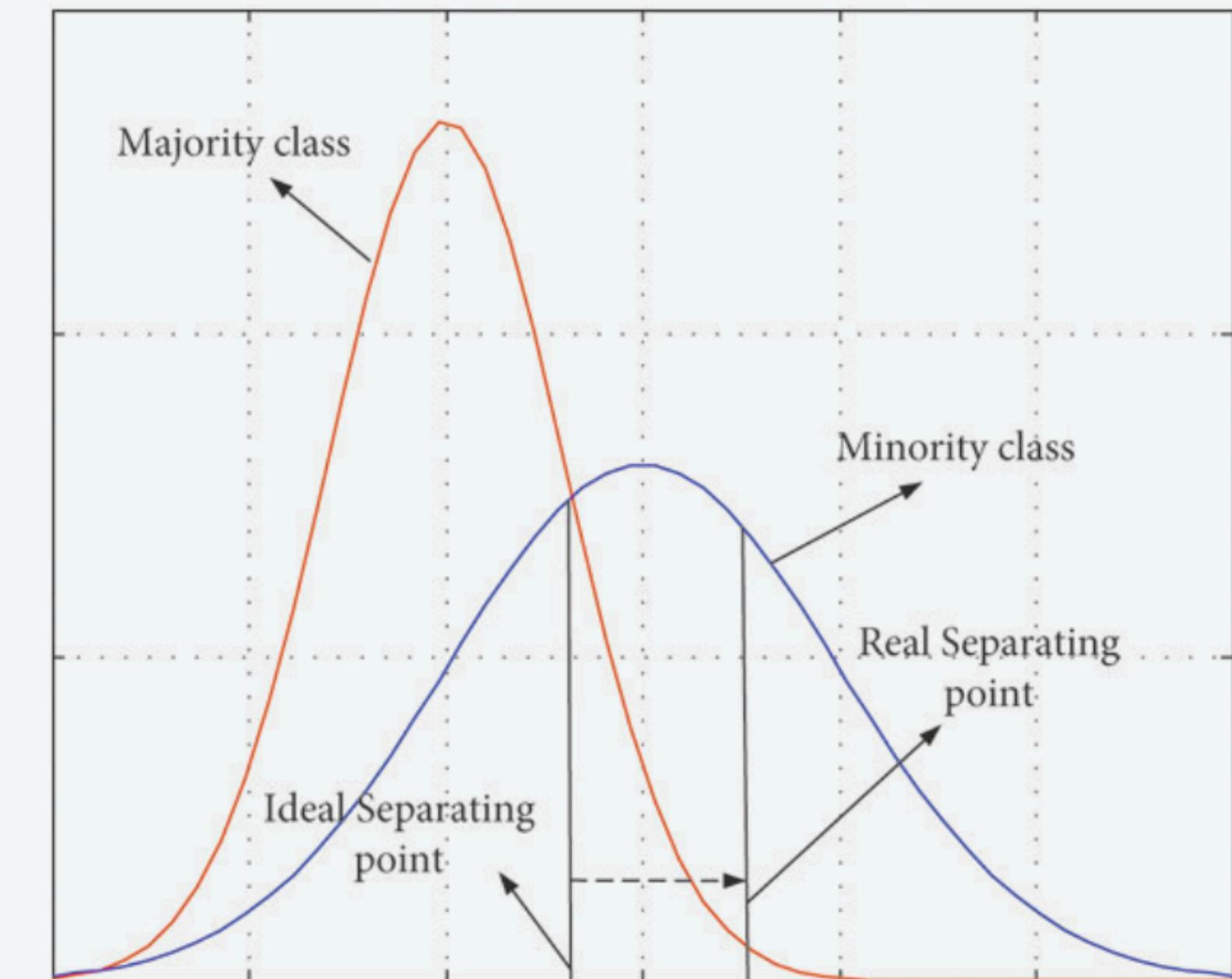
- A LOSS FUNCTION IS USED TO MEASURE MODEL PERFORMANCE BY CALCULATING THE DEVIATION OF A MODEL'S PREDICTIONS FROM THE CORRECT, “GROUND TRUTH” PREDICTIONS.
- ALSO TERMED AS “RESIDUAL ERROR” IN TRADITIONAL STATISTICS MODELING



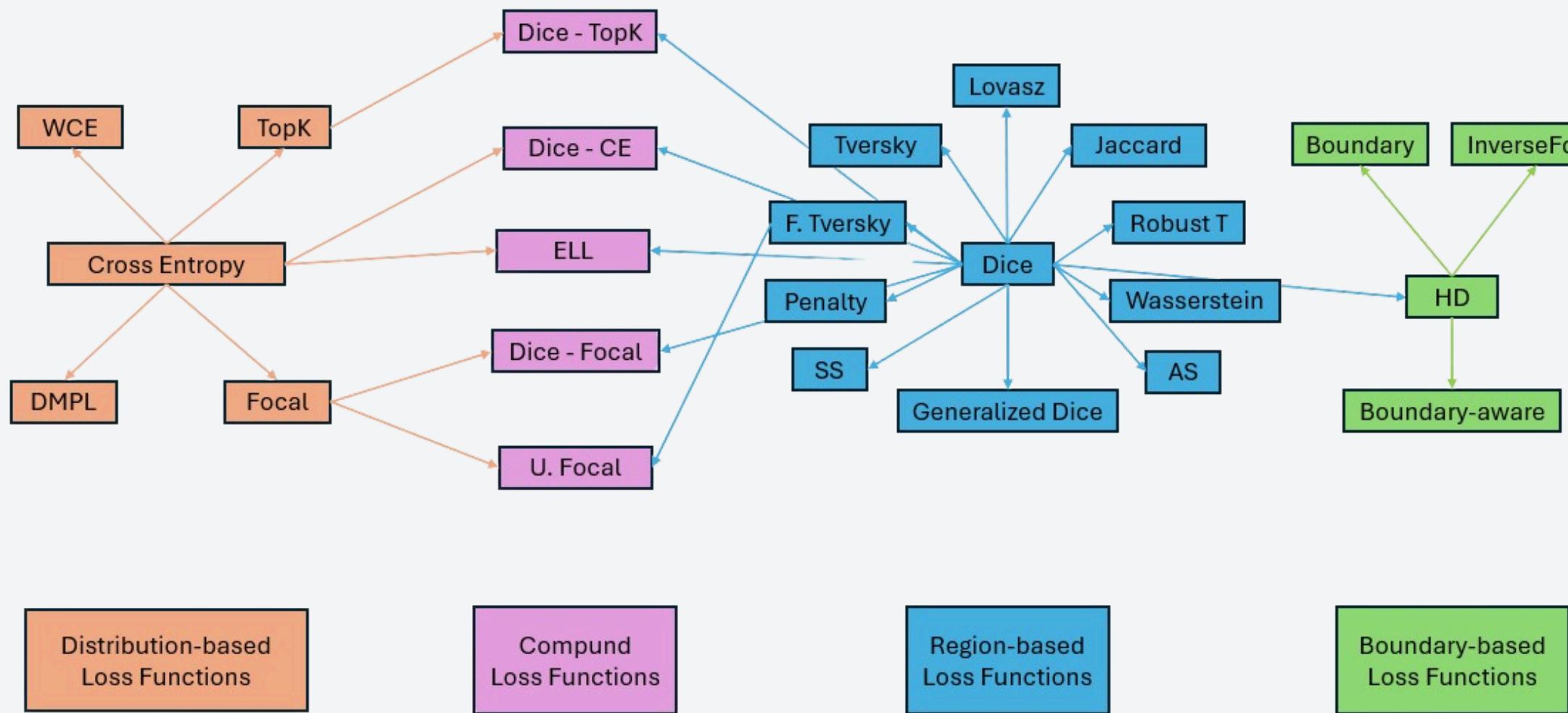
PROBLEM STATEMENT

USING LOSS FUNCTIONS TO BETTER IMPROVE DL PARAMETER ESTIMATION

- DIFFERENT LOSS FUNCTIONS OVERCOME IMBALANCED DATASETS BY -
 - I. **WBCE**: HIGHER WEIGHTS TO MINORITY CLASSES
 - II. **FOCAL LOSS**: HIGHER PENALTY ON HARD-TO-CLASSIFY REGIONS
 - III. **DICE LOSS**: USE OVERLAPPING METRICS SUCH AS DICE SIMILARITY COEFFICIENT
 - IV. **TVERSKY LOSS**: BALANCES BETWEEN FALSE POSITIVES VS FALSE NEGATIVES



STATE-OF-THE-ART ~ LOSS FUNCTIONS

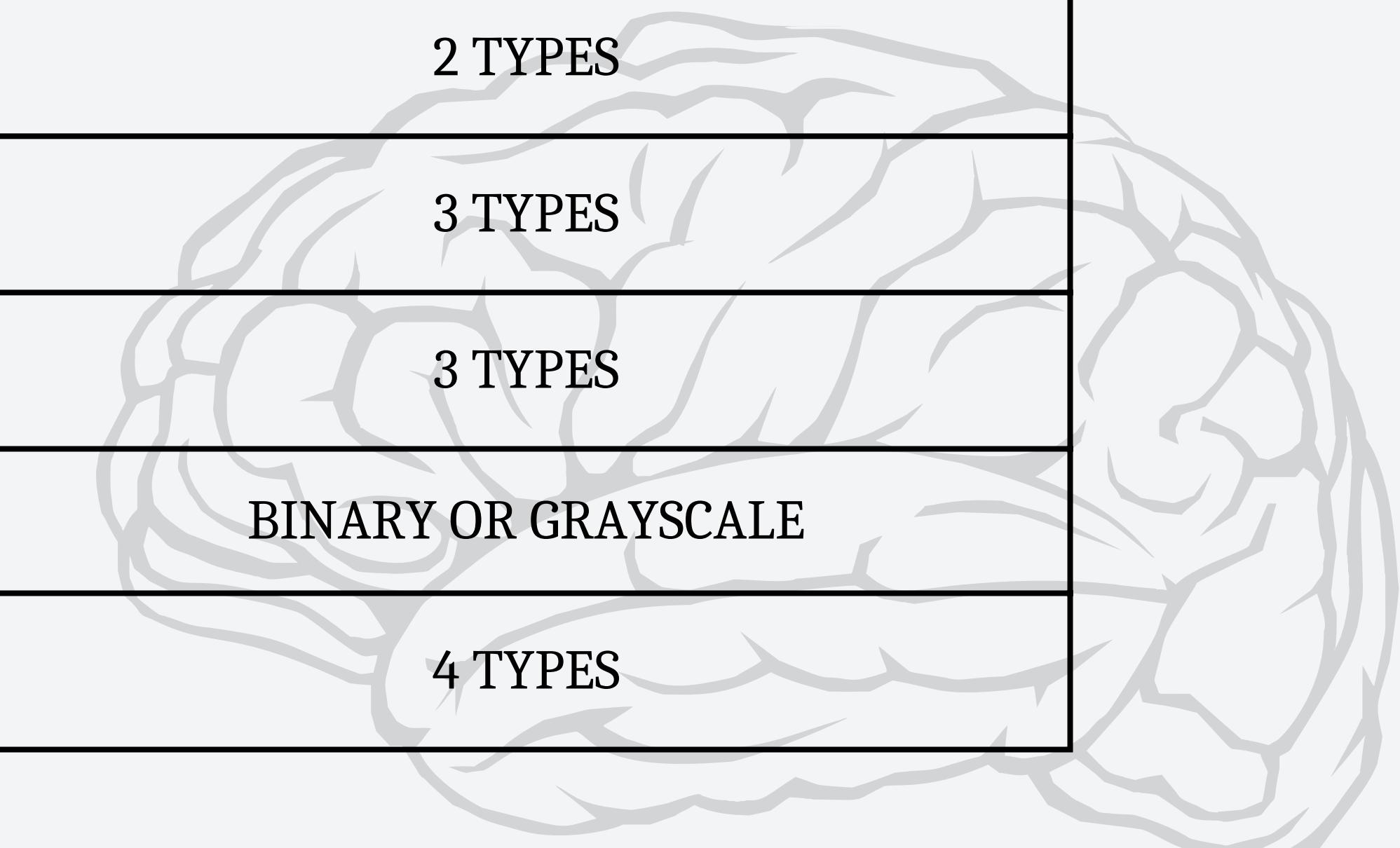


- HANDLING CLASS IMBALANCE
- IMPROVING BOUNDARY PRECISION
- CAPTURING SMALL STRUCTURES
- MINIMIZING FALSE NEGATIVES
- MINIMIZING FALSE POSITIVES
- HANDLING MULTI-CLASS DATA

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 highly imbalanced datasets, down-weight the contribution of easy examples, enabling model to learn hard examples
Distance Map Penalizing 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 segmentation
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 differ significantly and it is wanted to adjust the model's behavior accordingly
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
Sensitivity-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
Generalized 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 by taking 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 and 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
Boundary-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

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

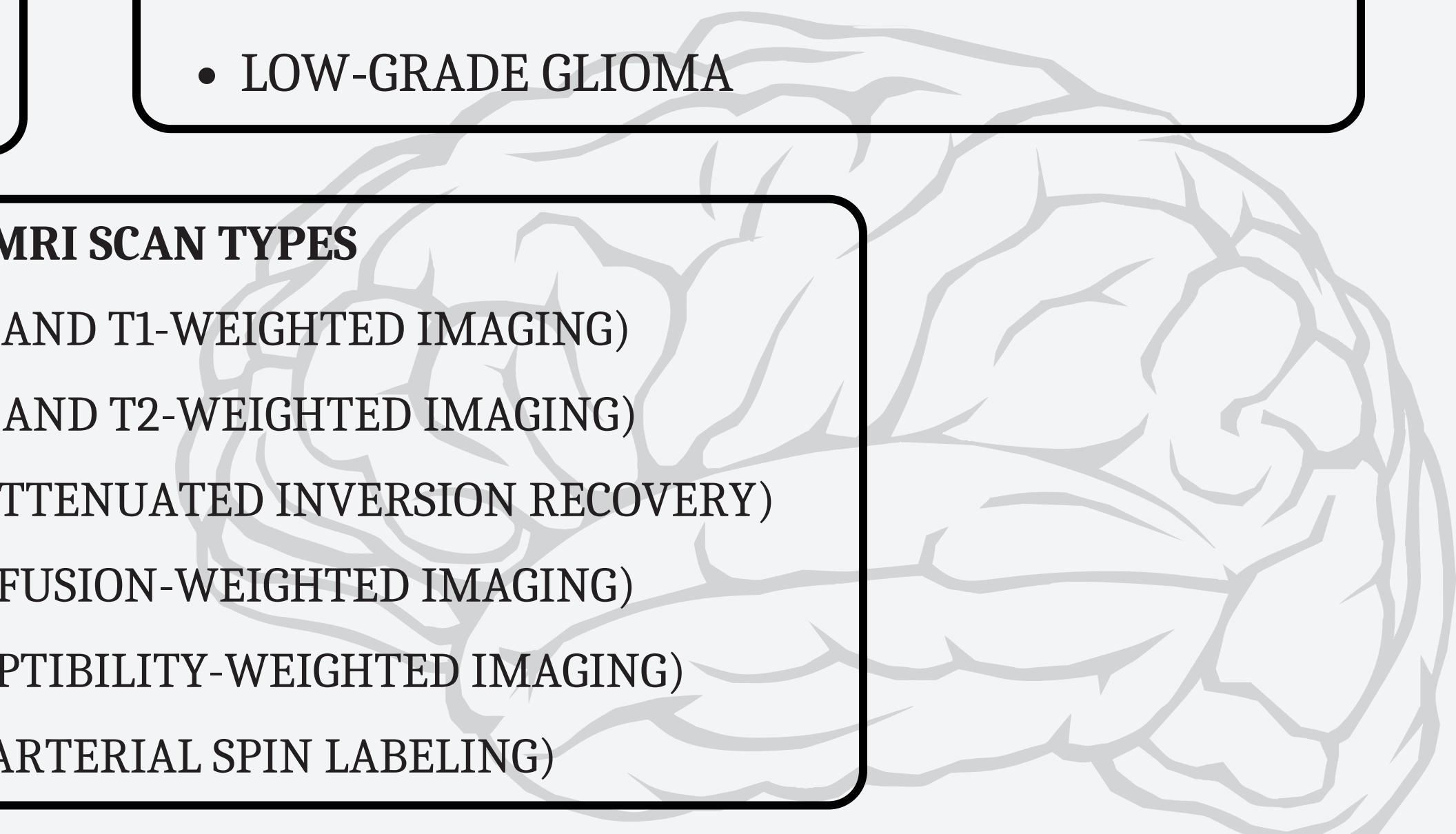
- **DICOM** (DIGITAL IMAGING AND COMMUNICATIONS IN MEDICINE)
- **NIFTI** (NEUROIMAGING INFORMATICS TECHNOLOGY INITIATIVE)
- **NRRD** (NEARLY RAW RASTER DATA)

CANCER TYPES

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

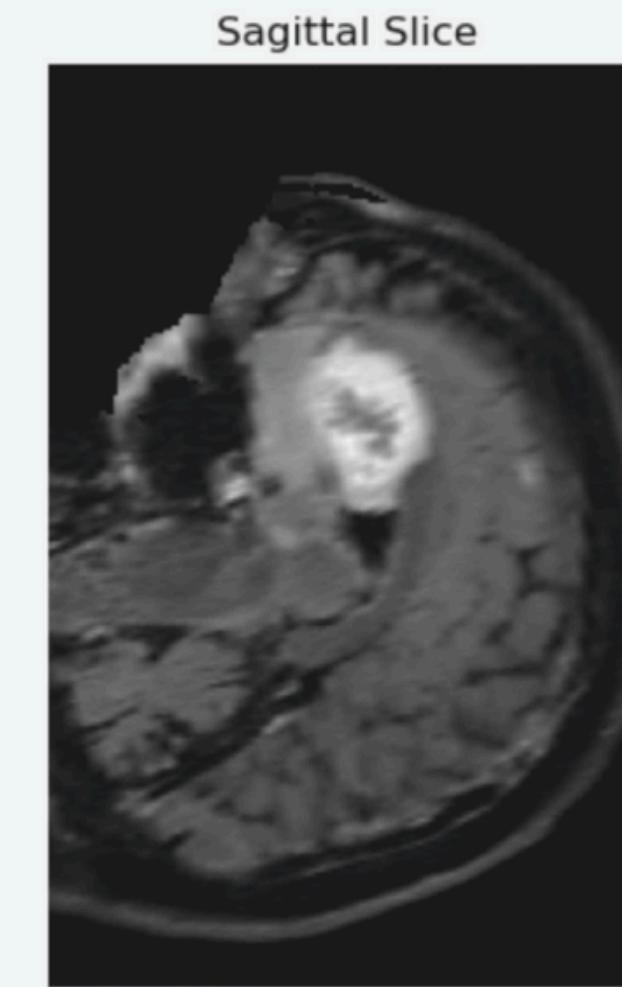
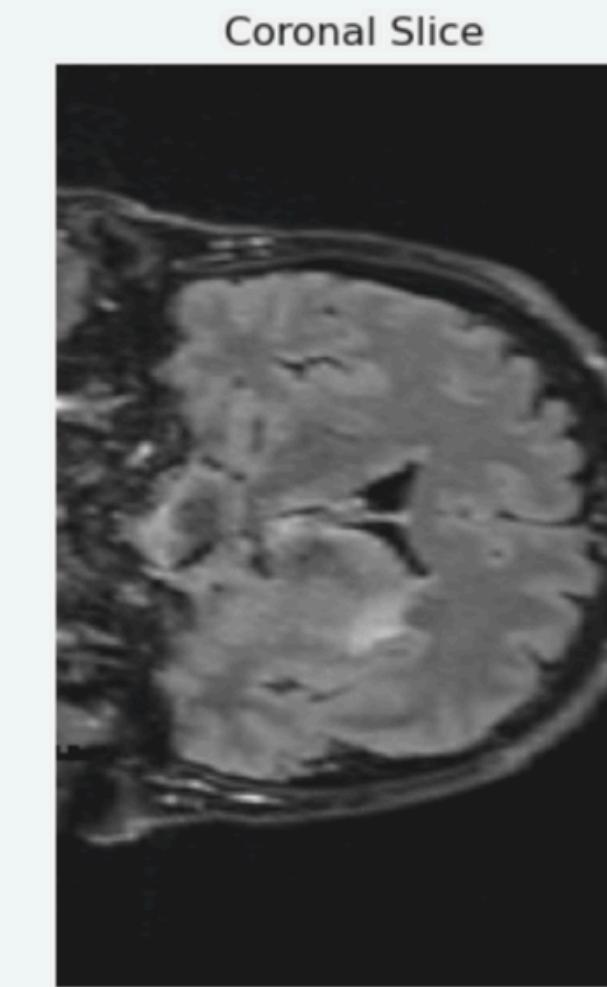
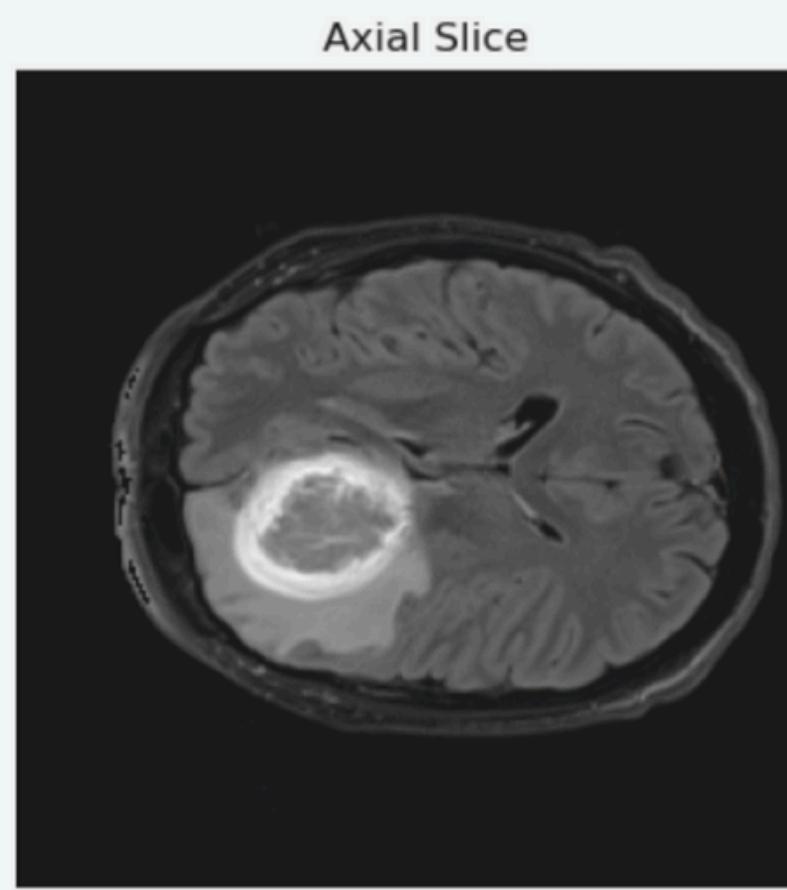
MRI SCAN TYPES

- **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)

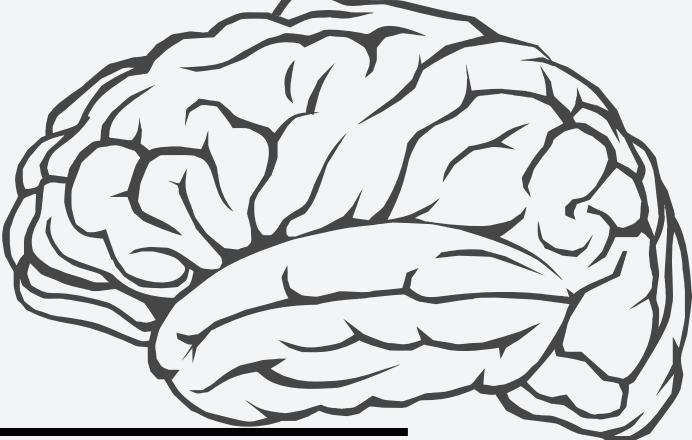


DATA REPORT

- **MRI PLANES:**
 - **AXIAL (AX):** HORIZONTAL SLICES DIVIDING THE BODY INTO UPPER AND LOWER PARTS
 - **CORONAL (COR):** VERTICAL SLICES DIVIDING THE BODY INTO FRONT AND BACK SECTIONS
 - **SAGITTAL (SAG):** VERTICAL SLICES DIVIDING THE BODY INTO LEFT AND RIGHT SECTIONS



DATASET - 1



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

- MR
- MEASUREMENT

Cancer Type

- DIFFUSE GLIOMA

Patients

- 495

Public

- YES

Image Size

- 240, 240, 155

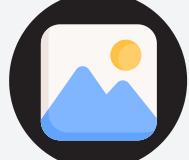
Tumor Size

- 240, 240, 155

UCSF-PDGM | THE UNIVERSITY OF CALIFORNIA SAN FRANCISCO

PREOPERATIVE DIFFUSE GLIOMA MR

MRI Images



T1, T2, FLAIR,
HARDI (FA), ADC,
ASL, DWI, SWI

Planes



Axial

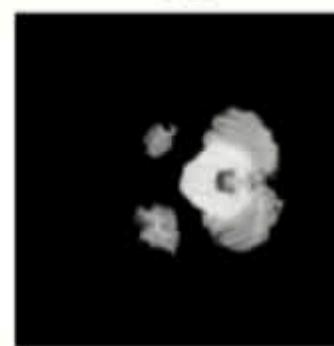
Distribution



Right
Skewed

Slice Number: 48 / 155

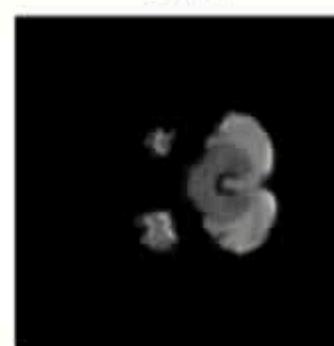
T1



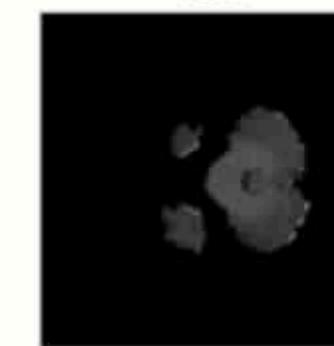
FLAIR



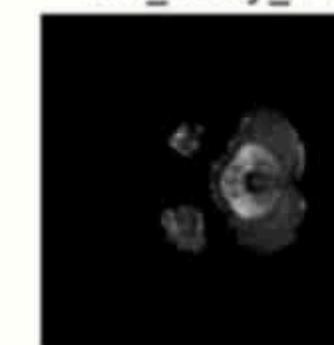
DWI



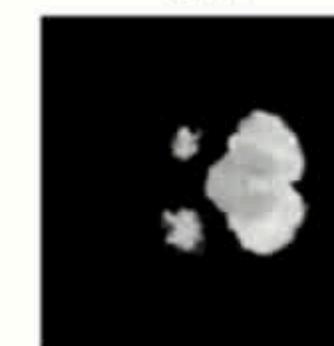
T1c



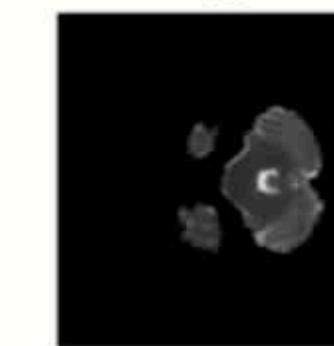
DTI_eddy_FA



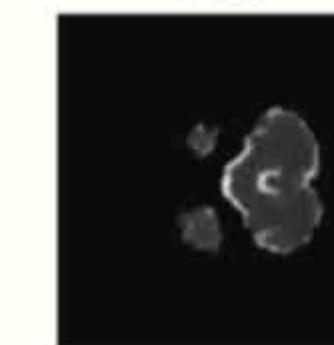
SWI



T2



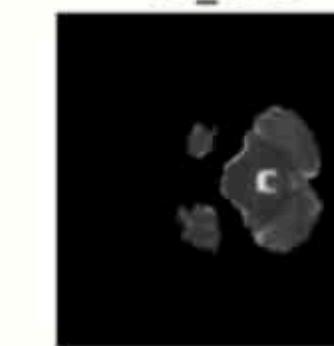
ADC



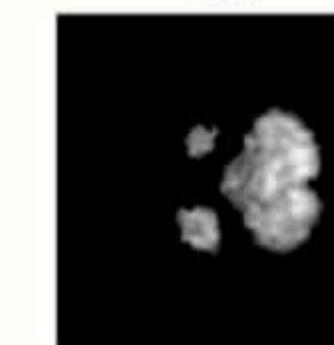
tumor_segmentation



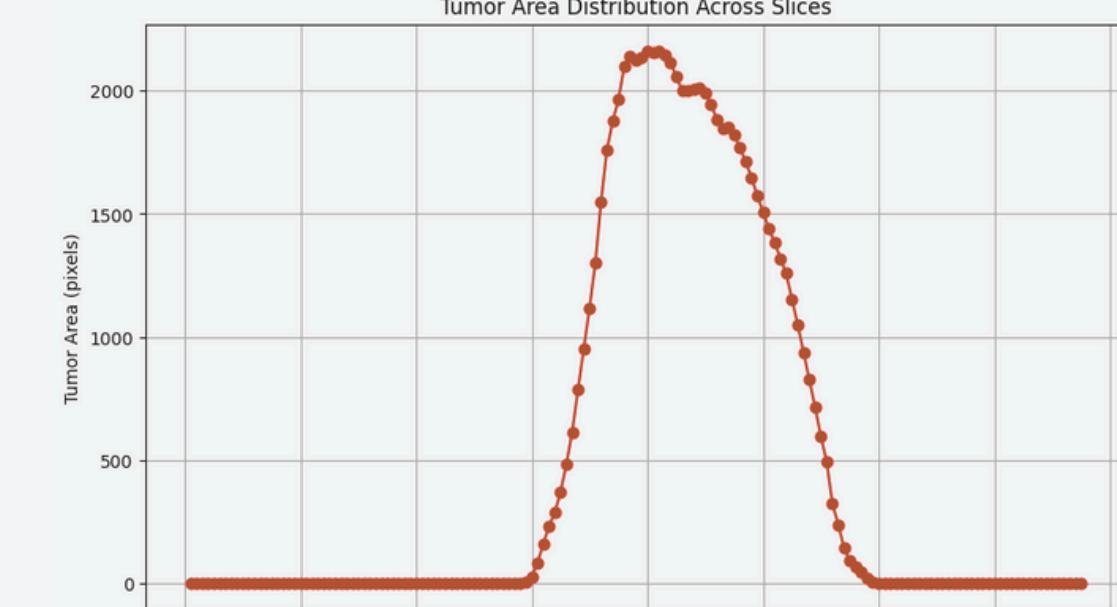
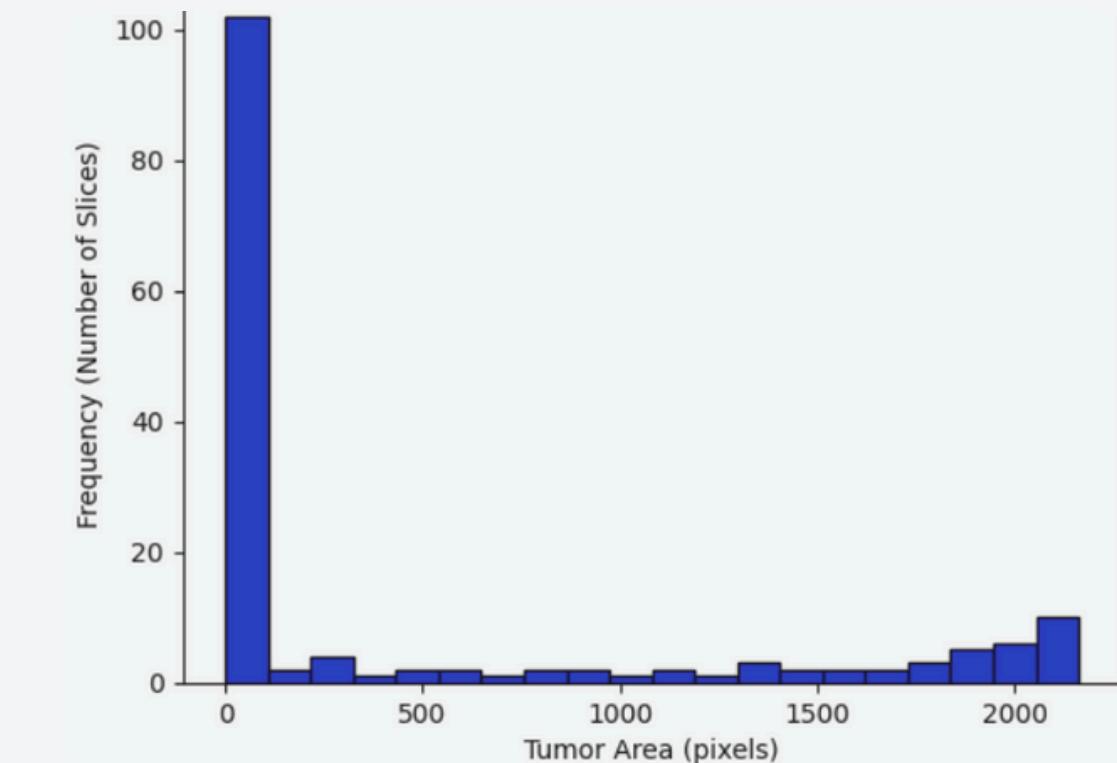
T2_bias



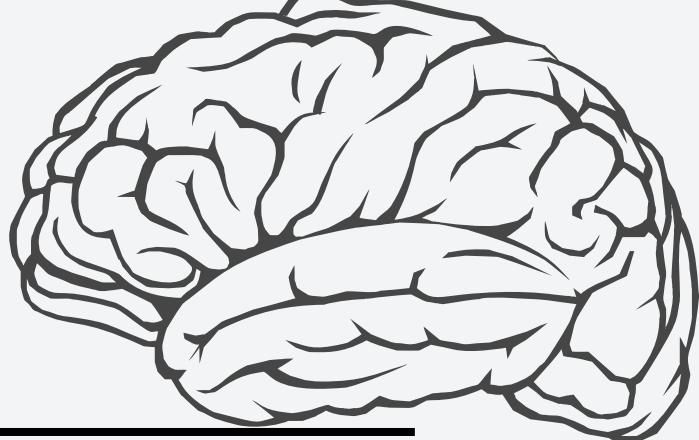
ASL



Tumor Seg. + T1 Base



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

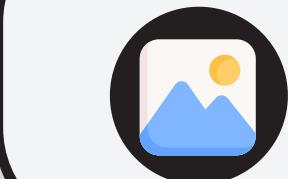
- 240, 240, 155

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



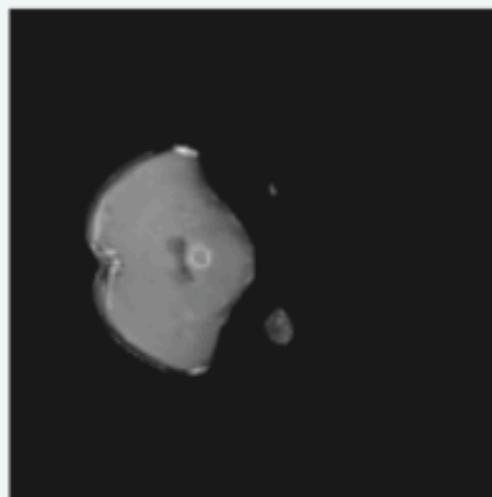
Axial

Distribution

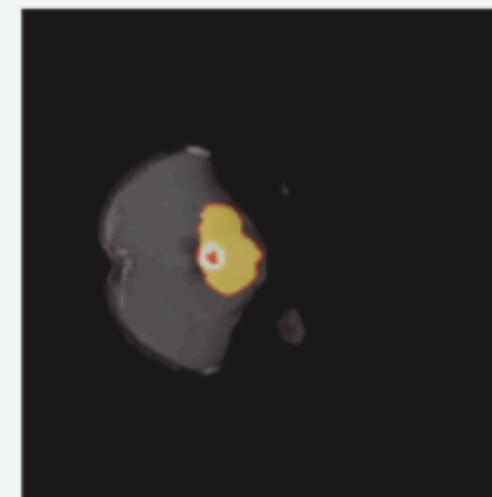


Right
Skewed

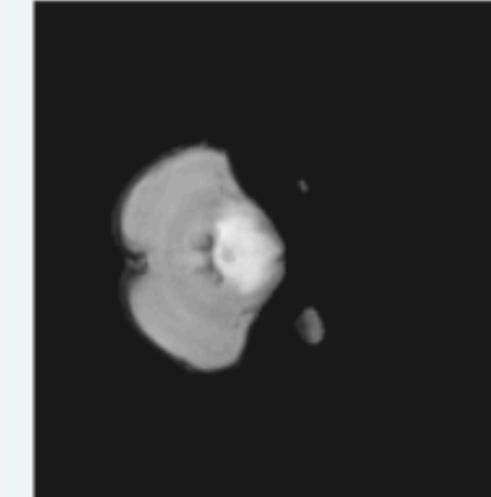
t1c



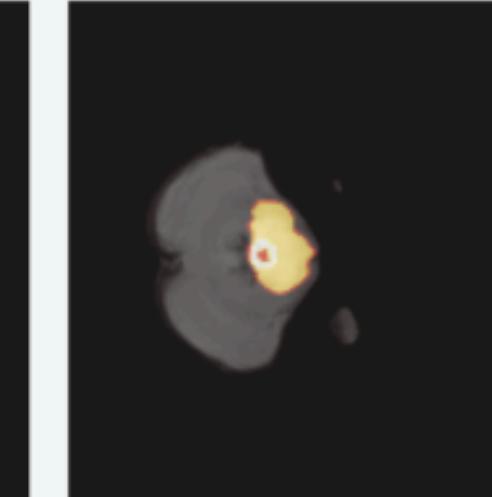
Tumor + t1c



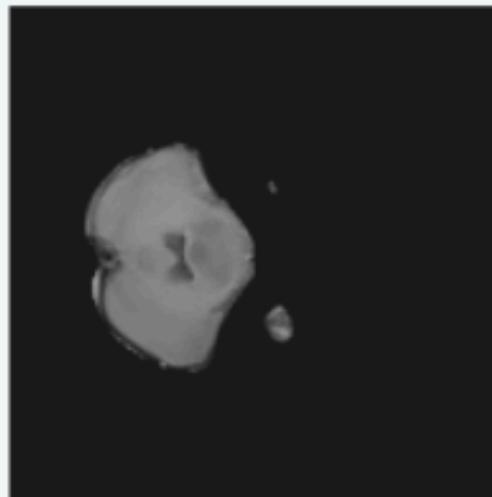
t2f



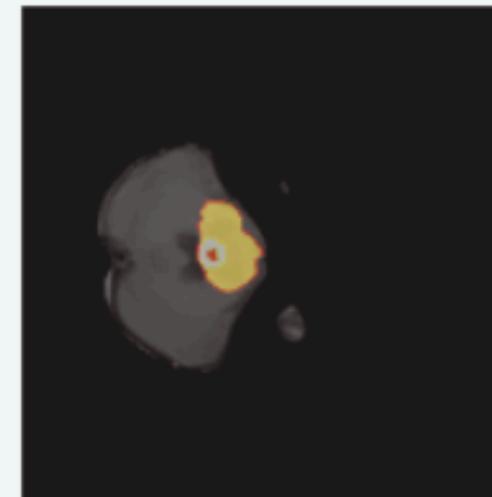
Tumor + t2f



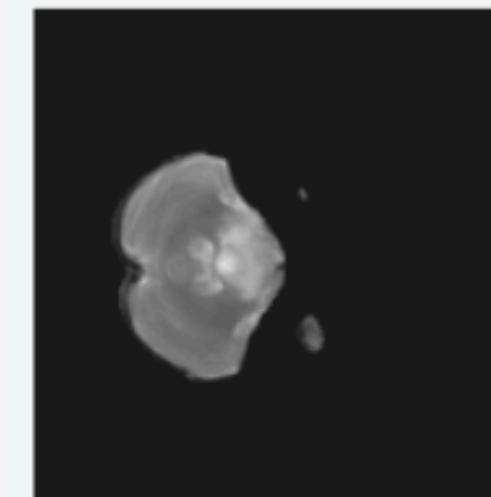
t1n



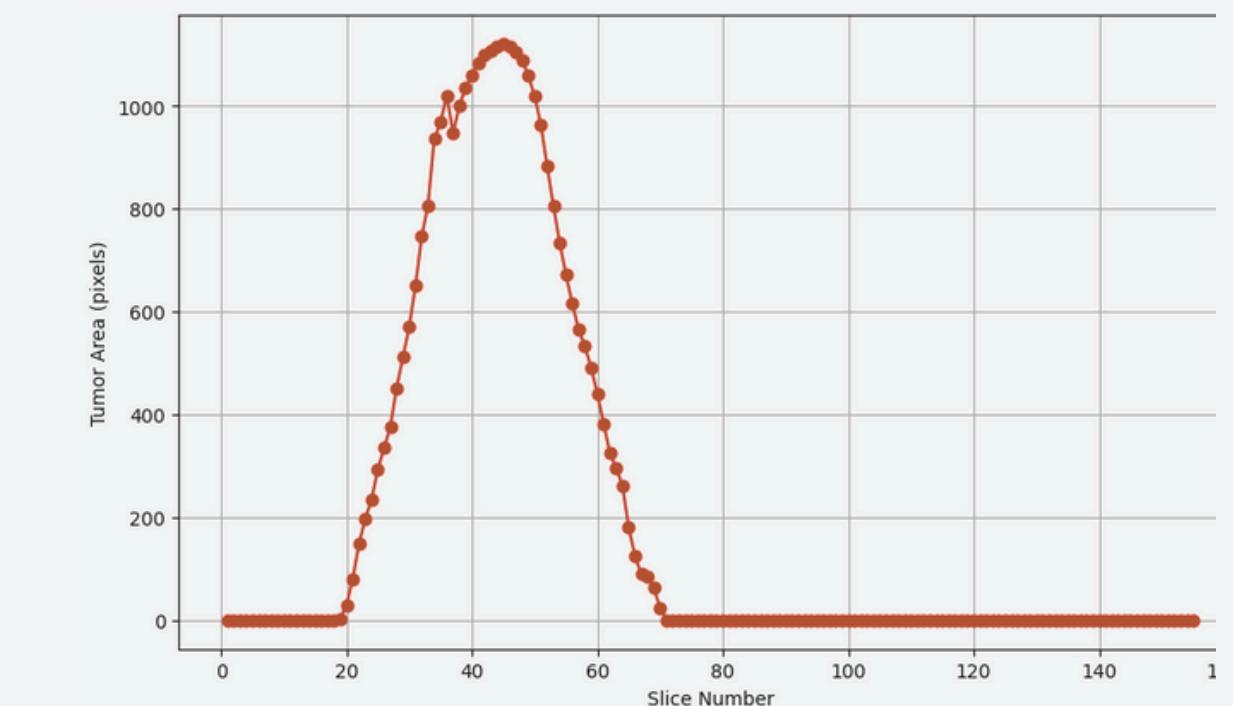
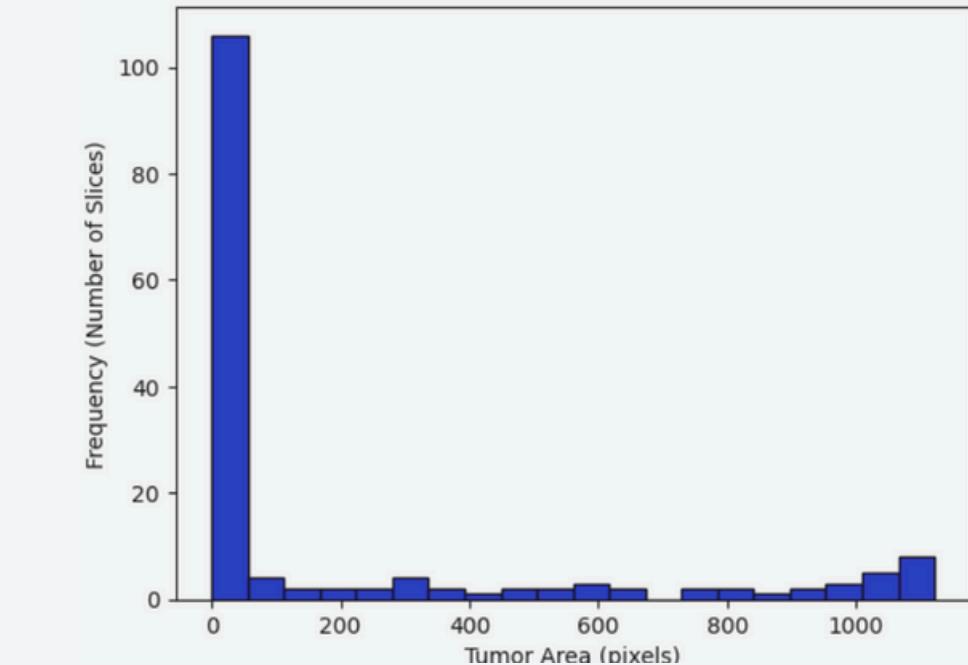
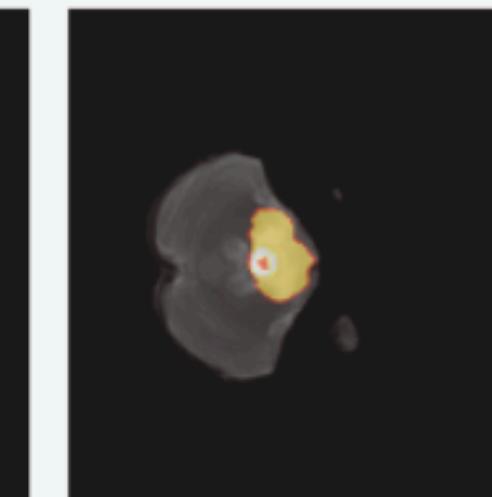
Tumor + t1n



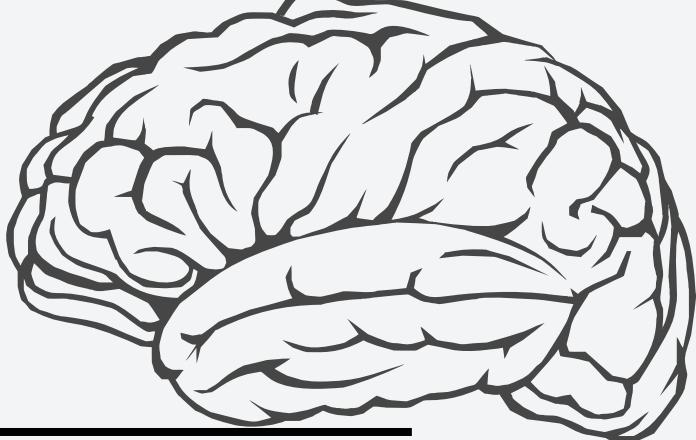
t2w



Tumor + t2w



DATASET - 3



Submit Your Data Access The Data Help

THE CANCER IMAGING ARCHIVE

About Us Research Activities News

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

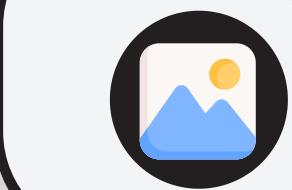
- 240, 240, 155

Tumor Size

- 240, 240, 155

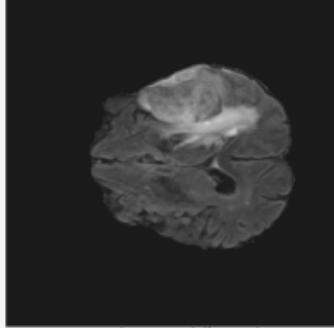
UPENN-GBM | MULTI-PARAMETRIC MAGNETIC RESONANCE IMAGING (MPMRI) SCANS FOR DE NOVO GLIOBLASTOMA (GBM) PATIENTS FROM THE UNIVERSITY OF PENNSYLVANIA HEALTH SYSTEM

MRI Images

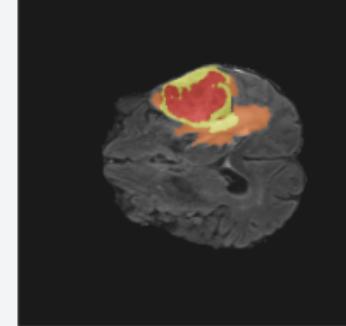


Flair, T1,
T1GD, T2

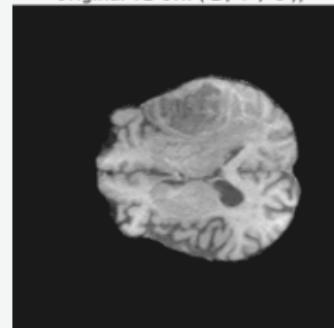
Original FLAIR Ori: ('L', 'P', 'S')



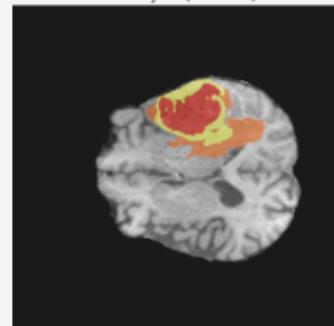
Overlay FLAIR (Slice: 77)



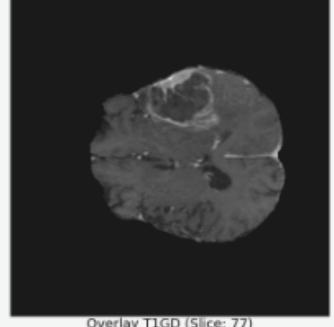
Original T1 Ori: ('L', 'P', 'S')



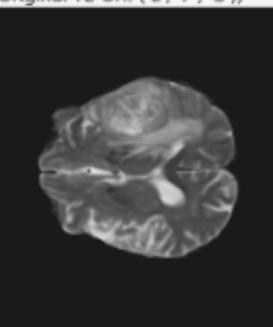
Overlay T1 (Slice: 77)



Original T1GD Ori: ('L', 'P', 'S')



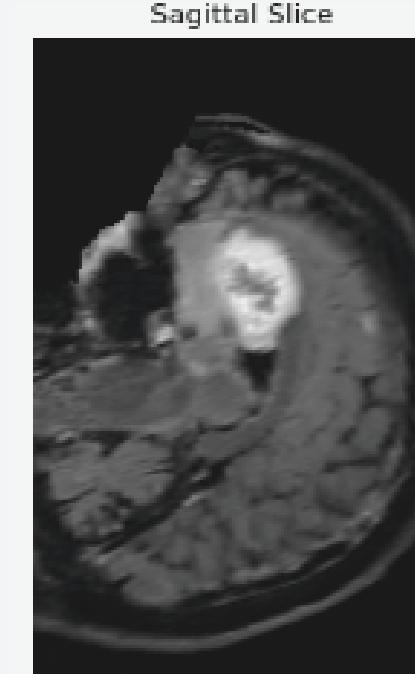
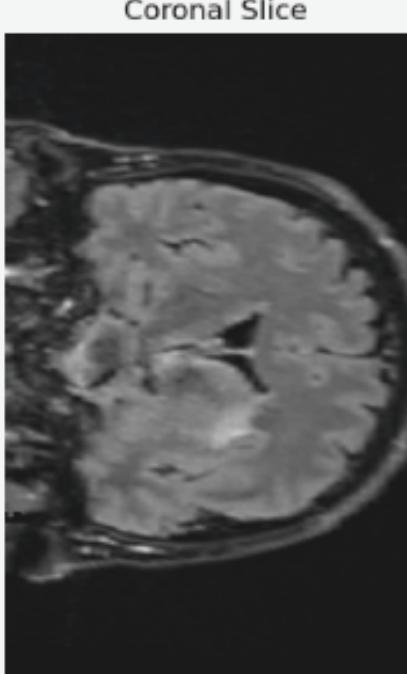
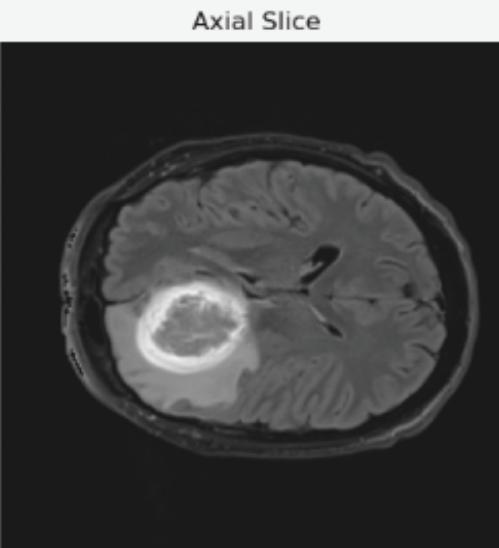
Overlay T1GD (Slice: 77)



Planes



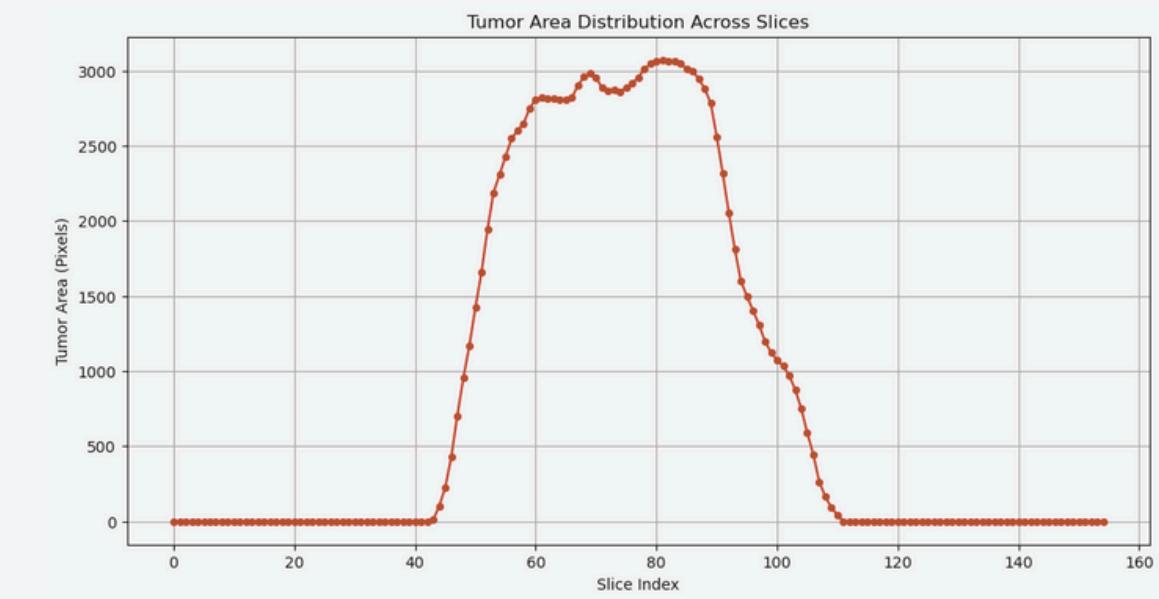
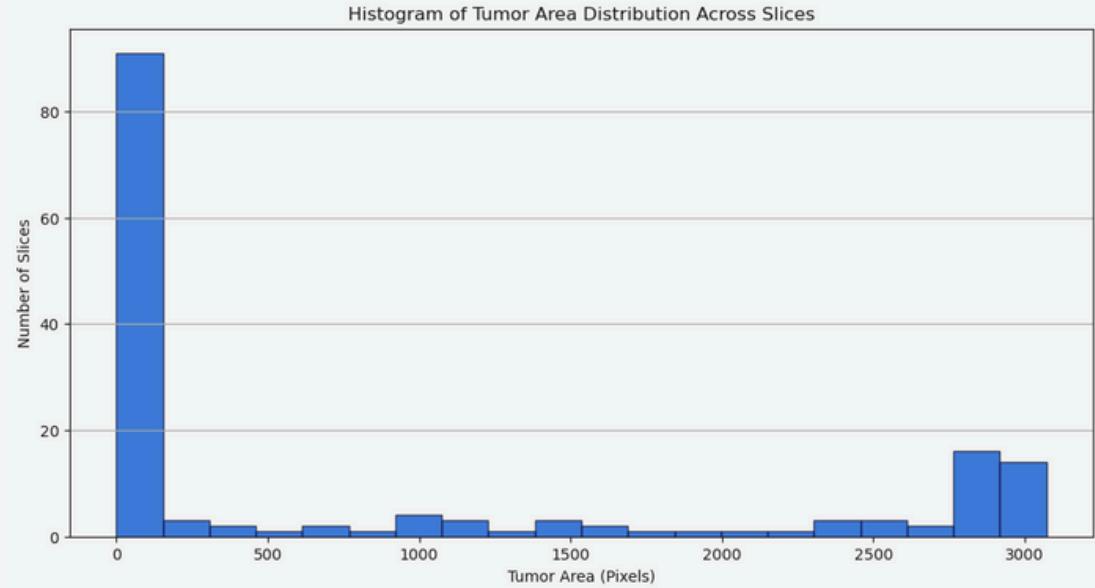
Axial,
Coronal,
Sagittal



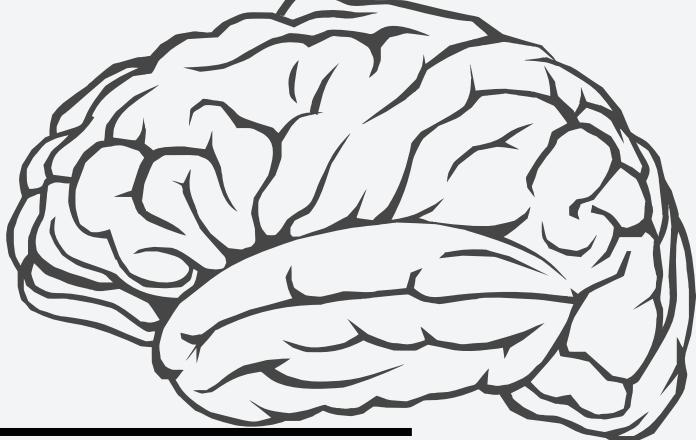
Distribution



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

- MR

Cancer Type

- LOW GRADE GLIOMA

Patients

- 159

Public

- NO

Image Size

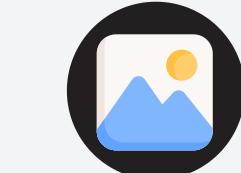
- M, 256, 256

Tumor Size

- N, 256, 256

LGG-1P19QDELETION | LGG-1P19QDELETION

MRI Images



T2

Planes



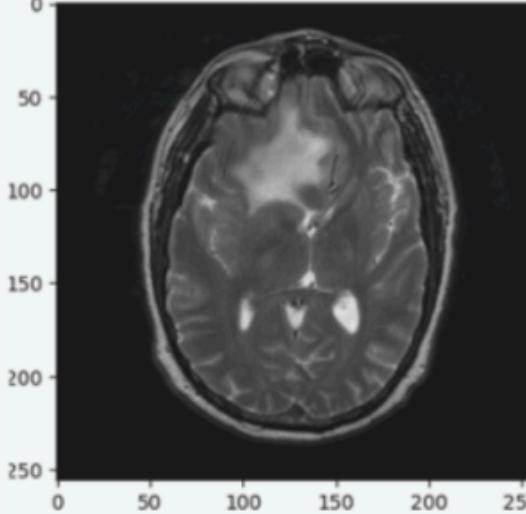
Axial

Distribution

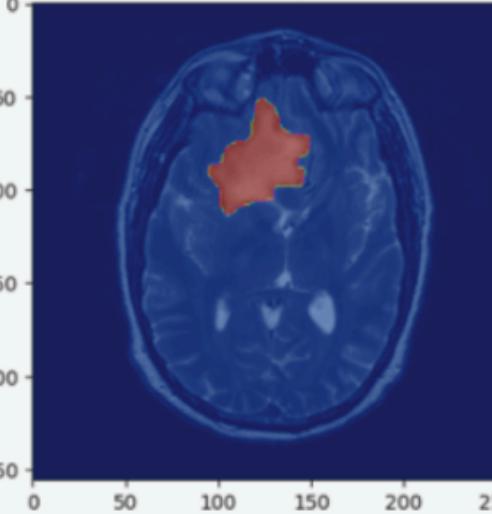


Right
Skewed

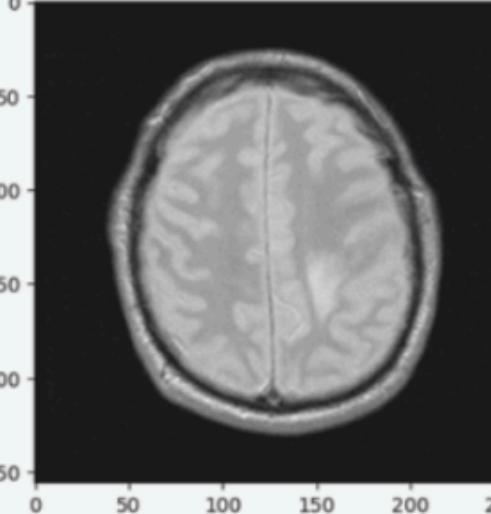
T2 Image - Slice 23/48



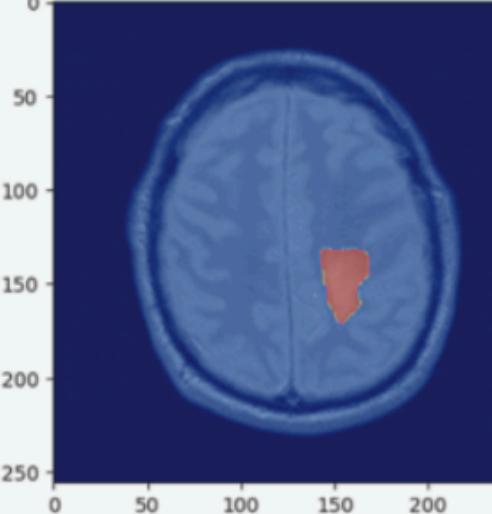
T2 + Tumor Overlay - Slice 23/48



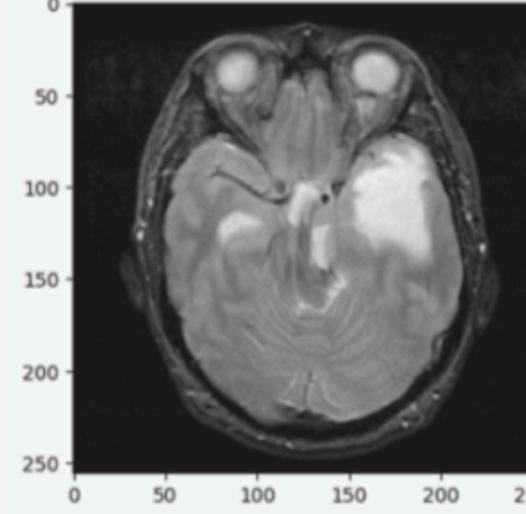
T2 Image - Slice 16/20



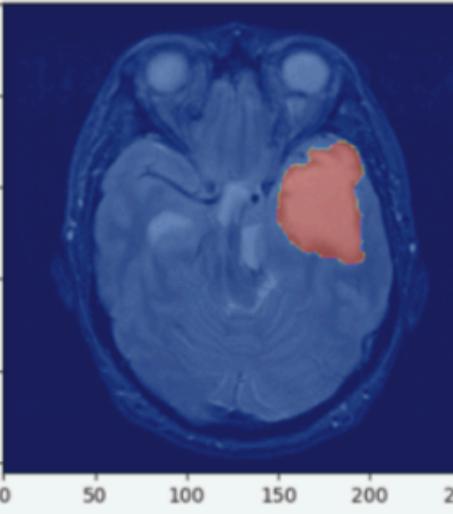
T2 + Tumor Overlay - Slice 16/20



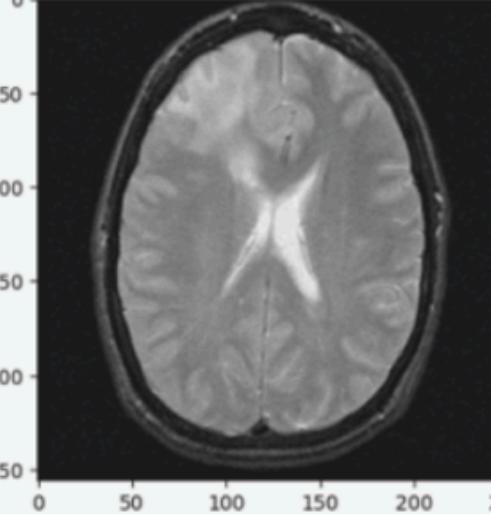
T2 Image - Slice 7/20



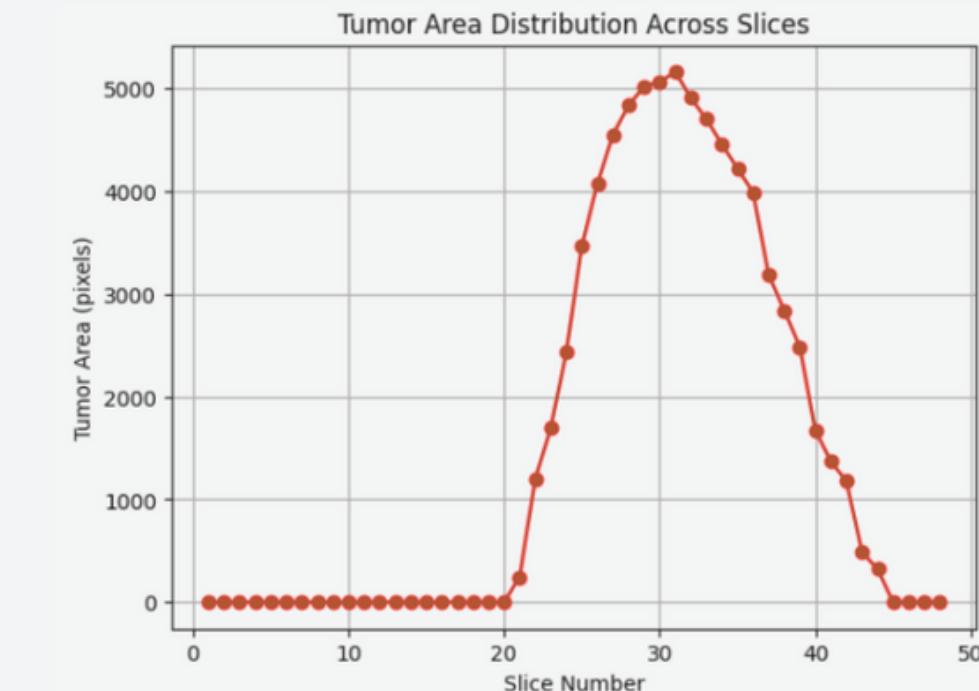
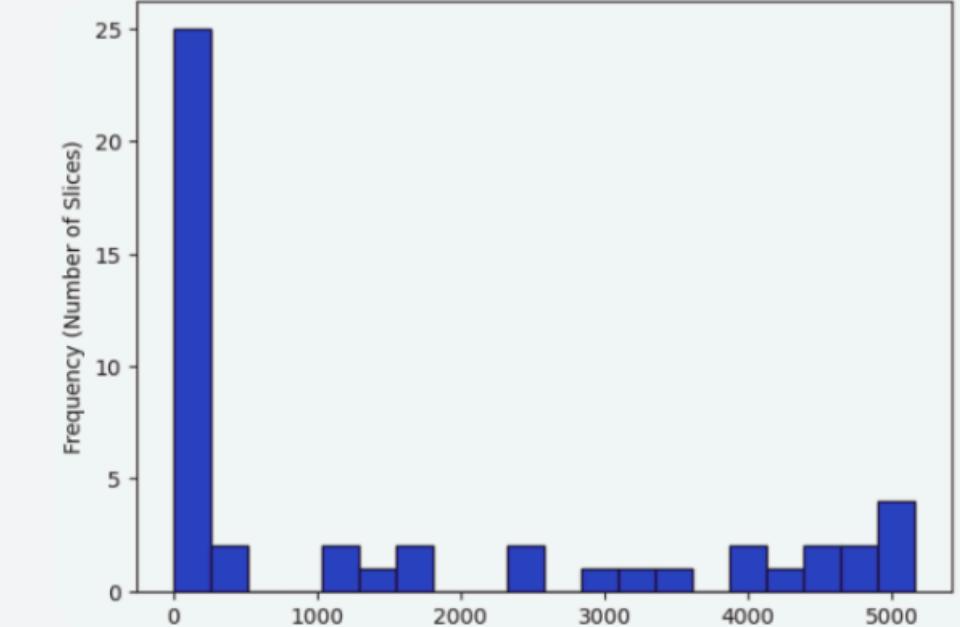
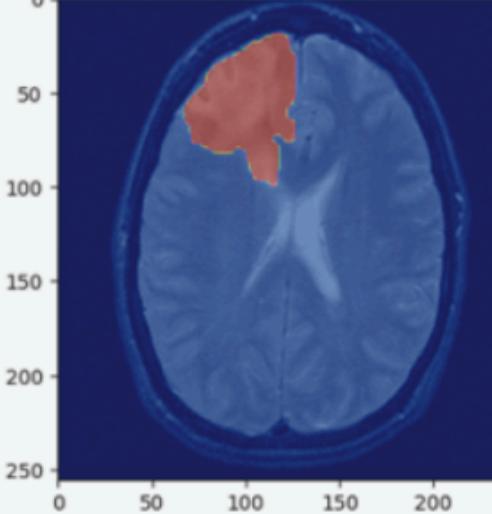
T2 + Tumor Overlay - Slice 7/20



T2 Image - Slice 12/20



T2 + Tumor Overlay - Slice 12/20



GENERAL WORKFLOW - DATASET

3D MRI IMAGES

FORMAT

- 1. NIFTI
- 2. DICOM

NON BINARY
SEGMENTATION



2D IMAGES

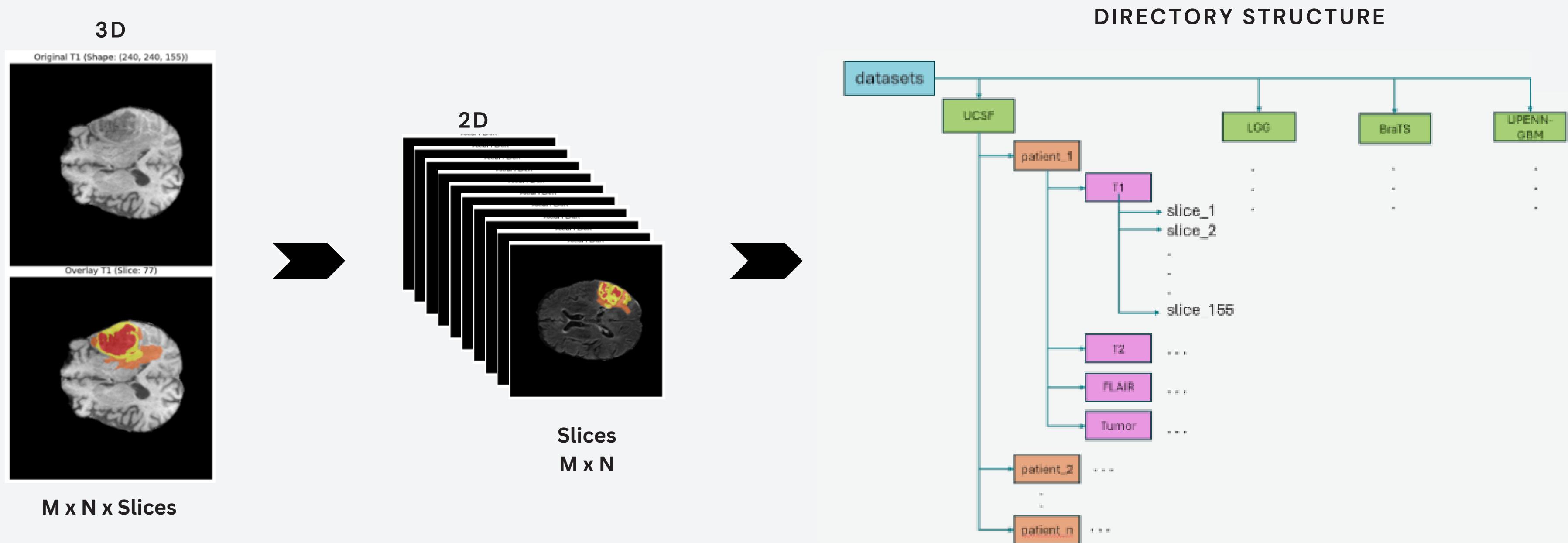
FORMAT

- PNG

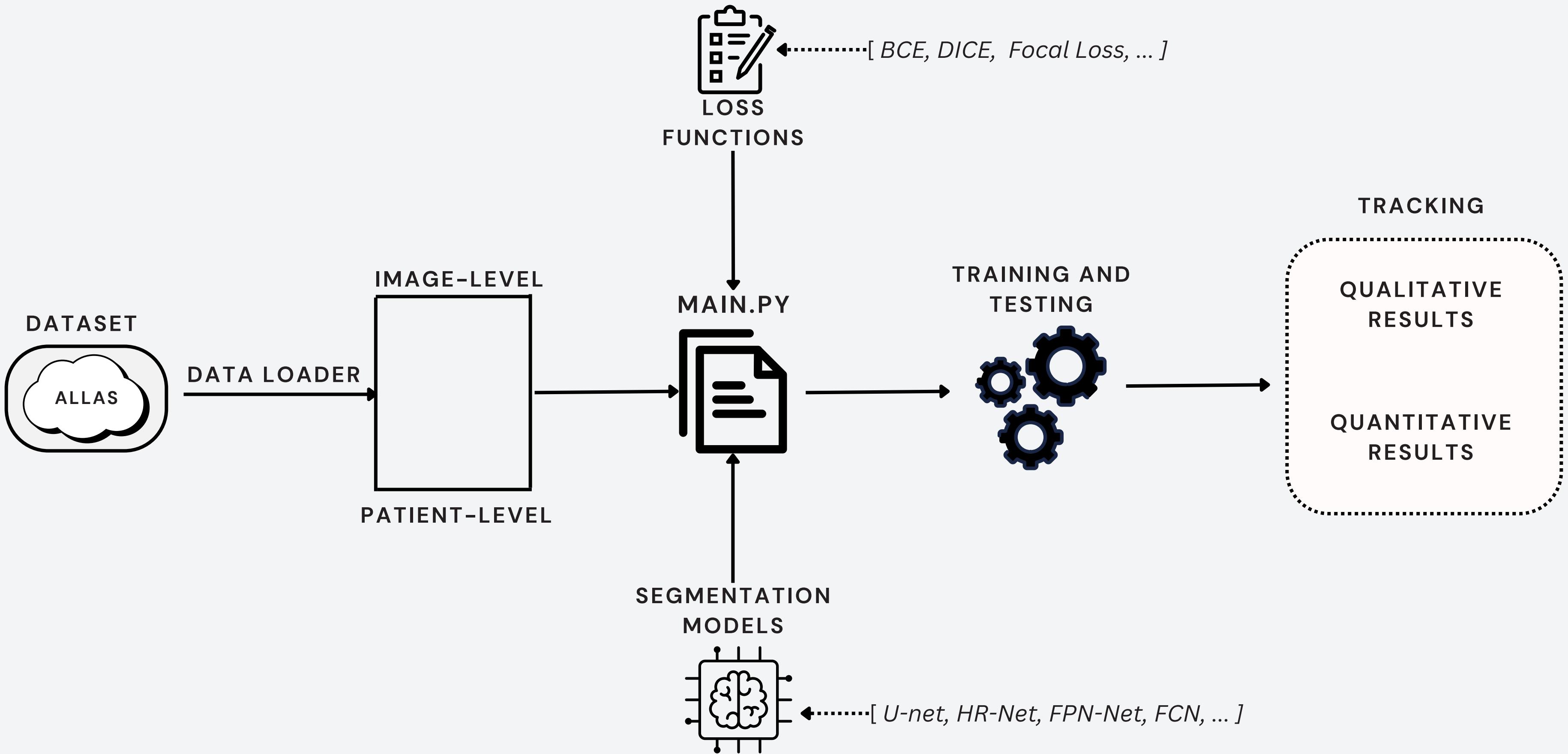
BINARY
SEGMENTATION



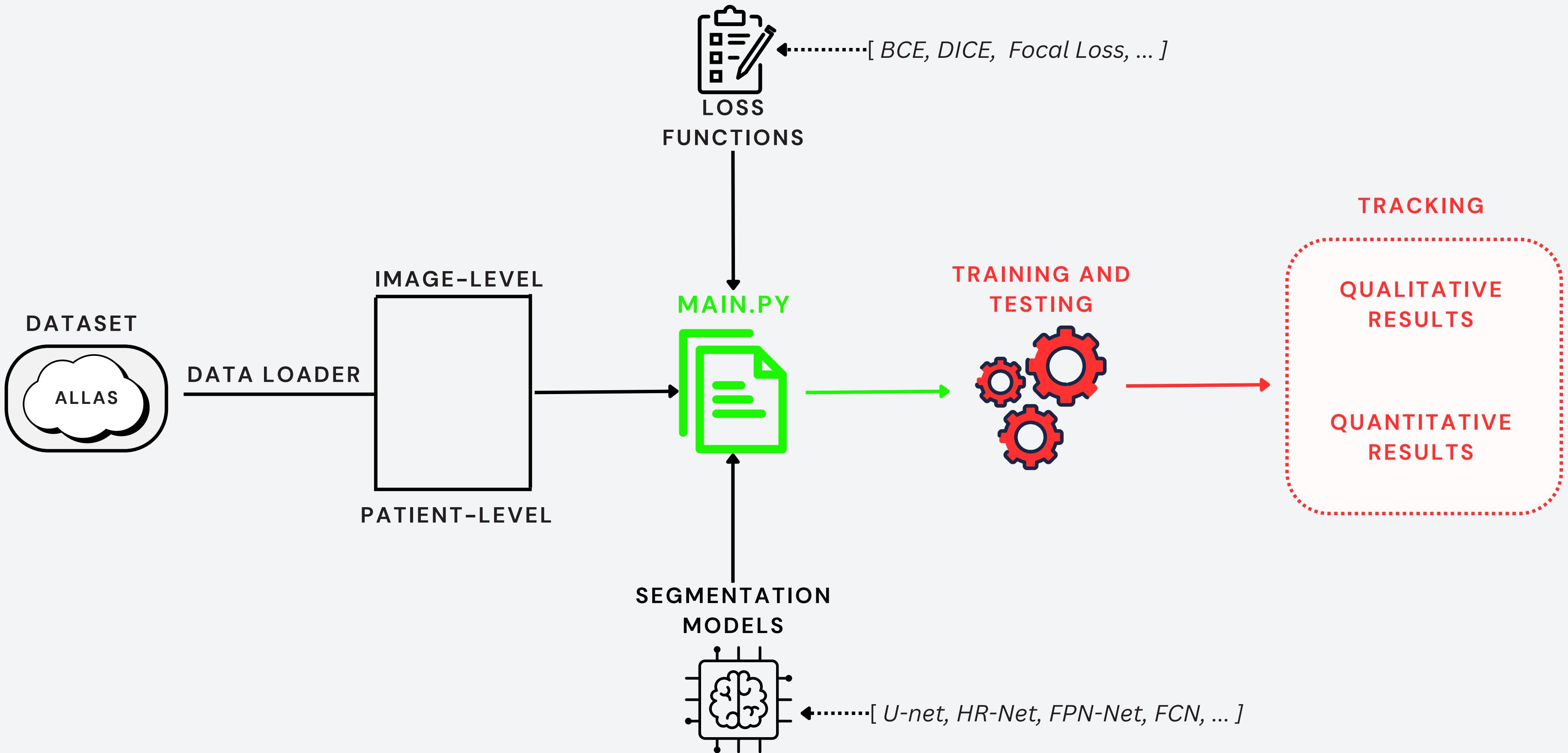
IMAGE CONVERSION



GENERAL WORKFLOW



GENERAL WORKFLOW



STRENGTHS

S

A GUIDE ON LOSS FUNCTIONS

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

W

WELL-DOCUMENTED AND PROCESSED DATASETS

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

O

INNOVATIVE APPROACH

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

T

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

WEAKNESSES

S

LACK OF MEDICAL KNOWLEDGE IN THE TEAM

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

W

LIMITED TIMEFRAME

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

O

GENERALIZABILITY CONCERNS

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

T

OPPORTUNITIES

S

EXPANDING APPLICATIONS

- EXPANSION TO OTHER CANCER TYPES
- INTEGRATION WITH NEW ARCHITECTURES

W

COLLABORATION WITH CLINICIANS

- ENGAGE WITH MEDICAL PROFESSIONALS TO IMPROVE OUR SOLUTION

O

PUBLICATIONS AND COLLABORATION OPPORTUNITIES

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

T

THREATS

S

SUBJECTIVITY AND ERROR IN CANCER ANNOTATIONS

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

W

DATA AVAILABILITY

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

O

OVERFITTING DUE TO HOMOGENEOUS DATASETS

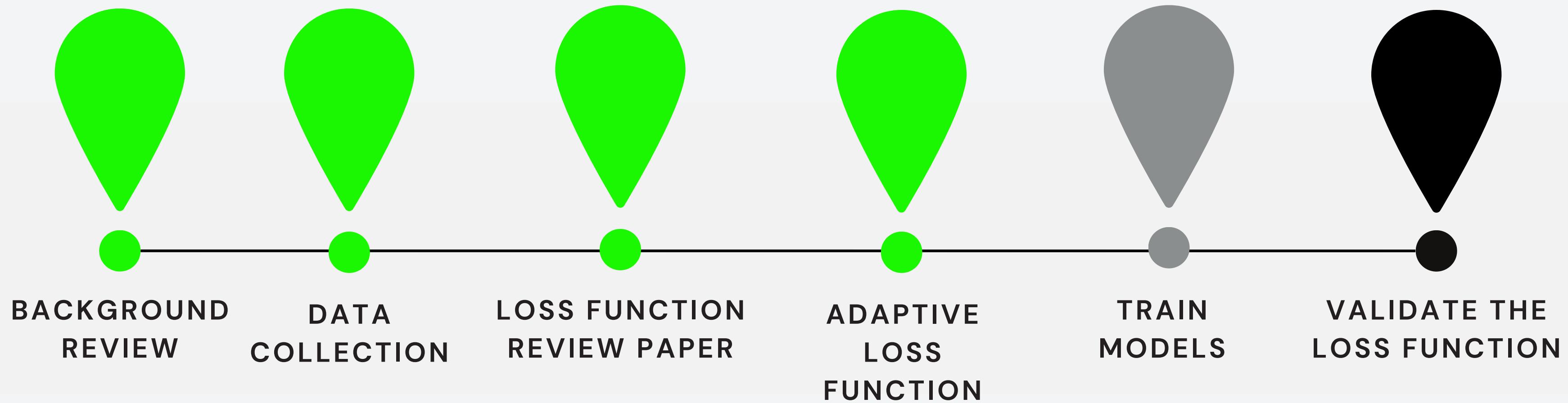
- MOST OF THE DATASETS HAVE SIMILAR TUMOR DISTRIBUTIONS
- RISK OF OVERFITTING TO SPECIFIC PATTERNS IN THE DATA.

T

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

MILESTONES



MILESTONES

IMPLEMENTATION



PAPERS

ADAPTIVE LOSS
FUNCTION



GUIDE TO EXISTING LOSS
FUNCTIONS



MILESTONES

PAPERS

ADAPTIVE LOSS FUNCTION



ADAPTIVE LOSS FUNCTION

- CLASSICAL LOSS FUNCTIONS
- OUR NOVEL STATISTICALLY DRIVEN LOSS FUNCTION
- EXTENSION IN REGION BASED ADAPTIVE LOSS FUNCTION
- EXPERIMENTS COMPARING THE RESULTS
- BENCHMARKING BASED ON TRAINING TIME, ACCURACY, HYPERPARAMETER ETC.

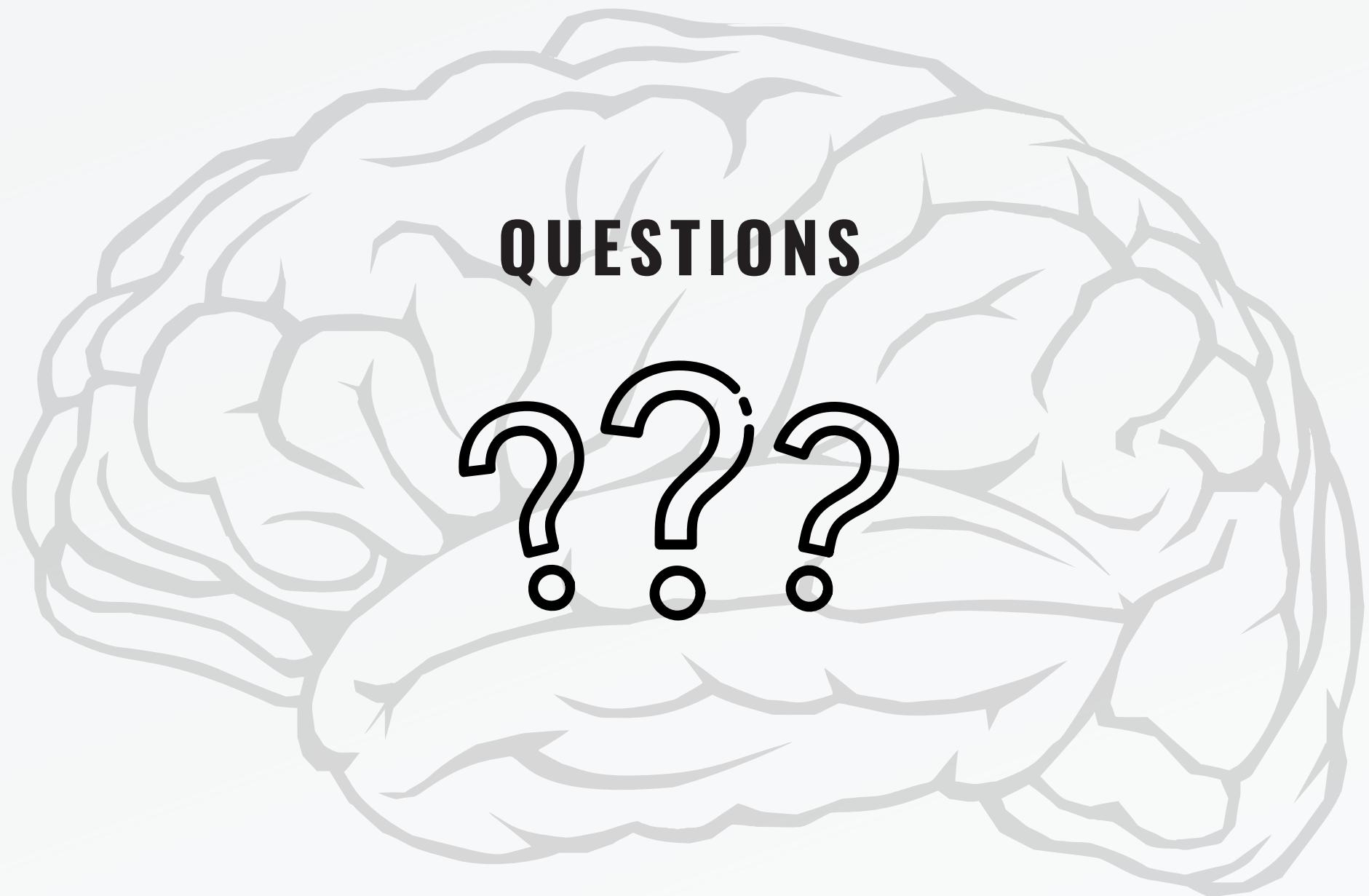
GUIDE TO EXISTING LOSS FUNCTIONS



GUIDE TO EXISTING LOSS FUNCTIONS

- CHARACTERISTICS
- PROS AND CONS
- AREA THEY ORIGINATE FROM
- WHERE THEY ARE USED
- POPULARITY
- TUTORIAL PAPER

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

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

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

- $\alpha \in \mathbb{R}$ 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** ($\alpha = 0$) AND **NORMAL** ($\alpha = 2$) DISTRIBUTIONS AND ANYTHING IN BETWEEN, ALSO FOR **NUMERICAL STABILITY**
- c IS FIXED TO MATCH THE FIXED SCALE ASSUMPTION OF THE BASELINE MODELS AND ROUGHLY MATCHES THE SHAPE OF ITS L1 LOSS

FUTURE WORK

A GENERAL AND ROBUST LOSS FUNCTION

$$\lim_{\alpha \rightarrow 2} f(x, \alpha, c) = \frac{1}{2} (x/c)^2$$

A -> 2 = L2 LOSS

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

**A = 1 = SMOOTHED
L1 LOSS**

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

**A = -2 = GEMAN-
MCCLURE LOSS**

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

**A -> 0 = CAUCHY (AKA
LORENTZIAN) LOSS**

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

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

FUTURE WORK

A GENERAL AND ROBUST LOSS FUNCTION

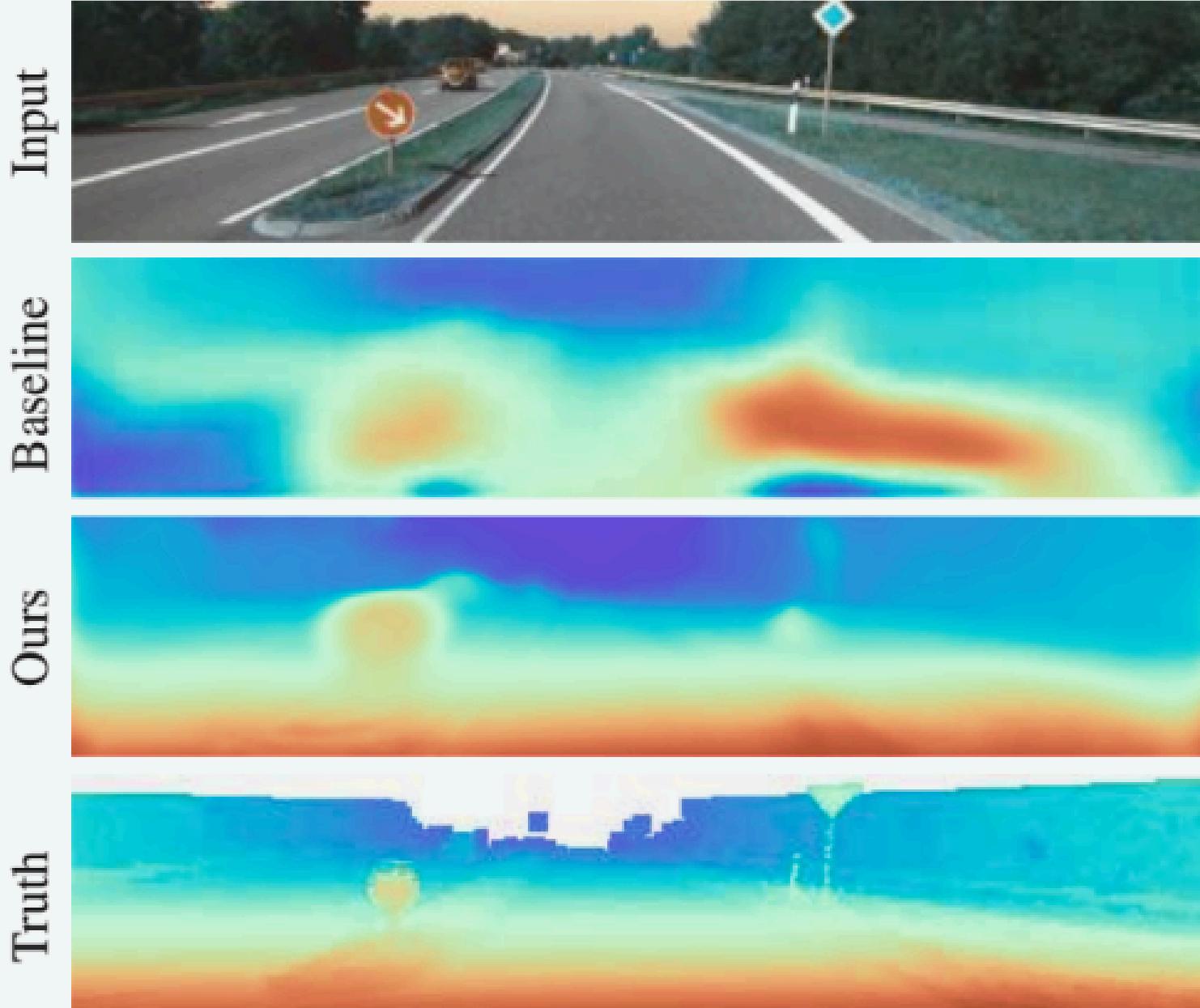
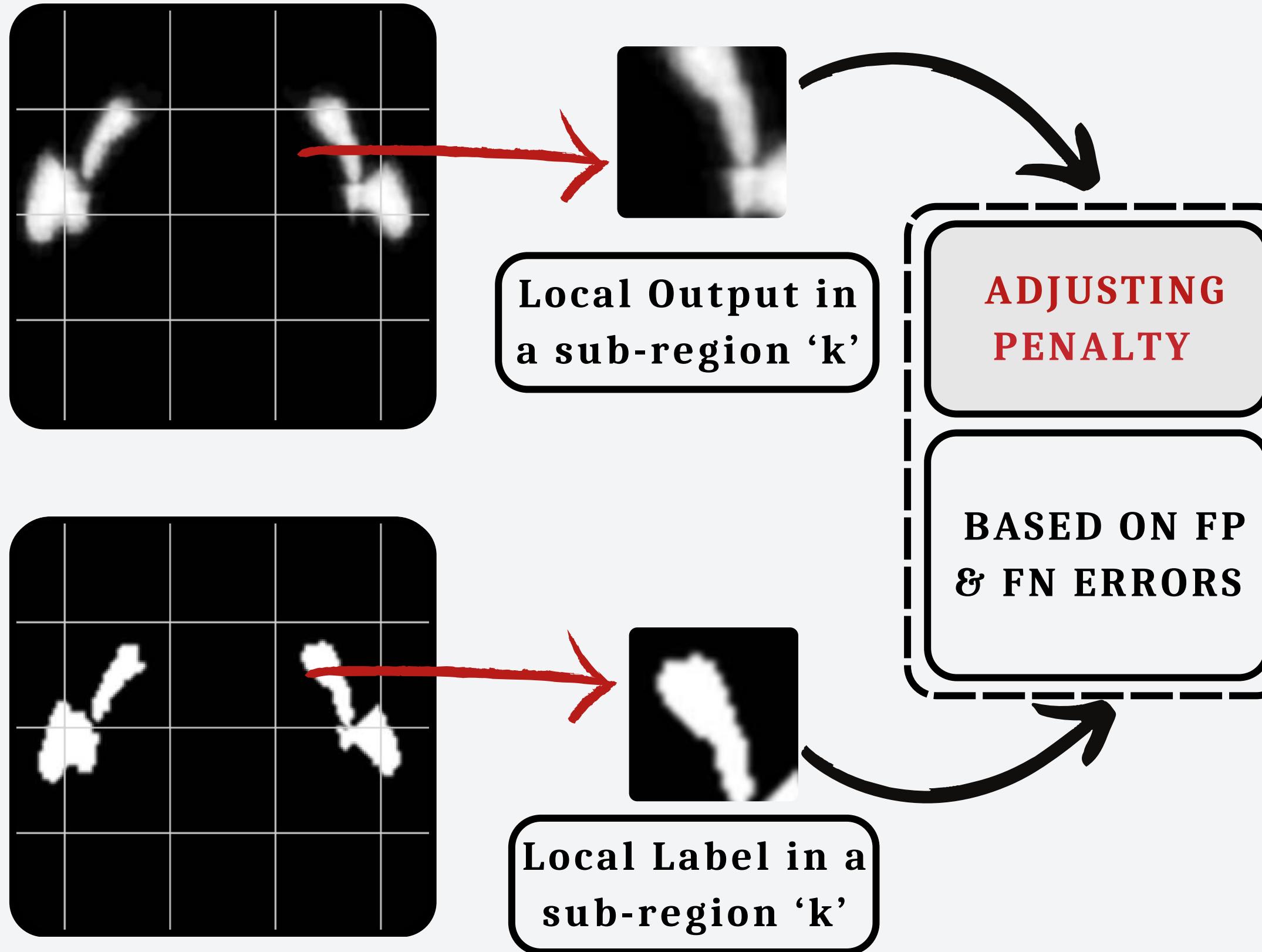


Figure 4. Monocular depth estimation results on the KITTI benchmark using the “Baseline” network of [41]. Replacing only the network’s loss function with our “adaptive” loss over wavelet coefficients results in significantly improved depth estimates.

- IN THE ADAPTIVE $A \in (0, 2)$ MODEL THEY ASSIGN EACH WAVELET COEFFICIENT ITS OWN SHAPE PARAMETER AS A FREE VARIABLE, WHICH 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



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

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

