

# THE CREATION OF A CONDITIONALLY ADAPTIVE LOSS FUNCTION FOR MEDICAL SEGMENTATION TASKS

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## INTRODUCTION

- Segmentation algorithms play a crucial role in isolating regions of interest from medical images, enabling disease diagnosis, biomarker discovery, and predictive analysis
- Challenges lie in the amount of high quality data for training, annotation precision, and imbalance
- Existing loss functions offer some solutions to handle class imbalances, but are influenced by the format of the training annotations
- Our project focuses on developing a statistically driven adaptive loss function tailored for imbalanced medical imaging datasets
- 4 large datasets focusing on brain tumor MRI scans

## OBJECTIVES

- Develop a statistically driven adaptive loss function
- Explore brain tumor datasets and preprocess
- Benchmark against popular loss functions on different segmentation models
- Develop a user interface for experimenting

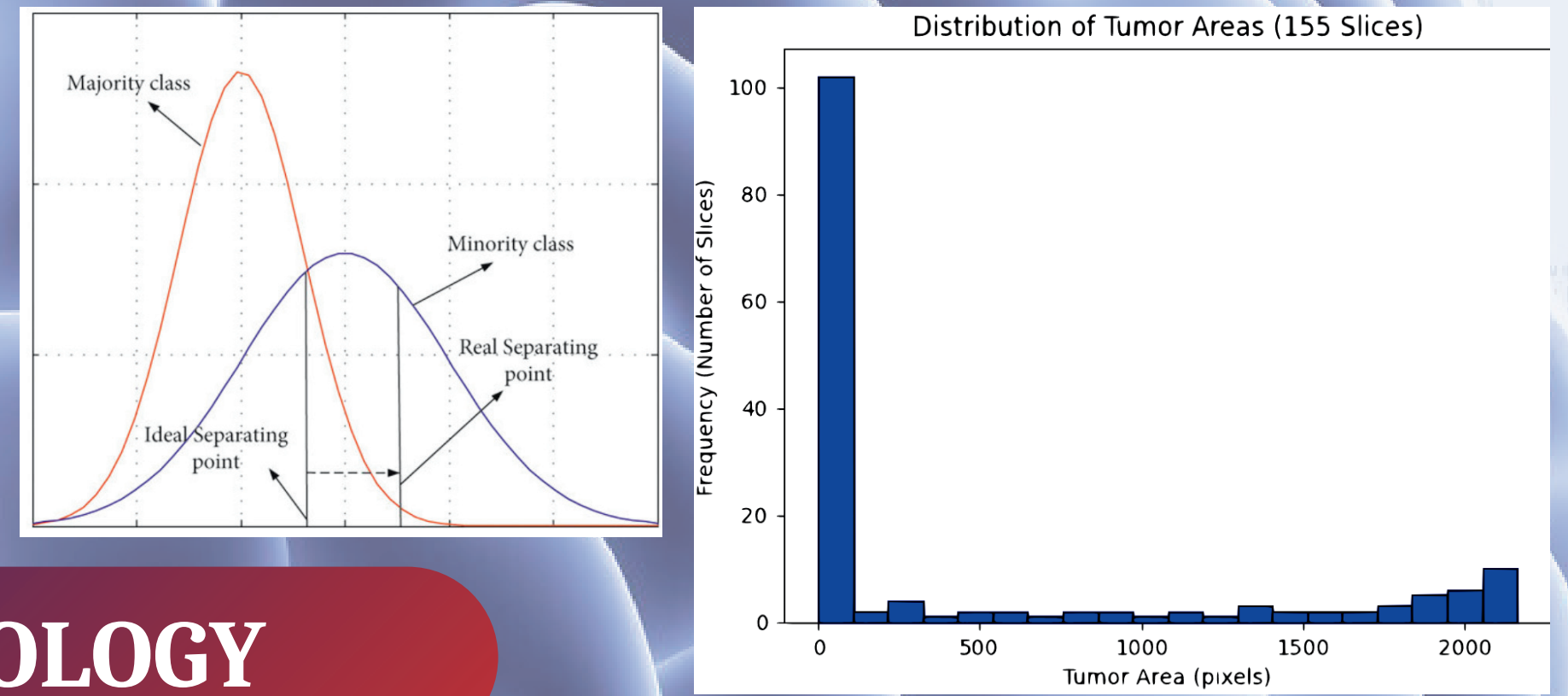
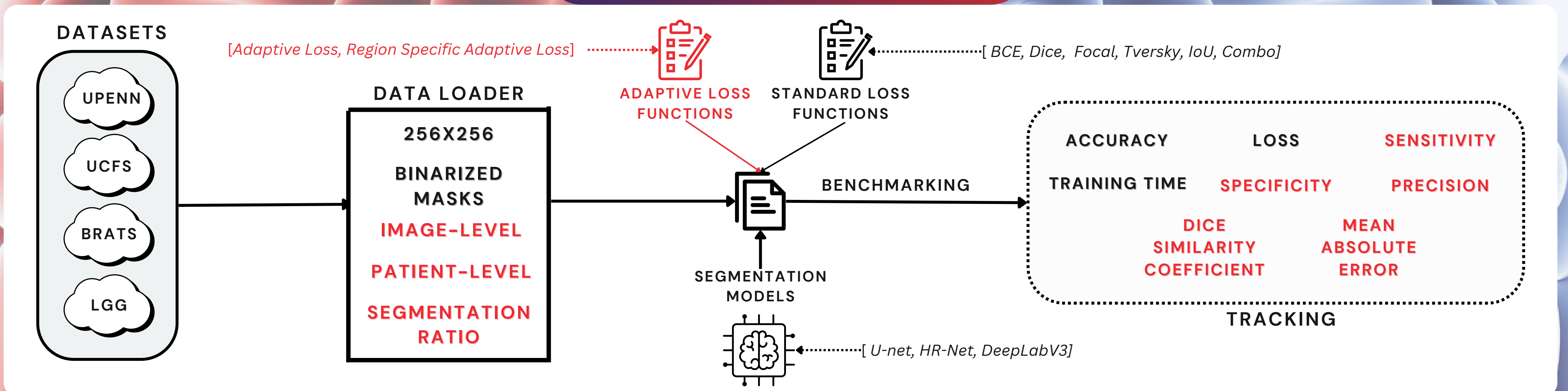


Fig 1. Class imbalance

## METHODOLOGY



## RESULTS

- BCE tends to oversegment, while adaptive loss can undersegment if not sure
- Adaptive loss can segment small tumor regions which are not part of the main tumor
- Focal loss and bce are the biggest competitors
- Not all models work well with all loss functions -> some loss functions are not consistent
- All have a high dice similarity coefficient, but make some crucial mistakes for extreme imbalance and small brain and tumor regions

Table 1. Results for different loss functions - U-net

Loss	Dice Coef	Specificity	Sensitivity	Precision	MAE
BCE	0.9589	0.9995	0.9546	0.9634	0.0008
Adaptive	0.9577	0.9997	0.933	0.9787	0.0009
Focal	0.9552	0.9996	0.9448	0.9711	0.0009

Fig 3. User interface - model prediction and overlays

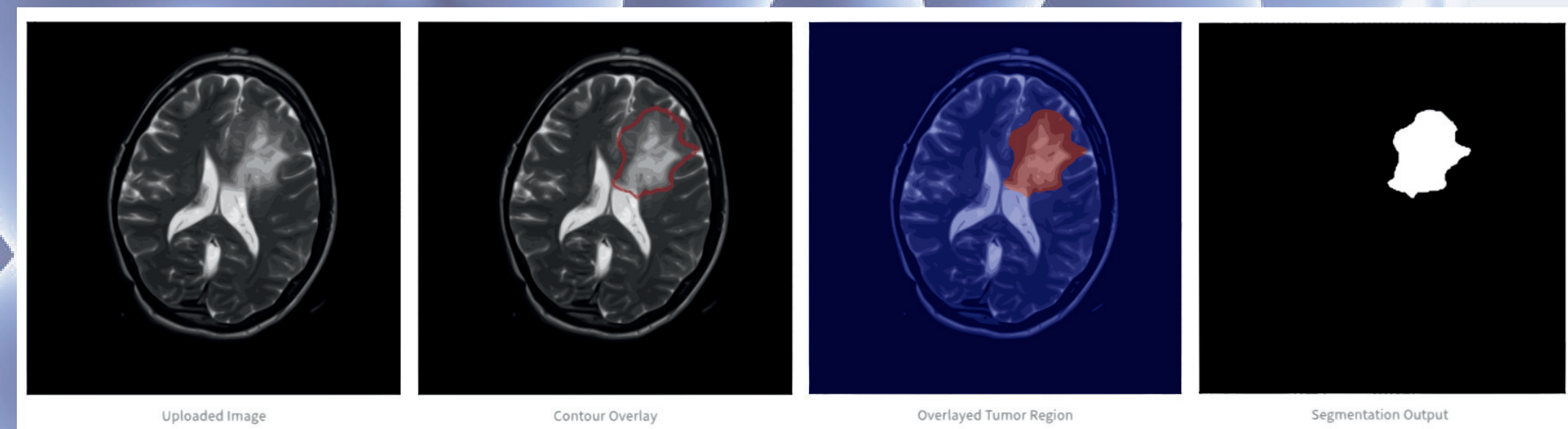


Fig 4. User interface - model prediction analysis

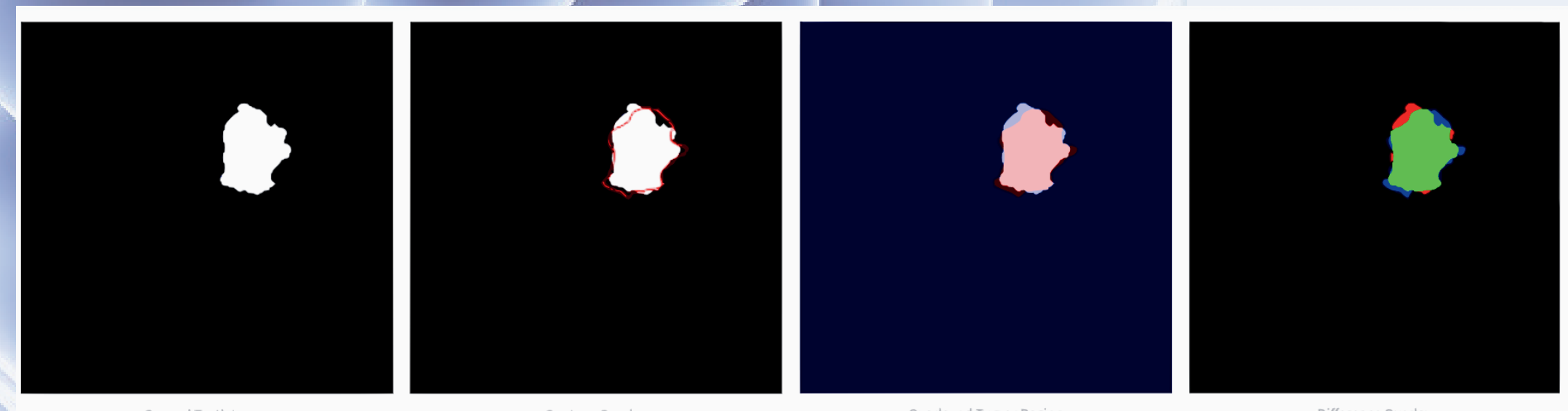
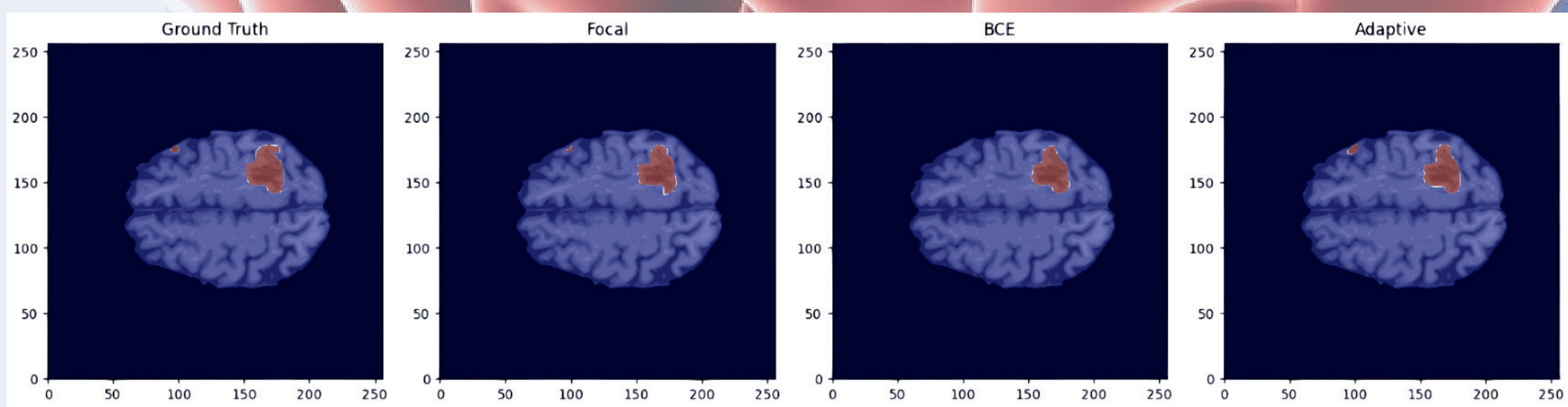


Fig 2. Predictions from different loss functions - U-net



## CONCLUSION

- Most popular functions imitate the shape of training annotations, leading to false positives
- Being consistent with true positives is crucial
- Oversegmenting is debatably a bigger issue than undersegmenting