Loss Functions for Image Segmentation

Pixel-wise Losses

Loss Function	Technical Name	Meaning	Example	Analogy	Goal	Use Case
Binary Cross Entropy	BCE	Pixel-wise error for binary segmentation	Tumor vs background classification	Yes/No quiz graded per answer	Minimize per-pixel classification error	Standard for binary segmentation
$L = -(1/N) \Sigma [y \log(\hat{y}) + (1-y) \log(1-\hat{y})]$						
Categorical Cross Entropy	CCE	Pixel-level classification for multi-class	City scene: road, car, sky	Multiple-choice exam graded per pixel	Penalize wrong class probability	Semantic segmentation baseline
$L = -(1/N) \Sigma \Sigma y_c \log(\hat{y}_c)$						
Weighted Cross Entropy	WCE	Cross entropy with class weights	Rare tumor pixels emphasized	Exam where rare questions count more	Penalize misclassification of minority class more	Imbalanced datasets
$L = -\Sigma w_c y_c \log(\hat{y}_c)$						

Overlap-based Losses

Loss Function	Technical Name	Meaning	Example	Analogy	Goal	Use Case
Dice Loss	DL	1 - Dice overlap	Predicted tumor overlaps 70% with GT	Overlap of two circles	Maximize region overlap	Medical imaging with imbalance
$L = 1 - (2 \Sigma y \cdot \hat{y}) / (\Sigma y + \Sigma \hat{y})$						
IoU Loss	Jaccard Loss	1 - IoU overlap	Predicted organ overlaps 75%	Venn diagram overlap ratio	Maximize intersection, penalize union mismatches	Direct IoU optimization

$$L = 1 - (\Sigma\ y\cdot\hat{y}) / (\Sigma\ y + \Sigma\ \hat{y} - \Sigma\ y\cdot\hat{y})$$

Combined Losses

Loss Function	Technical Name	Meaning	Example	Analogy	Goal	Use Case
BCE + Dice Loss	Hybrid	Sum of BCE and Dice	Tumor: pixel and overlap accuracy	Check answers individually and overall	Penalize both misclassified pixels and poor overlap	Medical segmentation pipelines
$L = BCE + Dice$						
CE + IoU Loss	Hybrid	Sum of CE and IoU	Organs segmented by class and overlap	Judged by accuracy and consistency	Balance pixel correctness with region overlap	Multi-class tasks with imbalance
$L = CE + IoU$						

Boundary-aware Losses

Loss Function	Technical Name	Meaning	Example	Analogy	Goal	Use Case
Boundary Loss	BL	Distance-based boundary error	Thin blood vessel segmentation	Tracing outlines carefully	Minimize distance from predicted to true boundary	Thin or elongated structures
$L = \Sigma\ D(x)\cdot\hat{y}(x)$						
Hausdorff Loss	HD Loss	Largest boundary error	Tumor edge far off in one spot	Ruler measures farthest mismatch	Penalize worst-case contour deviation	Precise medical contours
$L = \max_{x\in A} \min_{y\in B} d(x,y)$						

Focal-type Losses

Loss Function	Technical Name	Meaning	Example	Analogy	Goal	Use Case
Focal Loss	FL	Focus on hard pixels	Small tumor emphasized	Teacher spends	Penalize easy	Severe class imbalance

			over background	more time on weak students	examples less, hard ones more	
$L = -\alpha (1-\hat{y})^\gamma y \log(\hat{y})$						
Tversky Loss	TL	Adjustable Dice variant	Missing tumors penalized more than false alarms	Exam where missing answers cost more	Penalize FN vs FP differently	When recall is critical (e.g. cancer)
$L = 1 - (\Sigma y \cdot \hat{y}) / (\Sigma y \cdot \hat{y} + \alpha FP + \beta FN)$						

Advanced Losses

Loss Function	Technical Name	Meaning	Example	Analogy	Goal	Use Case
Lovász-Softmax Loss	LS	IoU surrogate optimization	Cityscapes optimized for mIoU	Training for the exact final score	Directly minimize IoU surrogate	Benchmarks where IoU is key
$L = \text{Lovász extension of IoU}$						
Focal Tversky Loss	FTL	Focal + Tversky combo	Rare lesion segmentation	Hardest important questions emphasized	Focus on hard false negatives	Small, rare targets
$L = (\text{Tversky Index})^\gamma$						
Surface Loss	SL	Boundary distance error in 3D	Organ surfaces misaligned	Comparing outlines in 3D models	Minimize distance between predicted and true surface	3D organ and medical structures
$L = \Sigma \, \text{dist}(\text{surface\_pred}, \text{surface\_gt})$						