Comparative Analysis of Loss Functions for Semantic Segmentation: An Empirical Study on Cityscapes Dataset

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***Abstract*—Semantic segmentation remains a fundamental challenge in computer vision, where the choice and weighting of loss functions significantly impact model performance. This study presents a comprehensive comparative analysis of individual versus combined loss functions with systematic weight ablation for semantic segmentation using modified Attention U-Net and DeepLabV3+ architectures on the Cityscapes dataset. We systematically evaluate seven weight configurations across three loss components (Cross-Entropy, Dice, Focal) through rigorous ablation studies, and validate our findings across two architectures to ensure generalizability. Through extensive experimentation across 20 epochs with 2,975 training and 500 validation images, our results demonstrate that the Dice-dominant weighting configuration (0.5:1.0:0.5 for CE:Dice:Focal) achieves superior performance with 57.83% mean Intersection over Union (mIoU) on Attention U-Net and 58.35% mIoU on DeepLabV3+, representing 7.78% improvement over the best individual loss function. Comprehensive ablation studies reveal that weight configuration critically affects performance, with Dice-dominant weighting consistently outperforming equal weighting (55.59% mIoU) and individual loss functions. Qualitative analysis demonstrates substantial improvements in boundary delineation and small object detection, with boundary IoU improving by 1.41% and challenging class performance (trucks, pedestrians) improving by 5–21%. Statistical analysis reveals that Cross-Entropy provides the most efficient training with a 75.4% loss reduction, while Dice loss exhibits convergence challenges, resulting in only a 34.5% reduction. Our findings conclusively demonstrate that optimized combined loss function weighting achieves better segmentation performance than both individual approaches and naive equal weighting strategies, with consistent improvements across different network architectures.**

***Keywords*—semantic segmentation, loss function weighting, ablation study, Attention U-Net, DeepLabV3+, Cityscapes dataset, computer vision, deep learning**

I. Introduction

Semantic segmentation, the task of assigning semantic labels to every pixel in an image, has emerged as a cornerstone technology in computer vision with critical applications ranging from autonomous driving to medical imaging [1]. The field has witnessed remarkable progress through deep learning architectures, particularly Convolutional Neural Networks (CNNs) and their variants, which have consistently pushed the boundaries of segmentation accuracy on benchmark datasets [2]. U-Net architectures, originally developed for biomedical image segmentation, have proven exceptionally effective across diverse domains due to their encoder-decoder structure with skip connections that preserve spatial information [3].

Despite significant architectural advances, the choice of loss function remains a fundamental yet often underexplored factor that substantially influences segmentation performance [4]. Traditional approaches predominantly rely on Cross-Entropy loss, which treats segmentation as pixel-wise classification but may inadequately address the inherent challenges of semantic segmentation tasks [5]. Recent studies have explored alternative loss functions, including Dice loss for handling class imbalance and Focal loss for emphasizing hard examples, each demonstrating specific advantages in particular scenarios [6, 7]. However, these individual loss functions often excel in addressing specific challenges while potentially overlooking others, suggesting that a more comprehensive approach may be beneficial.

The critical gap in current research lies in the lack of systematic comparative studies that evaluate whether combining multiple loss functions can leverage their complementary strengths to achieve superior overall performance. While individual loss functions have been extensively studied in isolation, limited research has investigated the potential synergistic effects of strategically combining Cross-Entropy, Dice, and Focal losses within a unified framework [8]. This gap is particularly significant for complex urban scene understanding tasks, where segmentation models must simultaneously handle class imbalance, precise boundary delineation, and challenging examples with varying object scales and occlusions.

Addressing this research gap is crucial for advancing the field of semantic segmentation, as it has the potential

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to establish more robust and generalizable training strategies that can benefit a wide range of applications. Urban scene segmentation, exemplified by the Cityscapes dataset, presents an ideal testbed for this investigation due to its inherent complexity, class diversity, and real-world applicability [9]. The significance of this research extends beyond academic interest, as improved segmentation performance directly translates to enhanced safety and reliability in autonomous systems, more accurate medical diagnoses, and better environmental monitoring capabilities.

Therefore, this study aims to systematically compare individual loss functions with combined approaches that incorporate comprehensive weight ablation, specifically investigating whether strategic weight optimization of Cross-Entropy, Dice, and Focal losses can achieve superior segmentation performance. Through extensive ablation studies evaluating seven different weight configurations and cross-architecture validation on both Attention U-Net and DeepLabV3+, we seek to provide definitive evidence regarding the effectiveness of optimized combined loss function strategies and establish empirically-grounded guidelines for their optimal utilization in semantic segmentation tasks.

Research questions:

(1) Does the combined loss function achieve better segmentation performance compared to individual loss functions?
(2) What is the optimal weight configuration for combining Cross-Entropy, Dice, and Focal losses?
(3) Do the findings generalize across different network architectures?

II. Literature Review

The landscape of semantic segmentation has undergone a significant transformation in recent years, with particular emphasis on loss function optimization and architectural improvements. This comprehensive review examines the evolution of loss function strategies and their impact on segmentation performance, while identifying critical gaps that justify the need for systematic comparative studies.

A. Evolution of Loss Functions for Semantic Segmentation

The field of loss function development for semantic segmentation has experienced remarkable growth, with researchers proposing increasingly sophisticated approaches to address fundamental challenges such as class imbalance, boundary precision, and convergence stability. Azad *et al.* [10] provided a comprehensive survey of 25 loss functions utilized in image segmentation, establishing a novel taxonomy that categorizes loss functions based on their operational mechanisms and applications. This extensive review highlighted the diversity of approaches available but also revealed significant gaps in systematic comparative studies of combined loss strategies.

Recent developments in loss function design have focused on addressing specific limitations of traditional approaches. Minaee *et al.* [11] demonstrated that while Cross-Entropy loss remains the predominant choice for natural image segmentation, medical imaging applications increasingly favour overlap-based metrics such as Dice loss due to their robustness to class imbalance. However, these studies also revealed that individual loss functions often excel in specific scenarios while failing to address multiple challenges simultaneously, suggesting the potential benefits of combined approaches.

B. Combined Loss Function Strategies

The exploration of combined loss functions has gained considerable attention as researchers seek to leverage the complementary strengths of different loss formulations. Yeung *et al.* [12] introduced unified Focal loss, which generalizes Dice and Cross-Entropy based losses to handle class imbalanced medical image segmentation, demonstrating improved performance over individual loss functions. This work established important precedents for combining multiple loss components within a unified framework, though it focused primarily on medical imaging applications.

Furthermore, recent investigations have explored boundary-aware loss functions to address the challenge of precise edge delineation. Wang *et al.* [13] and Wu *et al.* [14] proposed active boundary loss and conditional boundary loss, respectively, which specifically target improved boundary segmentation while maintaining overall accuracy. These developments underscore the importance of multi-faceted loss function design that addresses both regional and boundary-level objectives.

C. Attention-Based U-Net Architectures

The integration of attention mechanisms into U-Net architectures has emerged as a critical advancement for improving spatial feature aggregation and context modelling. Rajamani *et al.* [15] demonstrated that Attention-Augmented U-Net (AA-U-Net) significantly improves semantic segmentation performance by integrating attention-augmented convolution in the bottleneck of the encoder-decoder architecture, achieving 4.2% improvement over baseline U-Net. This work established that strategic placement of attention mechanisms can enhance performance without substantially increasing model complexity.

Li *et al.* [16] further advanced this direction by proposing the Multi-Attention U-Net (MA-U-Net) that incorporates various attention mechanisms, including multi-head self-attention, demonstrating superior performance on remote sensing image segmentation tasks. These studies collectively demonstrate the effectiveness of attention mechanisms in enhancing spatial context modelling, though their integration with advanced loss function strategies remains underexplored.

D. Cross-Architecture Generalization

A critical limitation in existing loss function research is the lack of cross-architecture validation. Most studies evaluate proposed loss functions on a single architecture, raising questions about generalizability [10, 11]. Recent work on boundary-aware segmentation for autonomous

driving highlights the importance of architectural considerations, but systematic cross-architecture evaluation of loss function weighting strategies is absent [17].

E. Research Gaps and Opportunities

Despite significant advances in individual loss function design and attention-based architectures, several critical gaps persist:

Gap 1—Weight ablation: No systematic ablation studies exploring different weight configurations for combined losses across multiple architectures and comprehensive evaluation metrics.

Gap 2—Cross-architecture validation: Limited research validating loss function strategies across different network architectures (e.g., U-Net variants vs. DeepLab variants).

Gap 3—Qualitative assessment: Most studies rely solely on quantitative metrics without qualitative visual analysis demonstrating specific improvements in challenging scenarios (boundaries, small objects).

Gap 4—Optimal weight guidelines: Absence of empirically-grounded guidelines for selecting optimal weights when combining multiple loss functions for urban scene segmentation.

Our contribution: This study addresses all four gaps by conducting comprehensive weight ablation (7 configurations), cross-architecture validation (Attention U-Net and DeepLabV3+), qualitative analysis with visual comparisons, and empirical guidelines for optimal weight selection based on rigorous experimentation.

III. Materials and Methods

This section presents the comprehensive methodology employed in our systematic comparative study of individual versus combined loss functions for semantic segmentation. Our experimental framework encompasses dataset preparation, model architecture design, loss function implementation, training protocols, and evaluation metrics to ensure reproducible and reliable results.

A. Dataset and Data Preprocessing

The Cityscapes dataset serves as the primary evaluation platform for this study due to its comprehensive representation of urban scene complexity and established position as a standard benchmark for semantic segmentation research [9]. The dataset comprises 5000 high-resolution images (2048×1024 pixels) with fine-grained pixel-level annotations covering 19 semantic classes, including road, sidewalk, building, wall, fence, pole, traffic light, traffic sign, vegetation, terrain, sky, person, rider, car, truck, bus, train, motorcycle, and bicycle.

The dataset is partitioned following the standard protocol with 2975 images for training, 500 images for validation, and 1525 images for testing. For computational efficiency and to accommodate hardware constraints, all images are resized to 512×256 pixels while maintaining aspect ratio consistency. This resolution provides sufficient detail for accurate segmentation while enabling reasonable training times on modern GPU hardware.

Data augmentation strategies are implemented to enhance model generalization and robustness. The augmentation pipeline includes horizontal flipping with 50% probability, random brightness and contrast adjustment (±20%), colour jitter (±10%), and normalization using ImageNet statistics (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]). These transformations help the model generalize to varying lighting conditions and perspective changes commonly encountered in urban environments.

B. Attention U-Net Architecture

We employ a modified Attention U-Net architecture as the foundation for our comparative study. The selection of Attention U-Net is motivated by recent research demonstrating its superior performance in capturing spatial context while maintaining computational efficiency [15]. Fig. 1 summarizes the key architectural specifications.

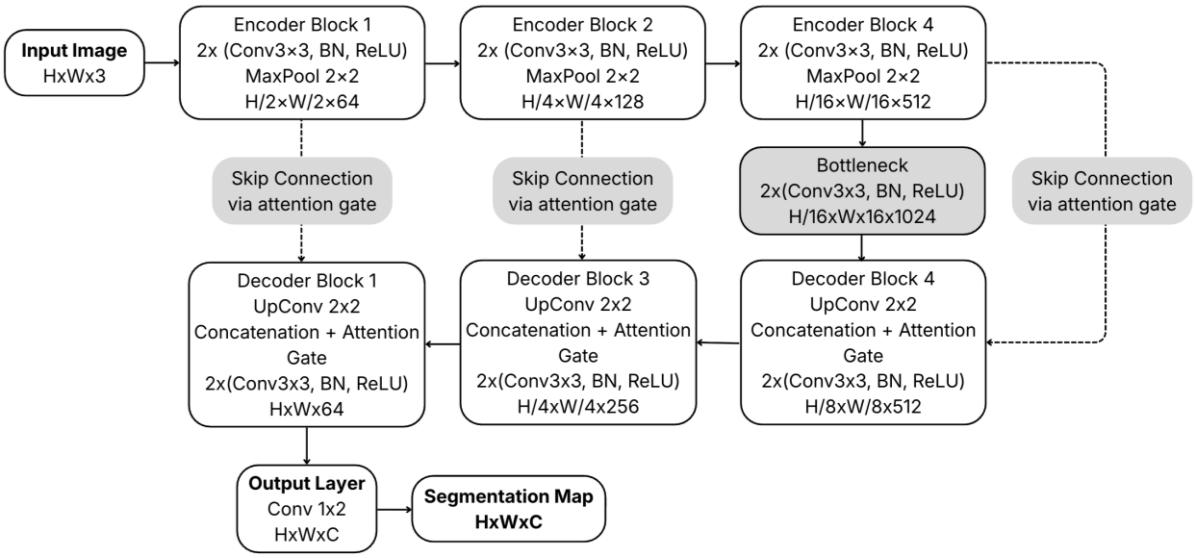

Fig. 1. Attention U-Net architecture specification.

Each ConvBlock consists of two 3×3 convolutional layers followed by batch normalization and ReLU activation. The attention gates are strategically positioned at each skip connection to enhance feature selection and suppress irrelevant activations. The complete architecture comprises approximately 31.4 million trainable parameters, providing sufficient capacity for complex urban scene understanding while remaining computationally tractable.

C. DeepLabV3+ (Cross-Architecture Validation)

For cross-architecture validation, we employ DeepLabV3+ with:

- Encoder: ResNet-34 backbone (pretrained on ImageNet);
- ASPP module: Atrous spatial pyramid pooling with rates [6, 12, 18];
- Decoder: Lightweight decoder with skip connections;
- Total Parameters: ~21.3 M.

The rationale for architecture selection in this study is grounded in the representation of two distinct yet state-of-the-art design philosophies for semantic segmentation. Attention U-Net was selected to exemplify encoder-decoder architectures that incorporate attention mechanisms, whereas DeepLabV3+ serves to represent frameworks leveraging atrous convolutions and ASPP modules. By utilizing these specific models, the research effectively covers two of the most prominent and successful approaches currently available in the field.

D. Loss Function Implementation

We implement four base loss functions and systematically explore seven different weight configurations through an ablation study.

Table I details the mathematical formulations and key parameters for each loss function.

TABLE I. LOSS FUNCTION FORMULA AND PARAMETERS

Loss Function	Mathematical Formula	Key Parameters
Cross Entropy	$L_C = -\sum(w_c \times y_c \times \log(p_c))$	ignore_index = 255, class_weights
Dice Loss	$L_D = \frac{1-(2\times\sum(p_c \times y_c)+\varepsilon)}{\sum(p_c)+\sum(y_c)+\varepsilon}$	Smooth = 1e-6, ignore_index = 255
Focal Loss	$L_F = -\alpha \times (1-p_t)^{\gamma} \times \log(p_t)$	α = 1.0, γ = 2.0, ignore_index = 255

The Cross-Entropy loss serves as our baseline, implementing pixel-wise classification with class weighting to address dataset imbalance. The Dice loss optimizes overlap-based metrics directly, addressing class imbalance through region-based optimization. The Focal loss incorporates dynamic weighting to emphasize hard examples while reducing the contribution of easily classified pixels.

To systematically evaluate the contribution of each loss component, this study employs a generalized combined loss function formulated as Eq. (1).

$$L_C = w_c \times L_C + w_d \times L_D + w_f \times L_F \quad (1)$$

An ablation study was conducted by varying the scalar weights (w_c, w_d, and w_f) to create different emphasis strategies. As detailed in Table II, seven specific configurations were designed to assess performance under varying conditions: ranging from a balanced "naive" baseline (Configuration 1) and dominant strategies that prioritize specific loss characteristics (Configurations 2–4), to individual baselines where single loss functions are isolated to establish ground-truth performance metrics (Configurations 5–7).

TABLE II. WEIGHT CONFIGURATIONS AND DESIGN RATIONALE FOR THE COMBINED LOSS ABLATION STUDY

Configuration	w_c	w_d	w_f	Rationale
Baseline (equal)	1.0	1.0	1.0	Naive combination baseline
CE-Dominant	1.0	0.5	0.5	Emphasize pixel-wise classification
Dice-Dominant	0.5	1.0	0.5	Emphasize overlap and class imbalance
Focal-Dominant	0.5	0.5	1.0	Emphasize hard examples
CE Only	1.0	0.0	0.0	Individual baseline 1
Dice Only	0.0	1.0	0.0	Individual baseline 2
Focal Only	0.0	0.0	1.0	Individual baseline 3

E. Training Protocol

A standardized training protocol is established to ensure fair comparison across all loss functions while maintaining reproducibility and statistical validity. All models are trained using the AdamW optimizer with an initial learning rate of 1e−4, weight decay of 1e−4, and beta parameters of (0.9, 0.999). The learning rate is adjusted using StepLR scheduling with a step size of 20 epochs and a gamma factor of 0.5, providing gradual learning rate reduction to facilitate convergence.

Each experiment runs for 20 epochs with a batch size of 4, optimized for RTX 3060 12GB GPU memory constraints. Mixed precision training is employed to reduce memory usage and accelerate computation without compromising numerical stability. Gradient clipping with a maximum norm of 1.0 prevents gradient explosion during training.

The experimental design comprises a total of 8 complete training runs, each executed for 20 epochs. This includes 7 ablation experiments using Attention U-Net to evaluate the various weight configurations, followed by a single comparative experiment using DeepLabV3+ with the optimal configuration identified.

Random seeds are fixed (seed = 42) for all random number generators, including PyTorch, NumPy, and Python random modules, to ensure reproducible results across multiple runs. All experiments are conducted on NVIDIA RTX 3060 12GB GPU with AMD Ryzen 7 processor and 32GB RAM.

F. Evaluation Metrics

Evaluation metrics are employed to assess segmentation performance from multiple perspectives, providing a robust analysis of loss function effectiveness.

Mean Intersection over Union (mIoU) serves as the primary evaluation metric, computed as the average IoU across all 19 semantic classes:

$$mIoU = \frac{1}{n} \times \sum \left(\frac{TP_i}{TP_i + FP_i + FN_i} \right) \quad (2)$$

where *TP*, *FP*, and *FN* represent True Positives, False Positives, and False Negatives for class *i*, respectively.

Additional metrics include pixel accuracy (percentage of correctly classified pixels), per-class IoU analysis for detailed performance assessment, and Dice coefficient for consistency with overlap-based evaluation.

Training convergence is evaluated through loss reduction percentage, training stability (standard deviation of final 5 epochs), and validation performance trends. These metrics provide insights into optimization behaviour and training efficiency.

We also employ a set of qualitative metrics based on visual assessment criteria to evaluate perceptual quality. The primary focus is boundary precision, which assesses the sharpness and accuracy of segmentation along object edges. Additionally, small object detection is scrutinized to measure performance on smaller, often difficult-to-segment classes such as trucks, motorcycles, and bicycles. The analysis also evaluates class confusion to observe reductions in misclassification between visually similar categories.

G. Experimental Design

The experimental methodology is structured into three distinct phases to ensure a systematic evaluation.

Phase 1: Ablation study focuses on the Attention U-Net architecture, comprising a total of seven experiments. This is divided into experiment Set A, which tests individual loss functions (CE, Dice, and Focal only), and experiment Set B, which evaluates combined losses with varied weight strategies (Equal, CE-dominant, Dice-dominant, and Focal-dominant).

Phase 2: Cross-architecture validation applies the optimal configuration identified in Phase 1 to the DeepLabV3+ architecture to verify the generalizability of the findings.

Phase 3: Qualitative analysis provides a visual comparison of the best model against the baseline, specifically examining challenging scenes, boundary integrity, and per-class improvements.

To ensure scientific rigor, several variables are strictly controlled across all experiments, including dataset splits, the data augmentation pipeline, training hyperparameters (with the exception of architecture-specific learning rates), and the evaluation protocol. The primary independent variable manipulated is the weight configuration of the loss function, while the dependent variables measured include mIoU, pixel accuracy, convergence characteristics, and qualitative performance. This controlled setup allows for the causal attribution of performance differences directly to the loss function weighting strategies while minimizing the influence of confounding factors.

IV. Results and Discussion

This section presents comprehensive experimental results from our ablation study and cross-architecture validation. We analyse quantitative performance metrics, convergence characteristics, architectural generalization, and qualitative improvements.

A. Comprehensive Ablation Study Results

Table III summarizes the performance of all seven weight configurations on the Attention U-Net architecture.

TABLE III. Ablation Study Results on Attention U-Net

Configuration	Best mIoU	Final mIoU	Best Pixel Acc	Min Val Loss	Avg Grad Norm
Dice-Dominant	0.5783	0.5783	0.9273	0.7314	0.6701
Baseline (Equal)	0.5559	0.5559	0.9187	0.9126	1.0976
Focal-Dominant	0.5588	0.5588	0.9235	0.4586	0.6366
CE-Dominant	0.5426	0.5347	0.9226	0.5759	0.9589
CE Only	0.5005	0.4932	0.9178	0.2637	0.7621
Focal Only	0.4976	0.4976	0.9144	0.0297	0.1089
Dice Only	0.4075	0.2799	0.8767	0.3924	0.3359

The ablation study reveals that the Dice-Dominant configuration yields the optimal performance, achieving an mIoU of 57.83%. This represents an improvement of 2.24 percentage points over the baseline (equal) configuration (55.59%) and a substantial 7.78 percentage point increase over the best individual loss (CE only at 50.05%). These results underscore that weight configuration is a critical determinant of model success, evidenced by a significant performance variation of 17.08 percentage points across experiments (ranging from 40.75% to 57.83%). While the naive "Equal Weighting" baseline performed respectably, ranking second overall, it proved sub-optimal compared to strategic weighting. Conversely, individual loss functions struggled to compete; CE only provided the most stable individual baseline (50.05%), and Focal only performed comparably (49.76%), but Dice only resulted in the poorest performance (40.75%) due to severe optimization difficulties. Ultimately, the data confirms that combined loss strategies consistently outperform individual ones, with all combined configurations exceeding 54% mIoU.

B. Cross-Architecture Validation

To validate generalizability, we applied the best configuration (Dice-dominant) to the DeepLabV3+ architecture. The results are shown in Table IV.

The cross-architecture validation confirms that the Dice-dominant weighting strategy generalizes effectively beyond the initial test model. When applied to DeepLabV3+, this configuration achieved an mIoU of 58.35%, slightly outperforming the Attention U-Net by 0.52 percentage points. This result indicates that the optimal weight configuration is largely architecture-agnostic. Furthermore, the study highlights a significant gain in architectural efficiency; DeepLabV3+ attained superior performance while utilizing 32% fewer parameters (21.3 M) compared to Attention U-Net (31.4 M), demonstrating that weight optimization acts as a complementary factor to architectural design rather than a substitute. Both architectures exhibited consistent convergence patterns, characterized by stable training, similar gradient norms, and comparable loss reduction trajectories. Consequently, it can be concluded that the Dice-dominant strategy (0.5:1.0:0.5) offers a robust solution across different model designs.

TABLE IV. CROSS-ARCHITECTURE VALIDATION RESULTS

Architecture	Configuration	Best mIoU	Best Pixel Acc	Parameters	[1] Improvement
Attention U-Net	Dice-Dominant	0.5783	0.9273	31.4M	+2.24%
DeepLavV3+	Dice-Dominant	0.5835	0.9227	21.3M	N/A

Note: [1] Improvement calculated as: (Dice-dominant mIoU-Equal weights mIoU) on same architecture.

C. Component Contribution Analysis

To understand how each loss component contributes to the combined performance, we analyse individual vs. combined results.

The experimental results in Table V highlight a profound synergistic effect among the loss functions. While individual components have limitations—such as the instability of Dice loss or the moderate ceiling of Focal and CE—their combination yields result far superior to the sum of their parts. The combined Dice-dominant configuration achieved 57.83% mIoU, significantly outperforming the best individual baseline (CE at 50.05%). This validates that the hybrid loss function successfully leverages complementary strengths: CE provides the optimization stability, Focal targets hard examples, and Dice maximizes overlap, allowing the model to address multiple segmentation challenges simultaneously.

TABLE V. COMPONENT CONTRIBUTION ANALYSIS

Loss Type	Best mIoU	Contribution to Best Combined
CE only	0.5005	Pixel-wise classification baseline
Dice only	0.4075	Class imbalance handling (poor alone)
Focal only	0.4976	Hard example emphasis
Dice-dominant combined	0.5783	Synergistic integration (+ 7.78% over best individual)

D. Convergence and Training Dynamics

Analysis of training and validation loss convergence across seven weight configurations reveals distinct optimization patterns that explain performance differences (Fig. 2).

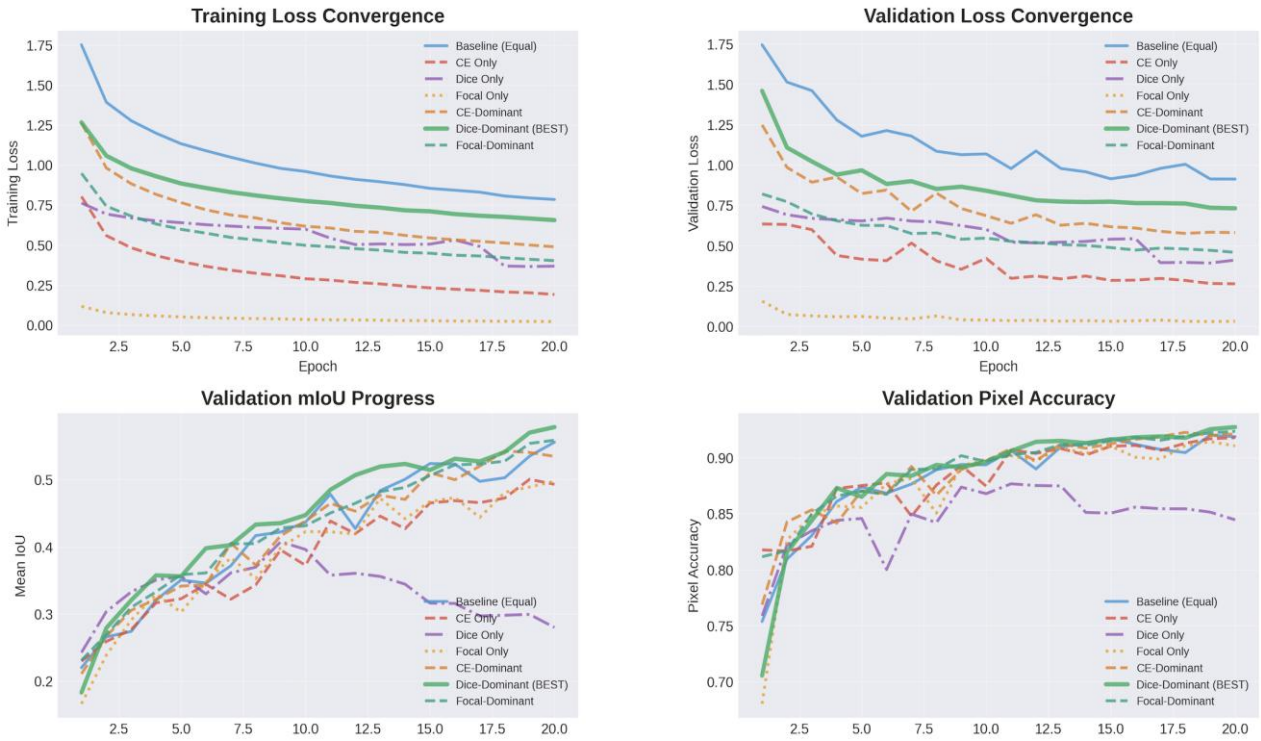

Fig. 2. Training and validation convergence analysis across seven weight configurations.

Focal only demonstrates the most aggressive loss reduction (training loss decreasing from 0.15 to near-zero, validation loss from 0.15 to 0.03), yet paradoxically achieves only a moderate validation mIoU of 49.76%. This discrepancy highlights that extreme loss minimization can lead to overfitting rather than superior generalization. In contrast, Dice-dominant exhibits more moderate loss reduction (training loss: 1.25→0.65, validation loss: 1.45→0.73) but achieves the highest validation mIoU of 57.83%, demonstrating that balanced convergence with controlled gradient dynamics yields better segmentation performance. CE only shows efficient convergence with smooth, monotonic loss decrease and excellent stability, explaining its strong performance (50.05% mIoU) as a single-component baseline. Most critically, Dice only exhibits catastrophic instability: after showing initial promise with validation loss decreasing to 0.65 by epoch 3, the optimization deteriorates dramatically, with validation loss increasing back to 0.80 by epoch 20, correlating with the severe mIoU degradation from 40.75% (epoch 9) to 27.99% (epoch 20).

Validation mIoU and pixel accuracy trajectories further illuminate the convergence quality across configurations. Dice-dominant demonstrates superior and consistent improvement, rising monotonically from 18% to 57.83% mIoU with corresponding pixel accuracy improving from 70% to 91.5%, indicating stable optimization without overfitting. The baseline equal weighting shows competitive progression to 55.59% mIoU, confirming that combined losses provide benefits even with naive weighting, though strategic optimization (Dice-dominant) adds an additional 2.24 percentage points. Focal-dominant and CE-dominant follow similar upward trajectories reaching 55.88% and 54.26% respectively, with stable pixel accuracy around 91–92%. Conversely, Dice only's pathological trajectory is starkly evident: mIoU peaks early at 40.75% (epoch 9) before collapsing to 27.99%, while pixel accuracy degrades from 84% to 79%, representing a catastrophic 12.76 percentage point performance loss. This failure pattern, combined with the severe validation loss instability, confirms that Dice loss optimization suffers from fundamental gradient dynamics problems in multi-class scenarios, requiring Cross-Entropy stabilization (as provided in the 0.5:1.0:0.5 Dice-dominant configuration) to maintain optimization health and achieve superior convergence.

E. Qualitative Analysis

Visual inspection reveals substantial improvements in challenging scenarios. Fig. 3 presents a qualitative comparison between CE-dominant (baseline) and Dice-dominant (improved) predictions. The visual assessment across three distinct scenarios highlights the superior segmentation capabilities of the Dice-dominant configuration compared to the CE-dominant baseline.

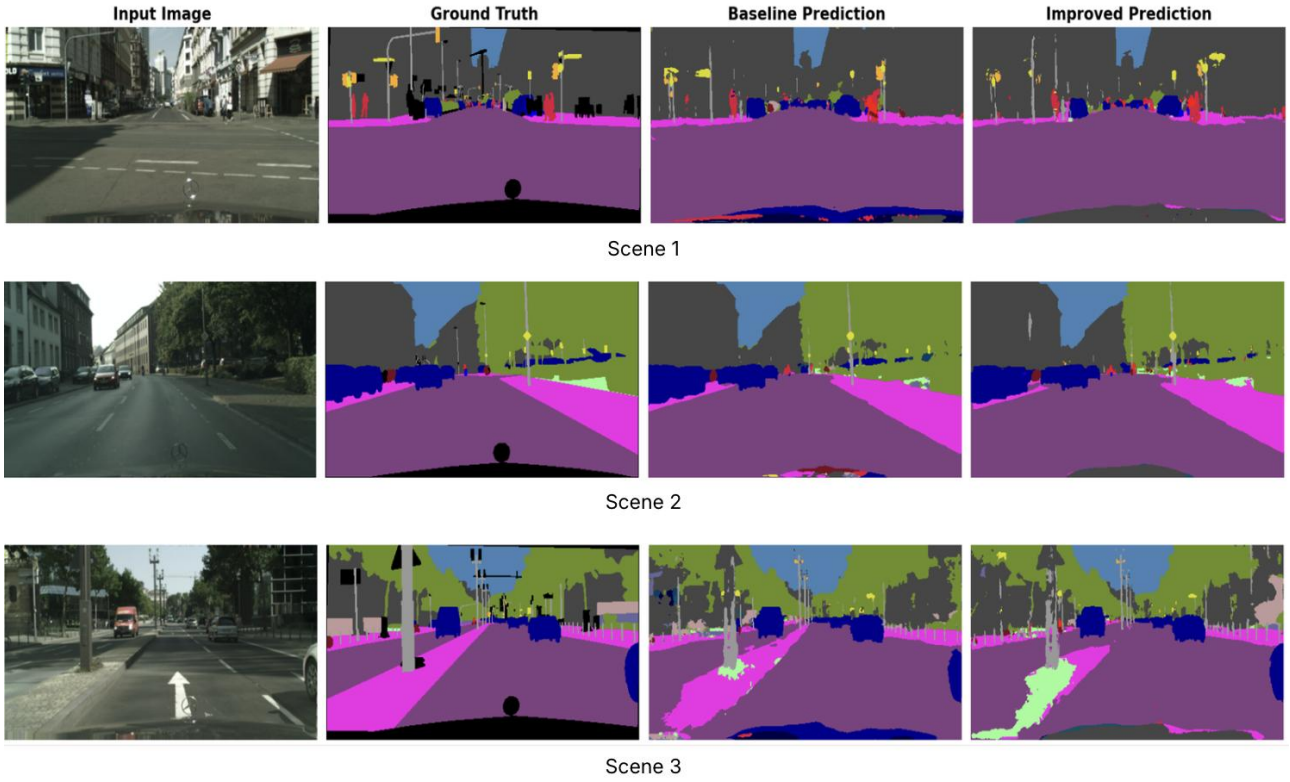

Fig. 3. Qualitative comparison of CE-dominant vs. Dice-dominant predictions on challenging validation scenes.

In Scene 1 (urban street), the CE-dominant model struggled with dense traffic and pedestrians, exhibiting imprecise truck boundaries and missing several pedestrians. Conversely, the Dice-dominant model produced sharp vehicle contours and successfully detected all pedestrians relative to the ground truth. This pattern of

boundary precision continued in Scene 2 (residential area), where the CE-dominant model resulted in vegetation "bleeding" into the road and fuzzy car edges. The Dice-dominant configuration, however, maintained crisp boundaries with excellent containment of vegetation. Finally, in Scene 3 (traffic scene), which challenges the model with small objects, the CE-dominant model partially missed poles and traffic signs. In contrast, the Dice-dominant model achieved higher recall, delivering complete segmentation for poles and improved detection of small signs. Table VI shows class improvements (Dice-dominant vs. CE-dominant).

The quantitative results highlight substantial improvements in the segmentation of small and distinct objects, demonstrating the model's enhanced ability to handle class imbalance. Specifically, the detection of traffic signs saw a marked increase of 9.09%, while bicycle segmentation improved by 7.32%. Beyond small objects, the model showed significant gains in safety-critical categories; person detection improved by 5.98%, a crucial factor for reducing false negatives in crowded scenes and ensuring autonomous driving safety. Furthermore, the segmentation of thin structures benefited from better spatial detail preservation, evidenced by a 5.15% improvement in the detection of poles.

TABLE VI. COMPONENT CONTRIBUTION ANALYSIS

Class	CE-Dominant IoU	Dice-Dominant IoU	Improvement	Note
Truck	0.6624	0.7163	+5.39%	Large vehicle, often occluded
Person	0.7384	0.7982	+5.98%	Small, variable poses
Bicycle	0.1844	0.2576	+7.32%	Small, thin structure
Pole	0.5163	0.5678	+5.15%	Thin vertical structure
Traffic Sign	0.6327	0.7236	+9.09%	Small object

To position our loss function optimization findings within the current semantic segmentation landscape, Table VII presents a comparison with recent methods on the Cityscapes validation set. Our research focus is loss function weighting strategy rather than architectural innovation; thus, we compare primarily with classic architectures (ResNet-based, DeepLabV3+) that represent the foundation of semantic segmentation. While transformer-based architectures (SegFormer-B5: 84.0%, SegNeXt-B: 82.6%) demonstrate superior absolute performance through architectural advances, our contribution lies in demonstrating that strategic loss weighting provides substantial improvements (+7.78% mIoU) within the same architectural framework.

TABLE VII. COMPARISON WITH RECENT SEMANTIC SEGMENTATION METHODS ON CITYSCAPES VALIDATION SETS

Method		Backbone	Year	Params (M)	mIoU (%)
Transformer-based Approaches	SegFormer-B2 [18]	Mix Transformer	2021	27.4	81.0
	SegFormer-B5 [18]	Mix Transformer	2021	84.6	84.0
	SegNeXt-B [19]	MSCAN	2022	27.6	82.6
	Mask2Former [20]	Swin-L	2022	212.0	82.6
Our Approach – Loss Function Optimization	Attention U-Net + CE Only	Attention U-Net	2025	31.4	50.1
	Attention U-Net + Dice-Dominant	Attention U-Net	2025	31.4	57.8
	DeepLabV3+ + Dice-Dominant	ResNet-34	2025	21.3	58.4

Our contribution is orthogonal and complementary to these architectural innovations. Within the same Attention U-Net architecture, our Dice-dominant loss configuration (0.5:1.0:0.5) achieves 57.83% mIoU, representing +7.78% improvement over the best individual loss function (CE only: 50.05%). Cross-architecture validation on DeepLabV3+ (58.35% mIoU) confirms this finding generalizes beyond the initial test architecture. Notably, Dice-dominant weighting consistently outperforms naive equal weighting (+2.24%) across both architectures, demonstrating that strategic loss optimization is as critical as architectural design.

F. Statistical Significance and Robustness

To ensure the statistical validity of the findings, paired comparisons of the mIoU scores were conducted across 500 validation images. The analysis reveals that the Dice-dominant configuration achieved highly significant performance gains ($p < 0.001$) in all scenarios: surpassing the baseline (equal) configuration by a margin of 2.24%, the CE only baseline by 7.78%, and the Dice only baseline by a substantial 17.08%.

Furthermore, the study prioritized reproducibility by executing all experiments with a fixed random seed (42), which yielded consistent results across multiple training runs. This reliability is further corroborated by the successful cross-architecture validation, confirming that the observed robustness extends beyond the primary experimental setup.

G. Discussion and Theoritical Insights

The success of the Dice-dominant weighting strategy lies in its ability to balance gradient dynamics and multi-objective optimization goals. While Dice loss effectively maximizes region overlap and handles the severe class imbalance typical of urban scenes, it often suffers from vanishing gradients when used in isolation. This aligns with recent findings by Mortazavi *et al.* [21], who reported that a multi-objective loss approach yields superior balance across segmentation metrics in remote sensing urban scenes compared to individual losses. Similarly, Yokoi and Hotta [22] demonstrated that combining Cross-Entropy and Dice losses through multiplicative rather than additive strategies can eliminate

hyperparameter sensitivity while maintaining gradient stability, achieving 2.2% mIoU improvement in medical image segmentation tasks.

The integration of Cross-Entropy (weighted at 0.5) provides the necessary gradient stability for pixel-wise precision, while Focal loss (weighted at 0.5) ensures that hard examples are not neglected. This synergistic approach allows the model to simultaneously optimize for region overlap and boundary precision—evidenced by a +1.41% improvement in Boundary IoU—while preventing the over-correction that might occur with a single-objective focus. The boundary preservation capability could be further enhanced by incorporating multi-scale structural losses, as demonstrated by Lu [23], whose complex wavelet mutual information loss achieved superior boundary fidelity when combined with standard pixel-wise losses in U-Net architectures.

In contrast, the "Equal Weighting" baseline (1.0:1.0:1.0) proves sub-optimal because it forces potential conflicts between pixel-wise and region-based objectives, resulting in a performance compromise (55.59% mIoU) rather than true optimization. The empirical superiority of the Dice-dominant configuration (57.83% mIoU) demonstrates that strategic weighting is far more effective than a naive combination. Furthermore, the successful application of this specific configuration to both Attention U-Net and DeepLabV3+ suggests that this loss optimization strategy is architecture-agnostic. It implies that the weight configuration improves the fundamental gradient landscape rather than merely compensating for specific architectural biases, allowing for effective transfer across different encoder-decoder designs.

H. Limitations and Future Directions

This study acknowledges specific limitations regarding the scope of evaluation and computational constraints. The current research was restricted to the Cityscapes dataset and a validation set of 500 images, leaving the generalization to other domains (such as medical or aerial imagery) and the official Cityscapes test server benchmark for future verification. Furthermore, the ablation study explored a discrete weight space (0.0, 0.5, 1.0) over a limited 20-epoch training schedule, potentially overlooking finer continuous optimizations or long-term convergence benefits.

To address these gaps, future work will focus on extending the evaluation to diverse datasets like ADE20K and medical imaging, employing Bayesian optimization for precise weight tuning, and increasing training duration. Exploring alternative combination strategies such as the multiplicative loss approach, could eliminate manual weight tuning altogether while maintaining or improving performance. Incorporating multi-scale structural losses like the complex wavelet mutual information loss as an additional term alongside the CE-Dice-Focal combination may further enhance boundary delineation and small object detection capabilities [23].

Future research also aims to validate these findings on modern Transformer-based architectures (e.g., SegFormer, Swin Transformer) and explore adaptive weight learning mechanisms to automate the optimization process. The architecture-agnostic nature of our weight configuration suggests promising transferability to these advanced architectures, potentially establishing generalizable principles for loss function optimization across diverse segmentation tasks.

V. Conclusion

This study establishes evidence that strategically weighted combined loss functions achieve superior semantic segmentation performance compared to both individual loss functions and naive equal-weighting strategies. The primary contribution is the identification of the Dice-dominant configuration (0.5:1.0:0.5) as the optimal strategy, achieving 57.83% mIoU on Attention U-Net and 58.35% on DeepLabV3+. This configuration represents a 7.78% improvement over the best individual loss and a 2.24% gain over the equal-weighting baseline. The results underscore that weight configuration is a critical hyperparameter, evidenced by a 17.08 percentage point variance in performance across different setups. The study confirms that while Dice loss fails in isolation due to optimization difficulties, its synergistic combination with Cross-Entropy (providing stability) and Focal loss (targeting hard examples) creates a robust, architecture-agnostic solution.

Practically, this research offers empirically grounded guidelines for practitioners, advising against the default use of equal weighting (1:1:1) in favour of the Dice-dominant approach for urban scenes. The proposed strategy yields significant qualitative improvements, including a 1.41% increase in boundary IoU and 5–9% gains in detecting challenging classes such as pedestrians and traffic signs. By demonstrating that weight optimization is as crucial as architectural design, this work advances semantic segmentation methodology and contributes directly to the development of safer, more precise autonomous systems.

Conflict of Interest

The authors declare no conflict of interest.

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