Comparative Study of Semantic Segmentation Architectures for ADAS

Evaluating U-Net, DeepLabV3+, and SegFormer on the Cityscapes Dataset

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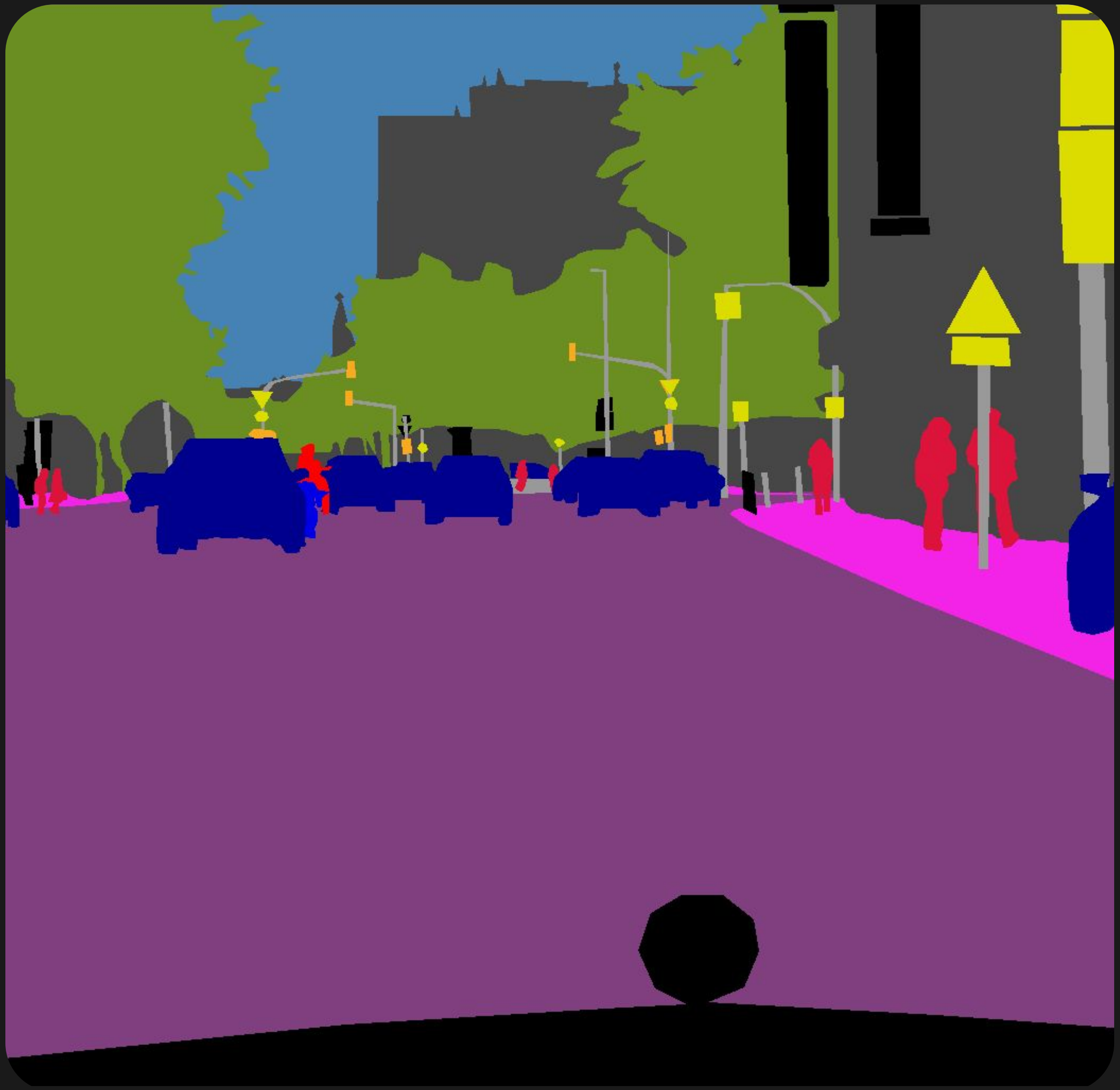
Introduction & Problem Statement

- **Objective**
  Pixel-level classification of urban street scenes to distinguish drivable surfaces from obstacles and other road users
- **Dataset**
  Cityscapes benchmark featuring 19 semantic classes and high-resolution (1024x2048) images.
- **Constraints**
  Scaling high-resolution segmentation research down to consumer-grade hardware (Single 8GB GPU).



Dataset

Diverse Urban Data

Captured across 50 cities in Germany and neighboring countries, providing varied weather and architectural contexts.

High-Volume Annotation

Contains **5,000 fine pixel-level annotations** and 20,000 coarse annotations for robust training.

19 Semantic Classes

Evaluated on critical classes including Road, Sidewalk, Pedestrian, Traffic Light, Signage, and Vehicle.

GROUP	SPECIFIC CLASSES
FLAT	road, sidewalk, parking+ rail track+
HUMAN	person, rider
VEHICLE	car, truck, bus, on rails, motorcycle, bicycle, caravan+, trailer+
CONSTRUCTION	building, wall, fence, guard rail+, bridge+, tunnel+
OBJECT	pole, pole group+, traffic sign, traffic light
NATURE	vegetation, terrain
SKY	sky
VOID	ground+, dynamic+, static+

The **+** denotes the classes excluded from the metric evaluation

Motivation

Architectural Evolution

Moving from classic CNNs (**U-Net**) to more advanced CNNs (**DeepLabV3+**) and modern Transformers (**SegFormer**).

Class Imbalance

Addressing the challenge where **safety-critical classes** like *Traffic Lights* and *Pedestrians* are **rare** compared to *Road* or *Building*.

Resource Engineering

Proving methodological rigor is possible without massive computational capabilities, focusing on **efficiency**.

Resource Engineering for 8GB VRAM

Mixed Precision

Used **Automatic Mixed Precision (AMP)** with float16/float32, reducing VRAM usage considerably.

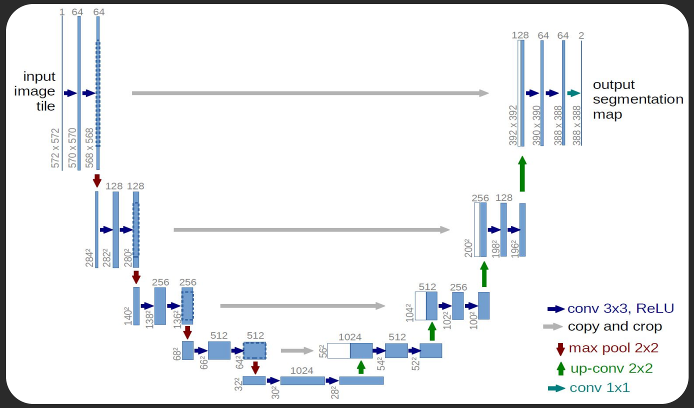
Gradient Accumulation

Accumulated gradients over **4 steps** to simulate an **Effective Batch Size of 4**, bypassing hardware limits.

Resolution strategy

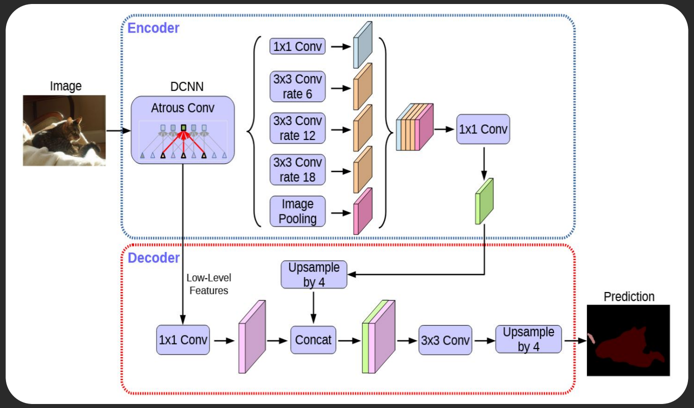
Trained on random **(512 x 1024) crops** to fit memory while maintaining high-resolution feature learning.

Methodology: Architecture Overview



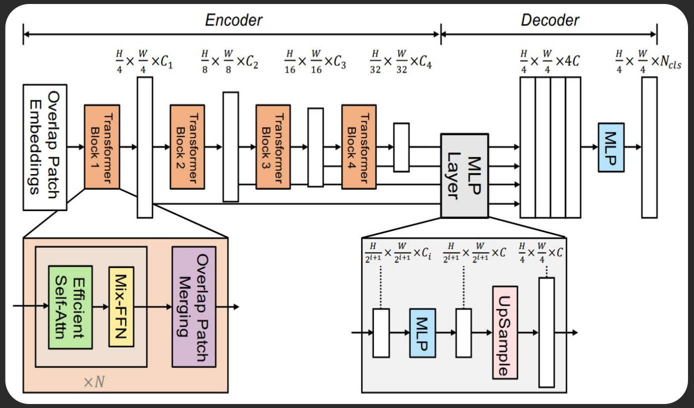
U-Net

Baseline **CNN Encoder-Decoder** utilizing skip connections for feature localization.



DeepLabV3+

CNN Encoder-Decoder using **ResNet-50** and **ASPP** (Atrous Spatial Pyramid Pooling).



SegFormer

Transformer-based approach with hierarchical encoder (**MiT-B0**) and **MLP decoder**.

U-Net

Encoder-Decoder

Skip Connections

Simmetry

- **Modification:** Replaced Batch Normalization with **Instance Normalization** to avoid variance calculation failure.
- **Structural Update:** Enforced **padding=1** to preserve spatial dimensions, removing cropping needs.
- **Upsampling:** Used deterministic **bilinear upsampling** instead of transposed convolutions to prevent checkerboard artifacts and reduce computational load.

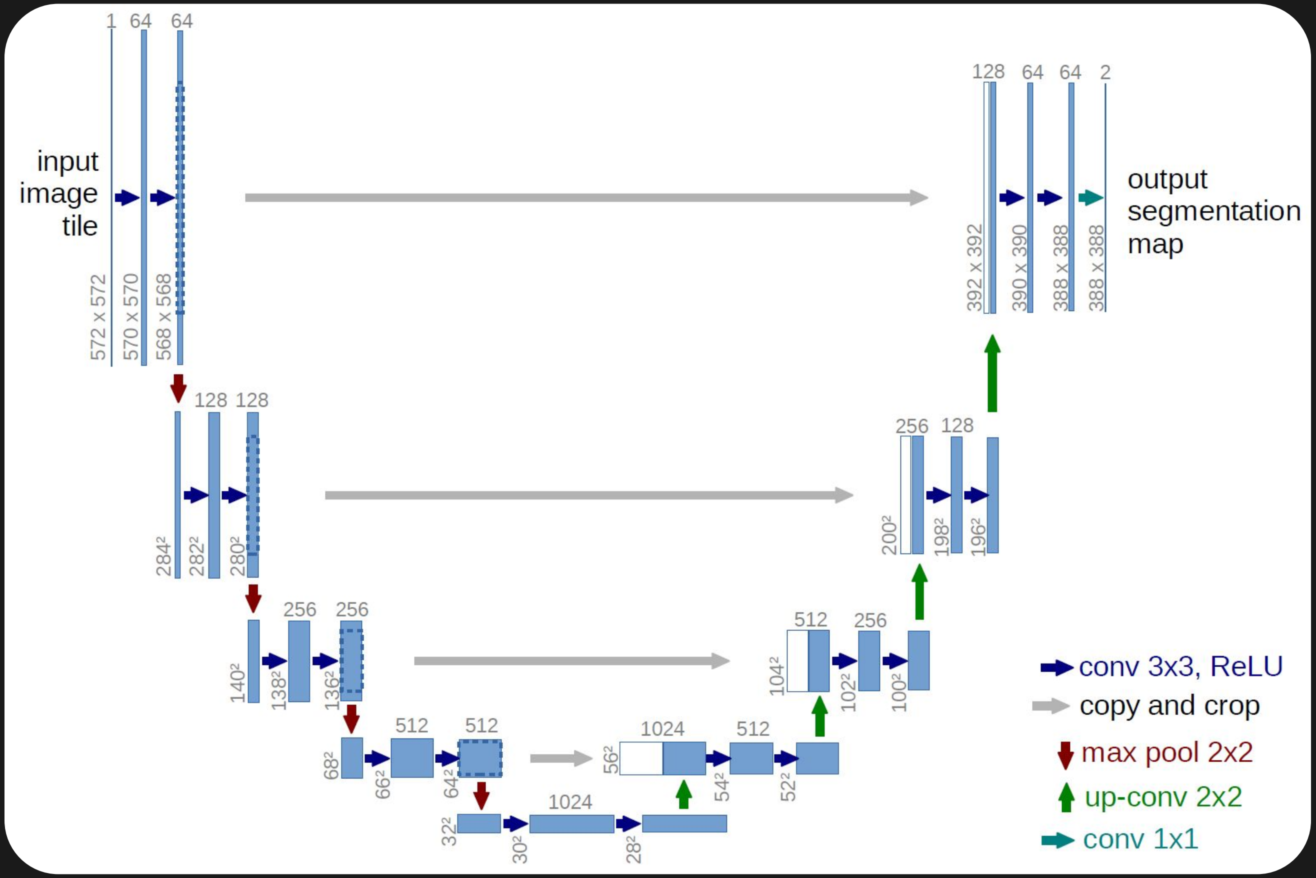


Image: https://doi.org/10.48550/arXiv.1505.04597

U-Net: Training

1

Weighted

U-Net trained for 10 epochs using a **weighted** loss function

1a

Unweighted

Training continued for other 10 epochs, this time with **unweighted** loss function

20 epoch training

U-Net: Training Results

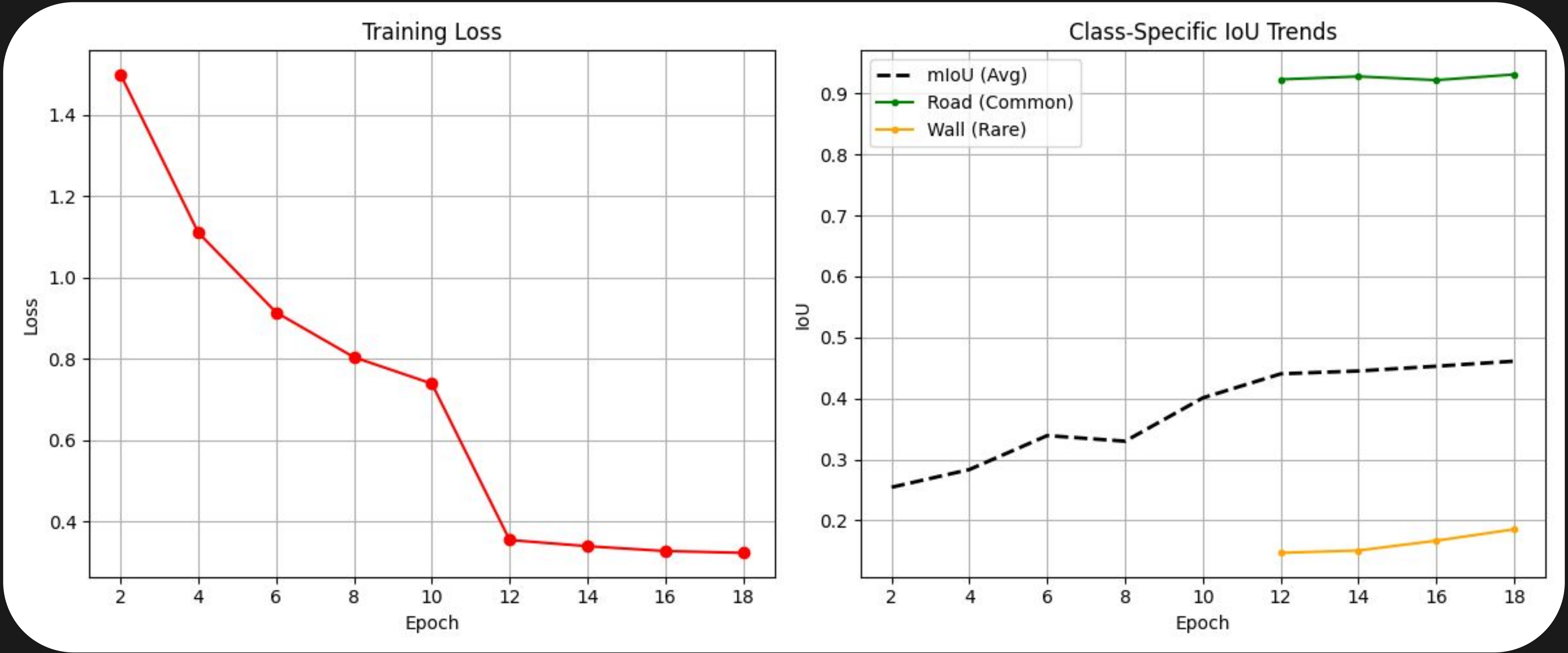


Image: Training plot of model U-Net 1a

U-Net: Validation Results

Reference image: frankfurt_000000_001236_leftImg8bit.png

DeepLabV3+

Encoder-Decoder

ResNet-50

Atrous Spatial Pyramid Pooling (ASPP)

High spatial resolution

- **Multi grid**: Used replace_stride_with_dilation in ResNet-50 to replace stride with atrous convolution which led us to **not** implement the multi grid logic of the original paper.
- **Operation Optimization**: Bypassed depthwise separable convolutions in favor of **standard convolutions** for the 8GB budget.

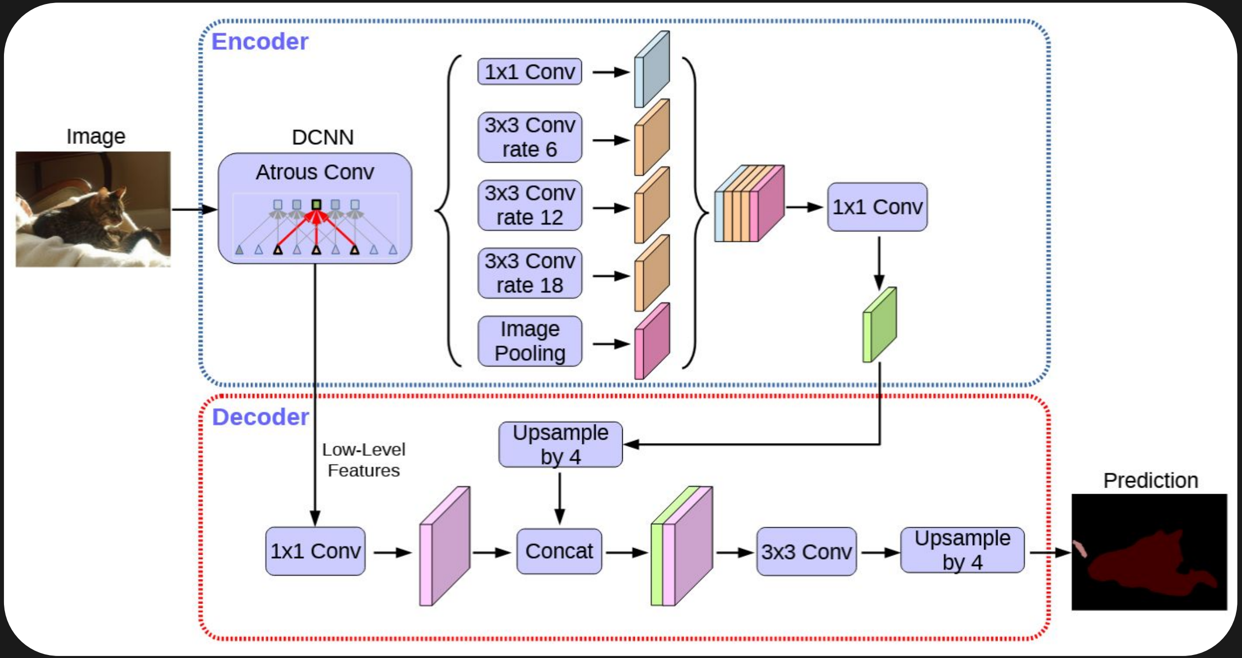


Image: https://doi.org/10.48550/arXiv.1802.02611

DeepLabV3+: Training 1

1

Unfrozen Weighted

DeepLabV3+ trained for 20 epochs with **unfrozen** backbone and **weighted** loss function

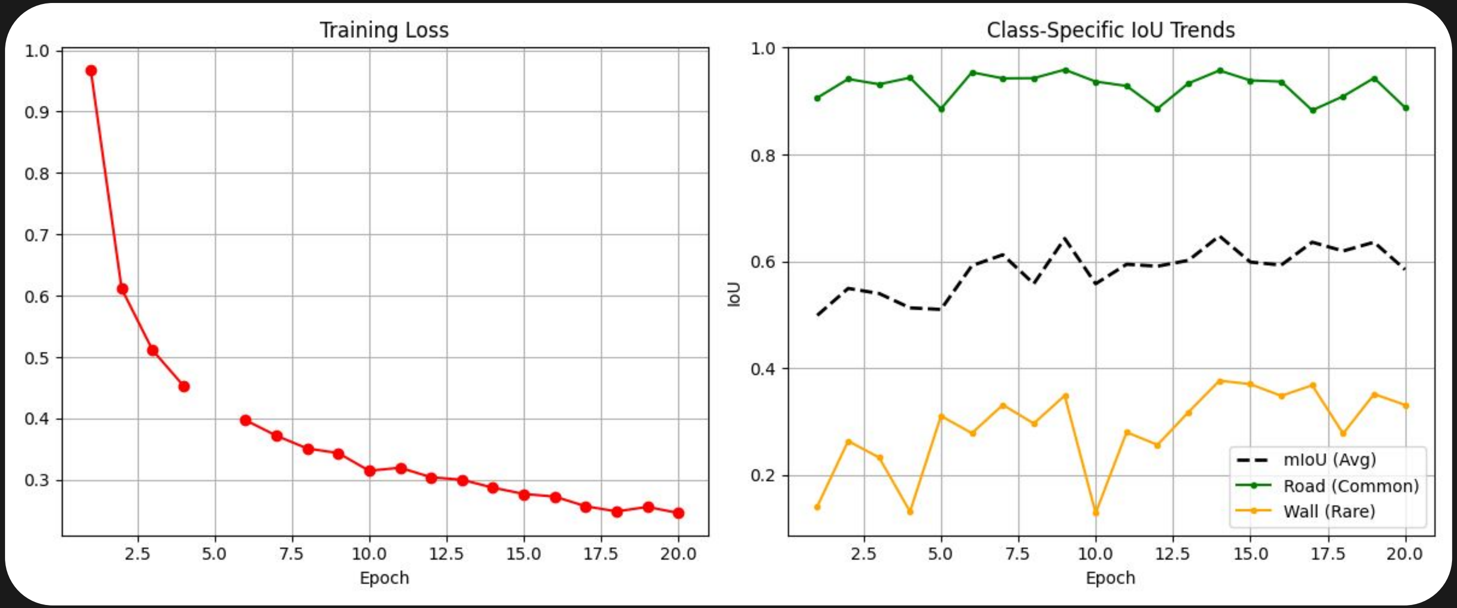


Image: Training plot of model DeepLab 1

20 epoch training

DeepLabV3+: Training 2

2

Frozen Weighted

DeepLabV3+ trained for 10 epochs with **frozen** backbone and **weighted** loss function

2a

Unfrozen Unweighted

★

Training continued for other 20 epochs with **unfrozen** backbone and **unweighted** loss function

2b

Unfrozen Weighted

Training continued for other 20 epochs with **unfrozen** backbone and **weighted** loss function

30 epoch training

DeepLabV3+: Training 2 Results

Image 1: Training plot of model DeepLab 2a

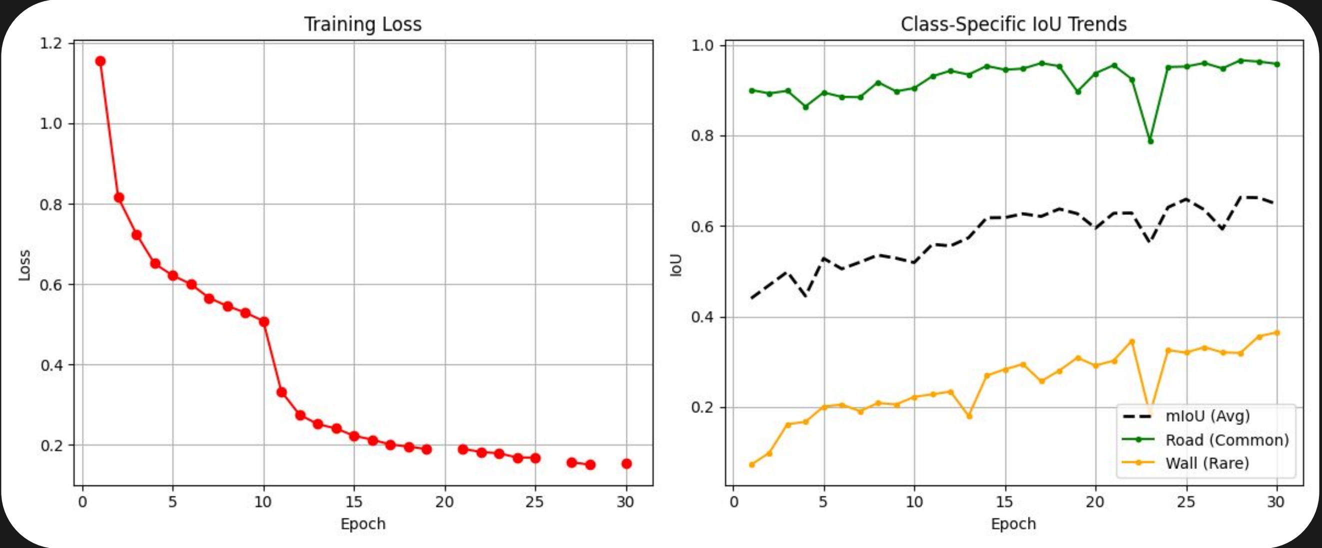
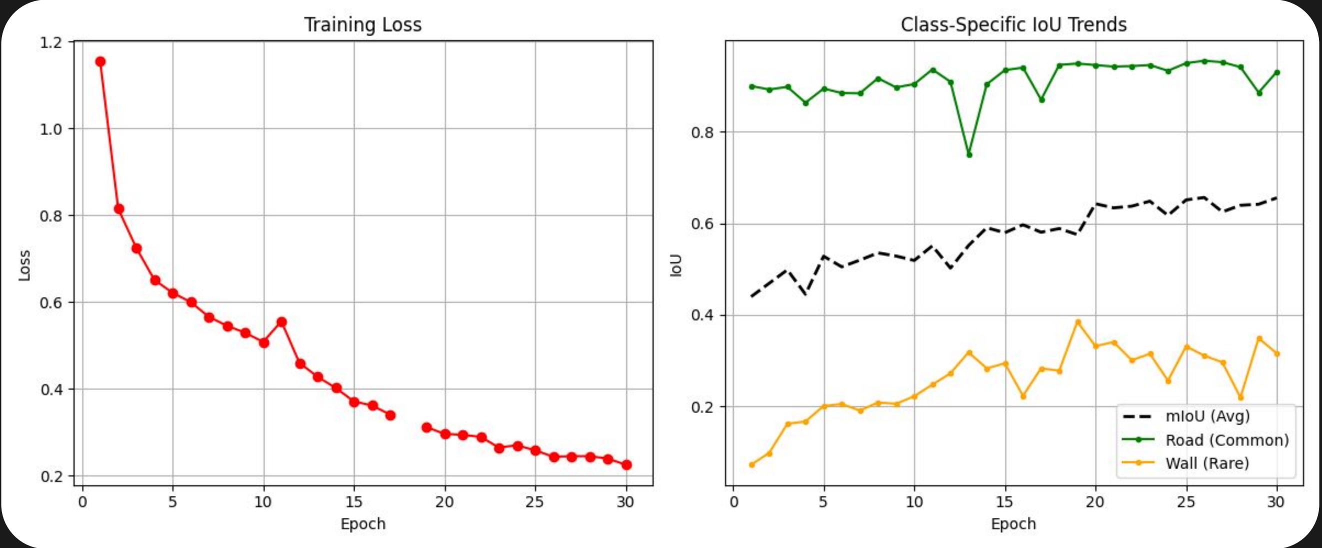


Image 2: Training plot of model DeepLab 2b



DeepLabV3+: Training 2 Results

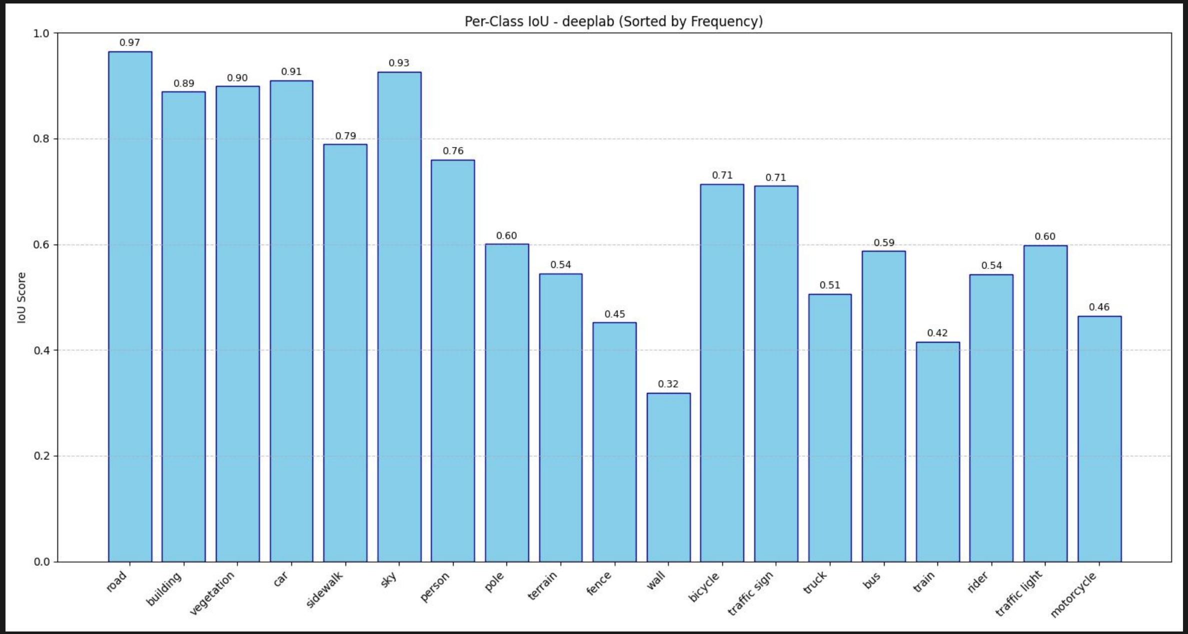


Image 1: Per-Class IoU plot of model DeepLab 2a

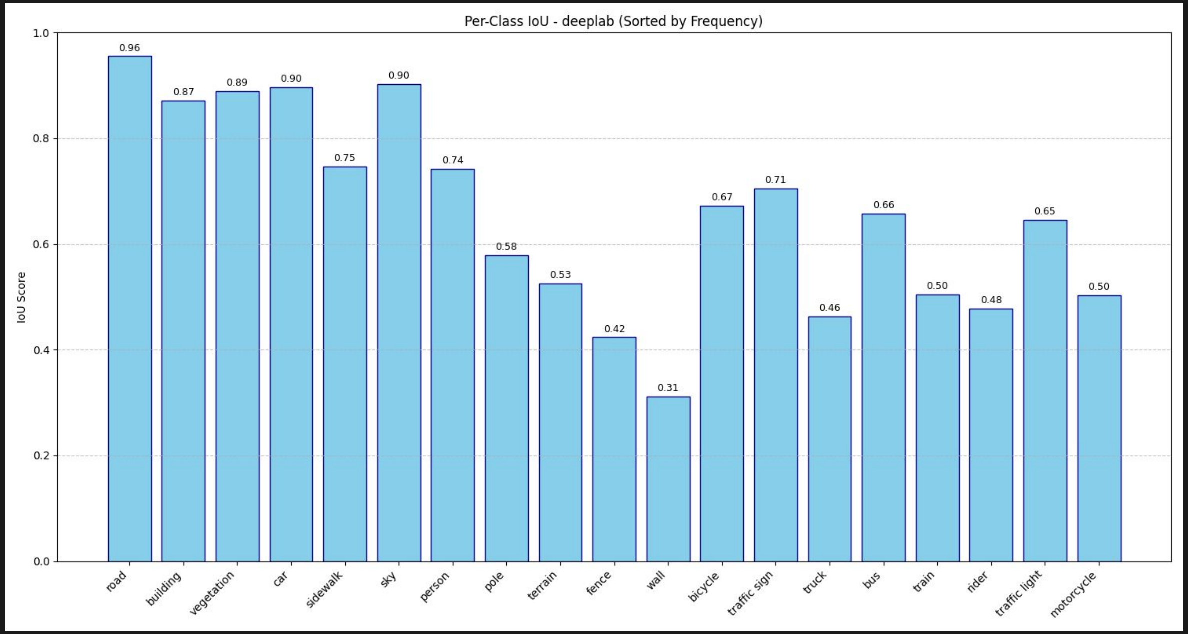
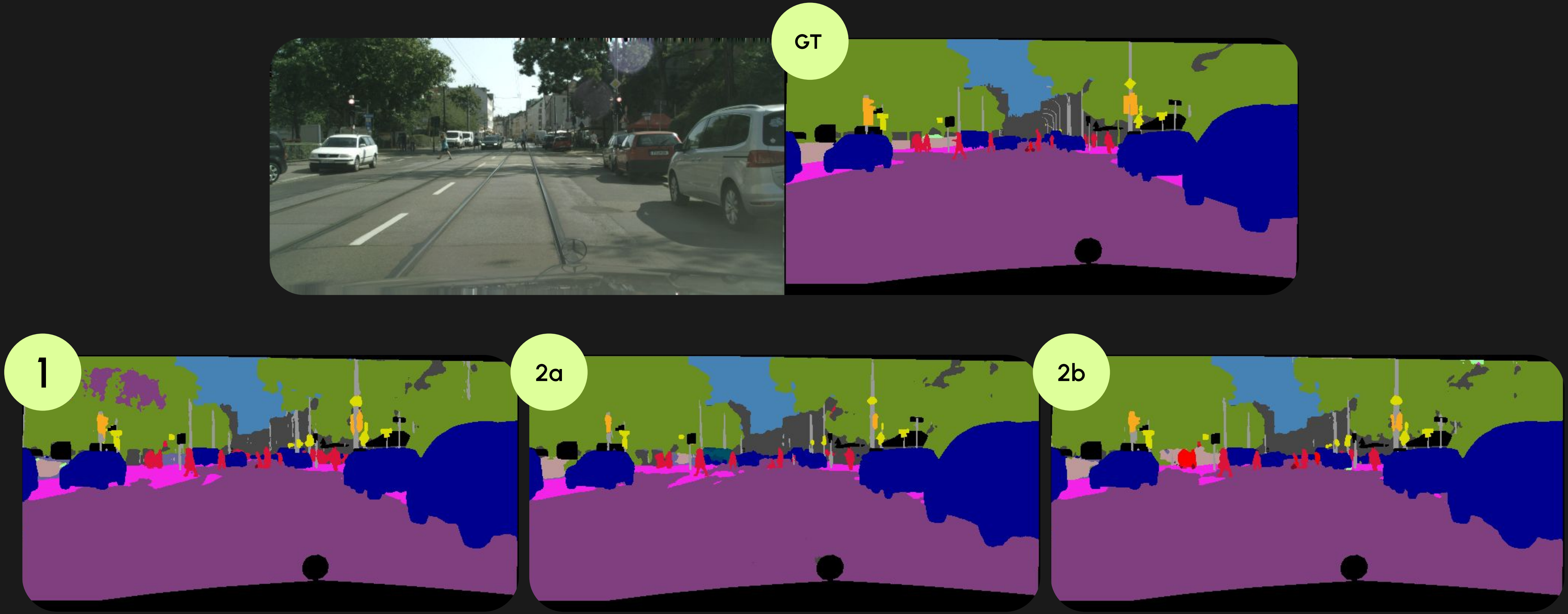


Image 2: Per-Class IoU plot of model DeepLab 2b

DeepLabV3+: Validation Results



Reference image: frankfurt_000000_001236_leftImg8bit.png

SegFormer

- Encoder-Decoder
- Hierarchical Transformer
- Simple MLP
- Positional-Encoding-Free
- MiT - B0

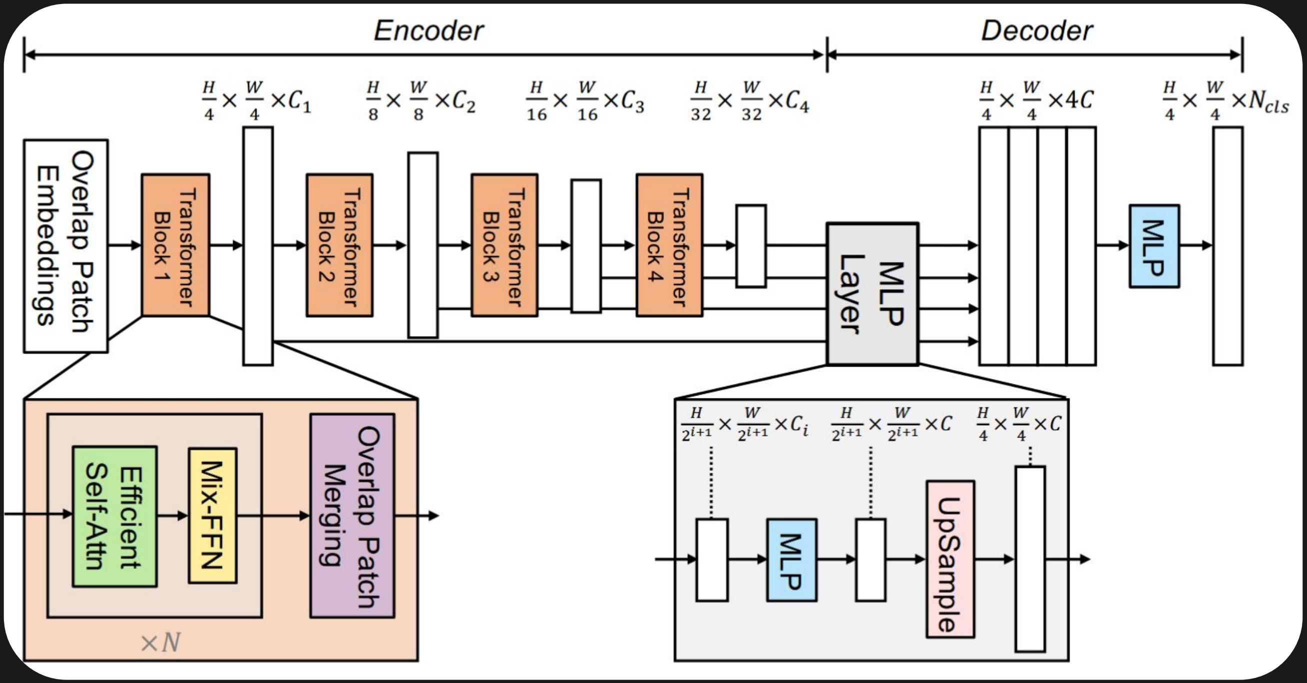


Image: https://doi.org/10.48550/arXiv.2105.15203

SegFormer: Training 1

1

Unfrozen Weighted

SegFormer trained for 20 epoch with **unfrozen** backbone and **weighted** loss function

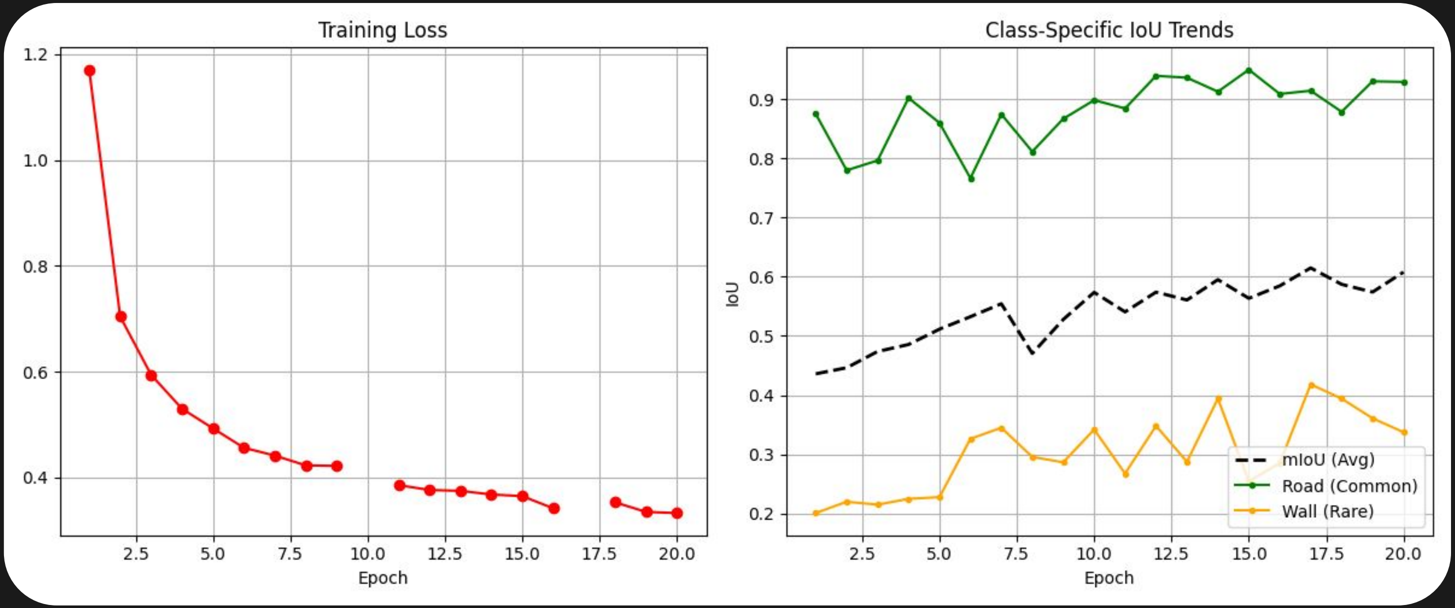


Image: Training plot of model SegFormer 1

20 epoch training

SegFormer: Training

2

Frozen Weighted

SegFormer trained for 10 epochs with **frozen** backbone and **weighted** loss function

2a

Unfrozen Unweighted

Training continued for other 20 epochs with **unfrozen** backbone and **unweighted** loss function

2b

Unfrozen Weighted

Training continued for other 20 epochs with **unfrozen** backbone and **weighted** loss function

30 epoch training

SegFormer: Training Results

Image 1: Training plot of model SegFormer 2a

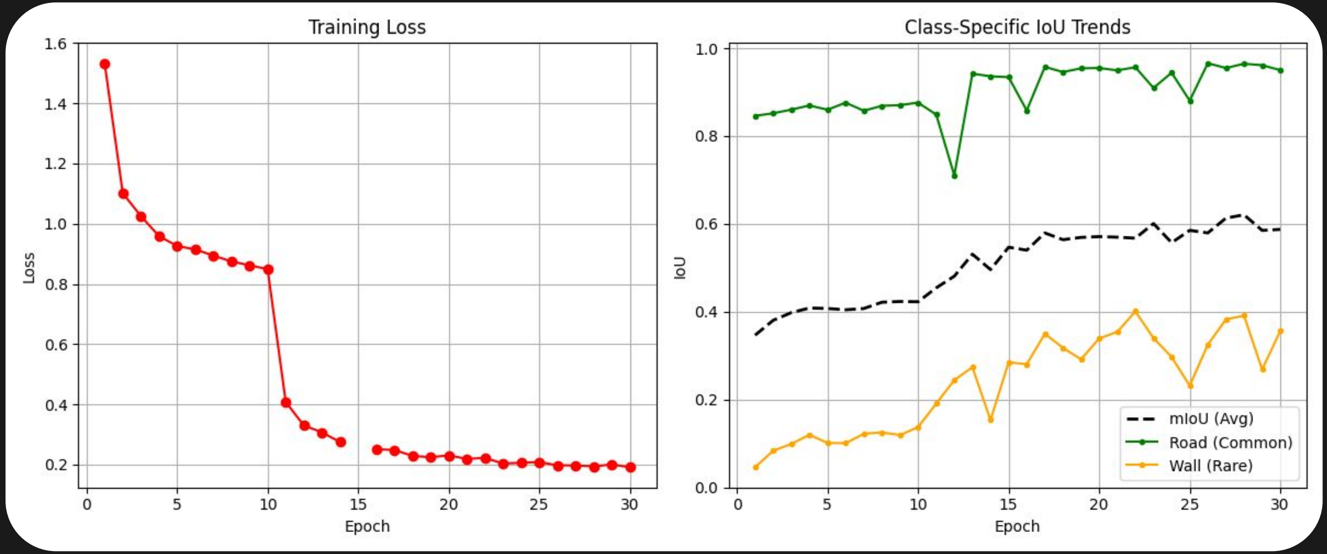
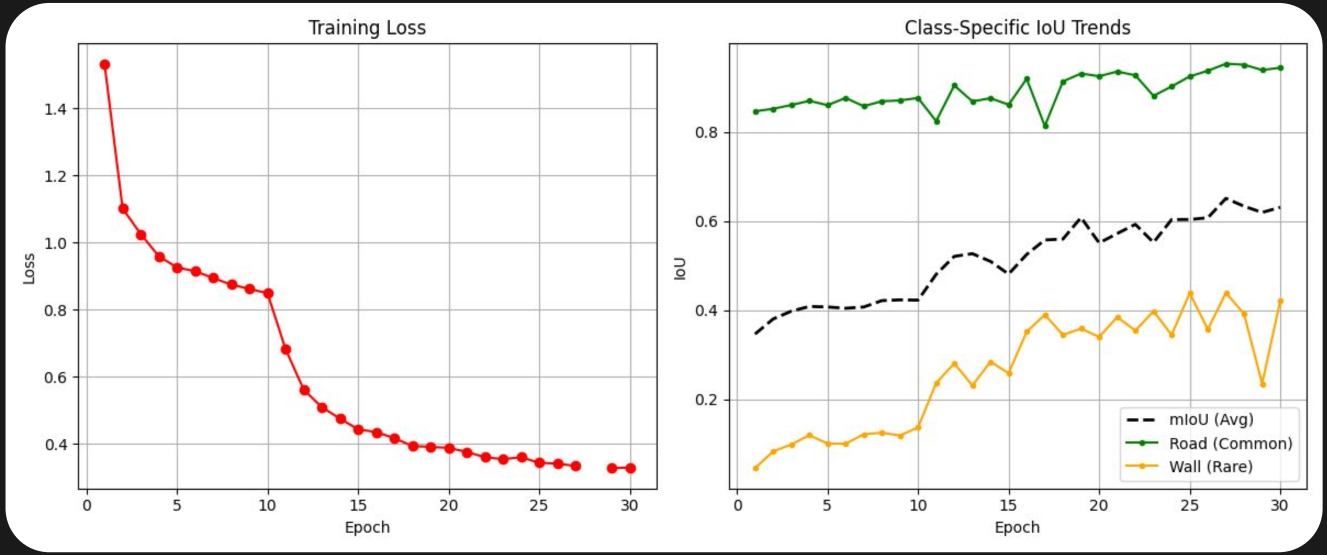


Image 2: Training plot of model SegFormer 2b



SegFormer: Training Results

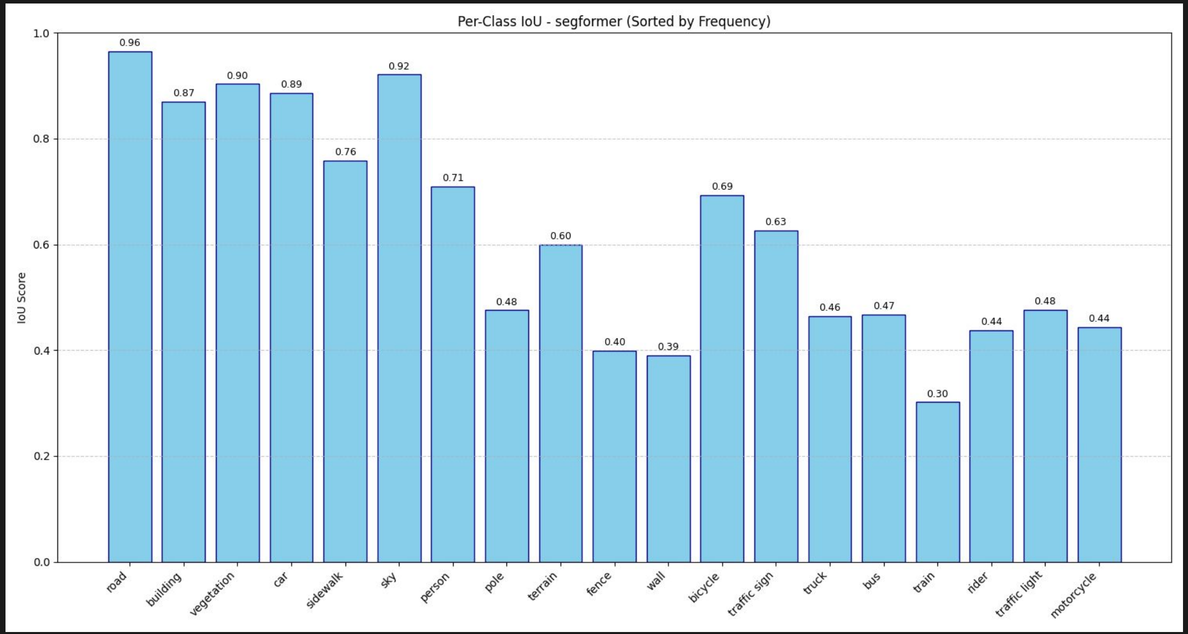


Image 1: Per-Class IoU plot of model SegFormer 2a

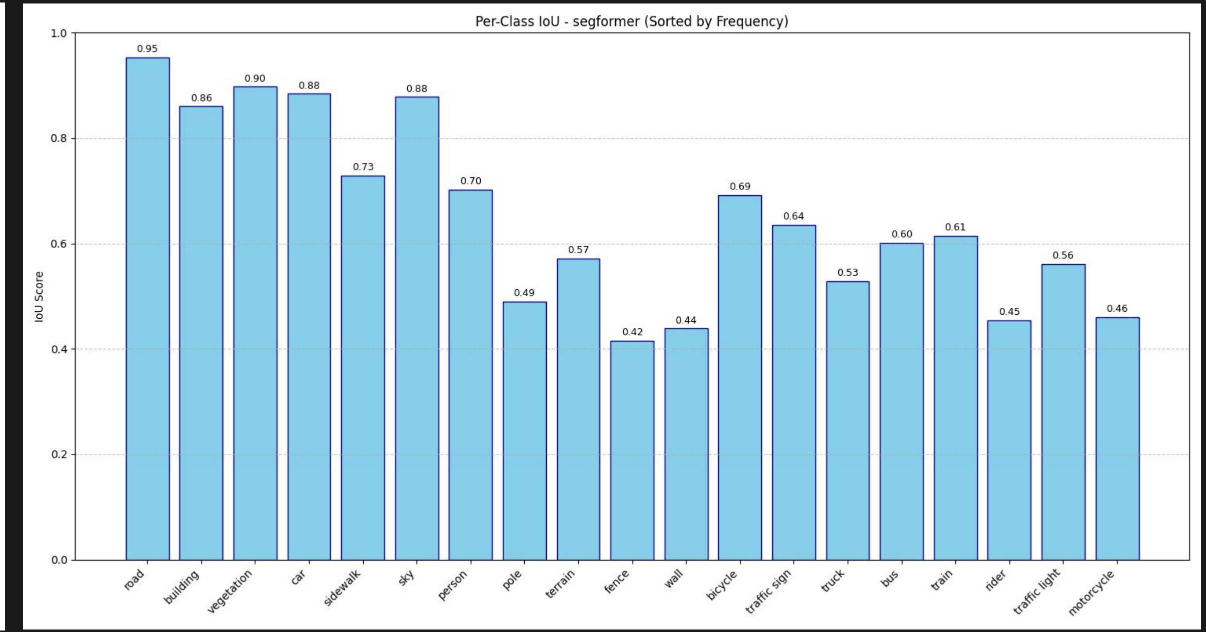
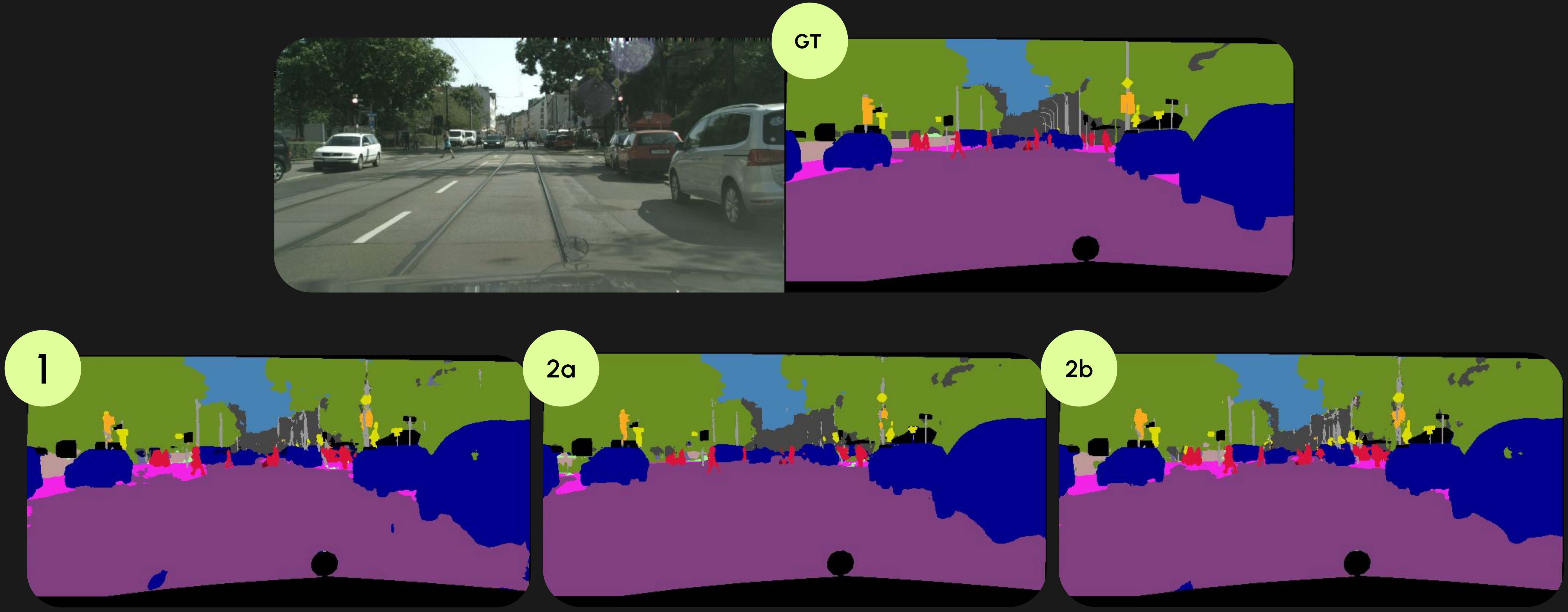


Image 2: Per-Class IoU plot of model SegFormer 2b

SegFormer: Validation Results



Reference image: frankfurt_000000_001236_leftImg8bit.png

Model Parameters

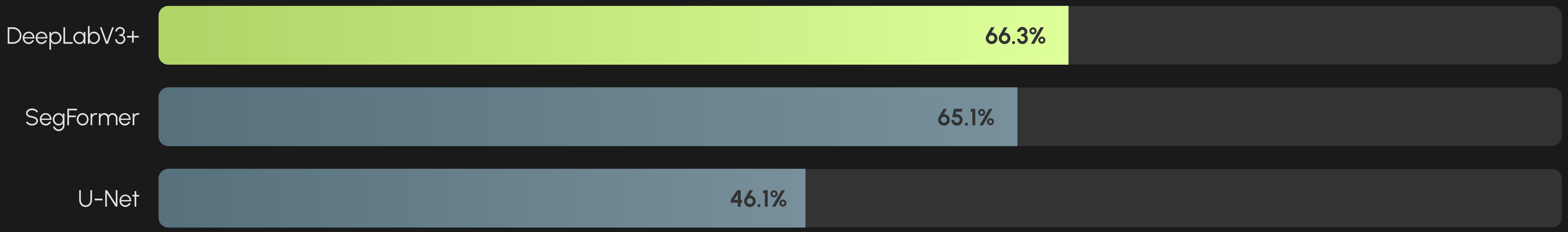
Model	Scenario	Total Params	Trainable Params	% Trainable
U-Net	No backbone	31.38M	31.38M	100.0%
DeepLabV3+	Unfrozen	42.40M	**42.40M**	100.0%
	Frozen	42.40M	16.84M	39.7%
SegFormer	Unfrozen	3.72M	3.72M	100.0%
	Frozen	3.72M	**0.40M**	10.7%

Comparative Evaluation Results

Model	Pixel Acc.	Mean Per-Class Acc.	mIoU class	mIoU category
DeepLab 2a	0.9408	0.7531	0.6629	0.8632
SegFormer 2b	0.9264	0.8069	0.6508	0.8300
U-Net 1a	0.8998	0.5491	0.4612	0,7869

- **DeepLabV3+:** Superior performer, benefiting from multi-scale ASPP context and large resolution
- **SegFormer:** Similar performance to DeepLabV3+ with a lighter backbone (4M parameters)
- **U-Net:** Least performing model with the heaviest computational load.

Results Deep Dive: mIoU Comparison



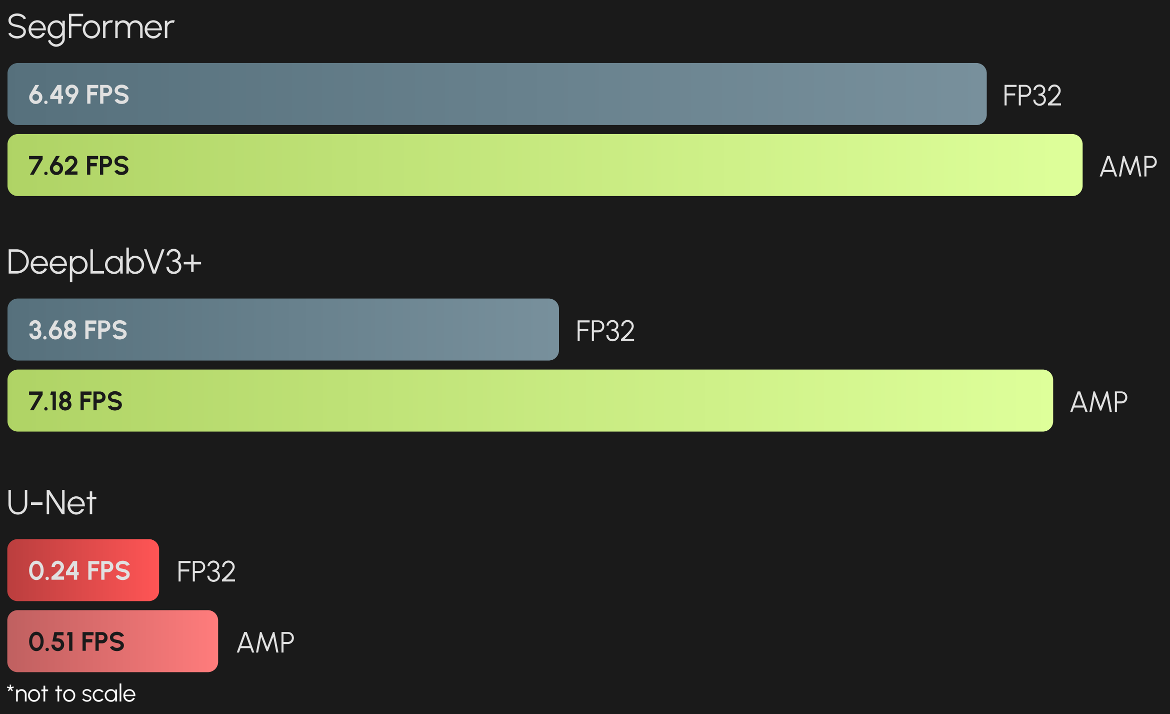
CNN Insight

U-Net and DeepLab benefit significantly from a **"Mixed" loss strategy** (Weighted → Unweighted).

Transformer Insight

SegFormer requires **persistent class weighting**. Removing weights caused a performance drop on less frequent classes.

Inference Speed: (1024x2048) Input



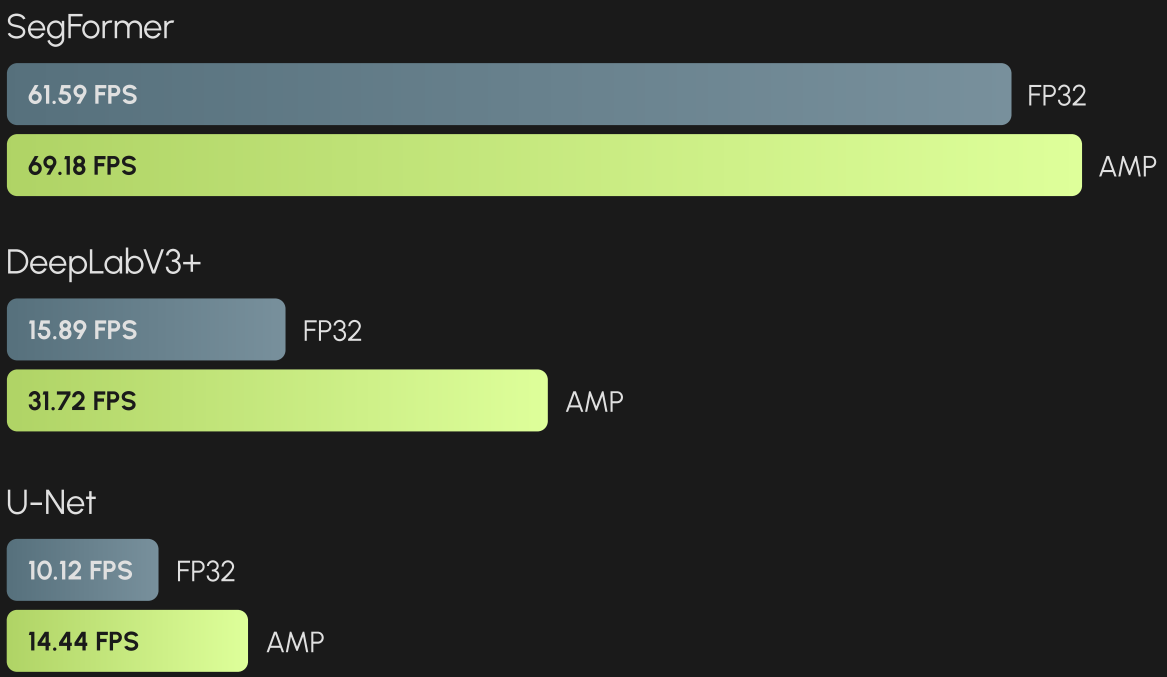
⚠ Memory Bottleneck

U-Net exceeds 8GB VRAM, forcing data swapping to system RAM.

Result: Latency spikes to ~4222ms without AMP

Model (AMP)	Latency	FPS
SegFormer	131.16 ms	**7.62**
DeepLabV3+	139.29 ms	**7.18**
U-Net	1974.98 ms	0.51

Inference Speed: 512x1024 Input



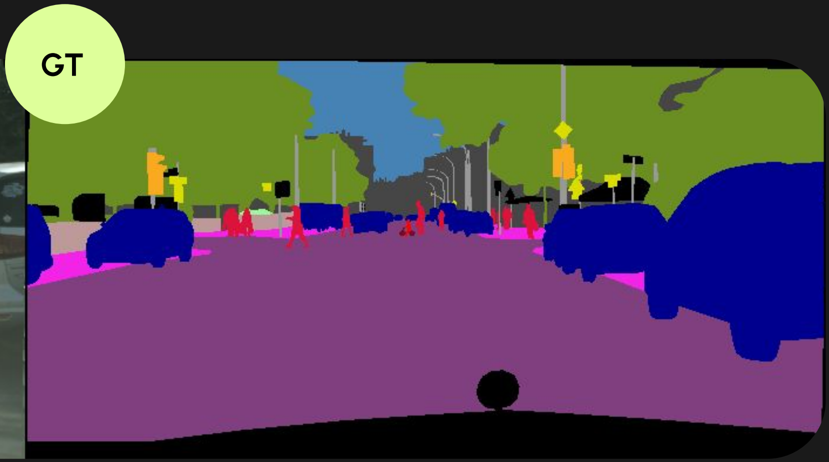
VRAM Constraint Resolved

At **512x1024**, U-Net fits in 8GB VRAM, eliminating system RAM swapping.

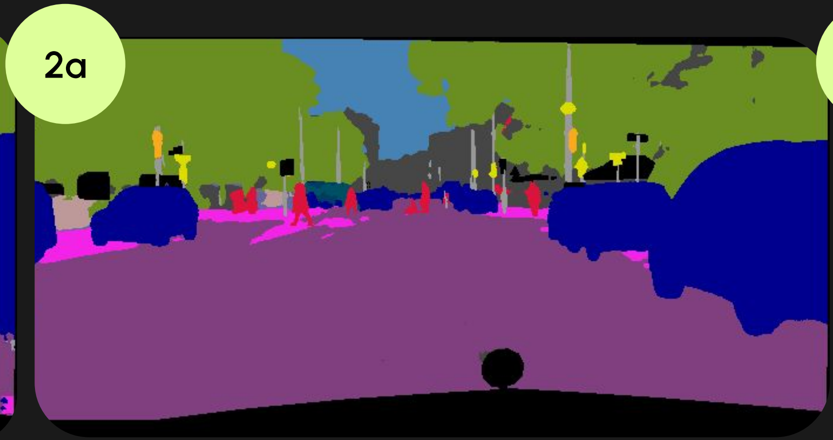
Note: SegFormer achieves ~69 FPS, being the most effective approach for real time systems.

Model (AMP)	Latency	FPS
SegFormer	**14.45 ms**	**69.18**
DeepLabV3+	31.52 ms	31.72
U-Net	69.26 ms	14.44

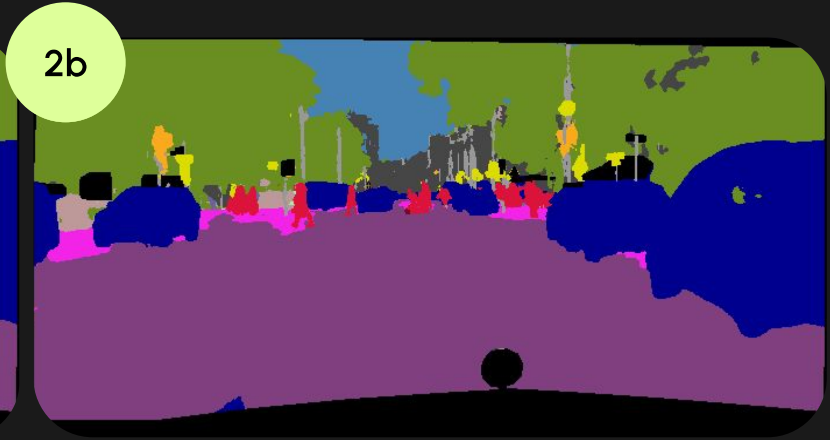
Qualitative analysis



U-Net 1a



DeepLab 2a



SegFormer 2b

Conclusion & Recommendations

Optimal Architecture

DeepLabV3+ obtained the best mIoU results on the validation dataset, followed by **SegFormer** which achieves similar results while being drastically more efficient.

Key Learnings

1. **Gradient Accumulation & AMP** are non-negotiable for high-res images on constrained hardware.
2. **Adaptations** (Instance/Group normalization) are mandatory to bypass small-batch instability.
3. **Class Weighting** is fundamental to address the "long-tail" distribution.

Thank you

Any question?

Bibliography

- **U-Net**
  Source: https://doi.org/10.48550/arXiv.1505.04597
- **DeepLabV2**
  Source: https://doi.org/10.48550/arXiv.1606.00915
- **DeepLabV3**
  Source: https://doi.org/10.48550/arXiv.1706.05587
- **DeepLabV3+**
  Source: https://doi.org/10.48550/arXiv.1802.02611
- **SegFormer**
  Source: https://doi.org/10.48550/arXiv.2105.15203
- **Demo semantic segmentation ADAS**
  Source: https://github.com/MarcelloCeresini/DemoSemanticSegmentationADAS.git
- **Cityscapes**
  Source: https://doi.org/10.48550/arXiv.1604.01685