Performance Evaluation of Road Marking Detection Models in Indian Conditions

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Team: **CV Project**

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Problem Statement

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Performance Evaluation of Road Marking Detection Models in Indian Conditions

This project aims to perform pixel-wise segmentation of Indian road scenes using deep learning models. The aim is to identify road elements such as lane markings, dividers, and road surfaces in drone or street-level images. This helps improve the understanding of the roads for autonomous driving and traffic analysis systems.

- Automate the pixel-wise classification of Indian road images into multiple classes.
- Handle real-world challenges like lighting variation, class imbalance, and faded markings.
- Evaluate and compare deep learning models to find the most accurate and efficient solution.

Instructor's Feedback

- Suggested improving results by deeper training and better augmentation, and focusing on other datasets with Drone-imagery
- Explore different loss functions.
- Recommended class-wise performance evaluation to handle imbalances.
- Explore different evaluation metrics

Our Approach: Models Used

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We implemented and fine-tuned three models:

- **DeepLabV3+** – Encoder-decoder with ASPP; high pixel accuracy.
- **U-Net** – Lightweight with skip connections; faster and interpretable.
- **SegFormer** – Transformer-based; efficient with better contextual understanding.

All models were pretrained on ImageNet and fine-tuned using transfer learning.

Dataset and Preprocessing

Dataset: AU-Drone Dataset with Indian roads captured from UAVs.

Preprocessing:

- Images and masks resized to 640×360.
- Converted RGB masks to single-channel class labels.
- Applied data augmentation: flips, color jitter, affine transforms.
- Normalized images using ImageNet statistics.

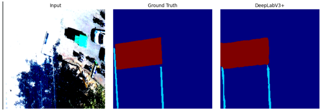
Results – Quantitative Metrics

Model	Pixel Accuracy	mIoU	F1 Score
U-Net	0.89	0.81	0.89
DeepLabV3+	0.98	0.65	–
SegFormer	0.97	0.64	–

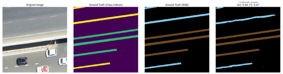
Table 1: Performance metrics across models after training

Observation: While U-Net shows high mIoU and F1, DeepLabV3+ gives the best pixel accuracy. SegFormer maintains competitive performance with lower training epochs.

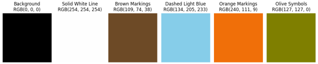
Results – Qualitative Visuals



DeepLabv3+ Output



SegFormer Output



UNet Output

Visual Insight: DeepLabv3+ captures clearer road edges and markings. U-Net performs well but struggles slightly with fine boundaries. Both perform better than baseline segmentation.

Results – Evaluation Metrics

Table 2: Evaluation Metrics Comparison

DeepLabV3+

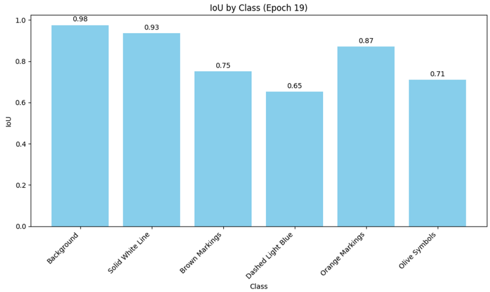
Metric	Value
Pixel Accuracy	0.9864
Mean IoU	0.6589
Class 0 IoU (BG)	0.9849
Class 1 IoU (Marking)	0.7105
Class 2 IoU (Other)	0.0000
Class 3 IoU (Road)	0.9401

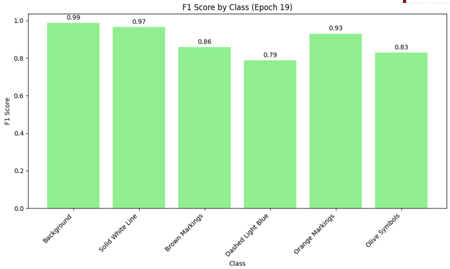
SegFormer

Metric	Value
Pixel Accuracy	0.9734
Mean IoU	0.6431
Class 0 IoU (BG)	0.9805
Class 1 IoU (Marking)	0.6923
Class 2 IoU (Other)	0.4437
Class 3 IoU (Road)	0.4569

Results

(a) Validation loss curve across training epochs.





(b) IoU and F1-score at epoch 19.

Fig. 2: UNet performance evaluation during training.

Validation Loss

UNet Metrics

Conclusion: Quantitative results reaffirm that DeepLabv3+ achieves higher pixel accuracy and cleaner segmentation. U-Net, with strong F1 and mIoU, is efficient but slightly less precise in boundary detection. DeepLabv3+ is better suited for tasks needing accuracy in complex road environments.

Future Work

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- Train for more epochs to improve generalization
- Use focal loss to handle class imbalance
- Try additional models and transformer variants
- Add real-time segmentation and post-processing filters
- Explore deployment on edge/embedded devices for field use
- Expand dataset diversity (weather, road types, angles)

References

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