

**Ahmedabad  
University**

# **Performance Evaluation of Indian Road Marking Detection Models**

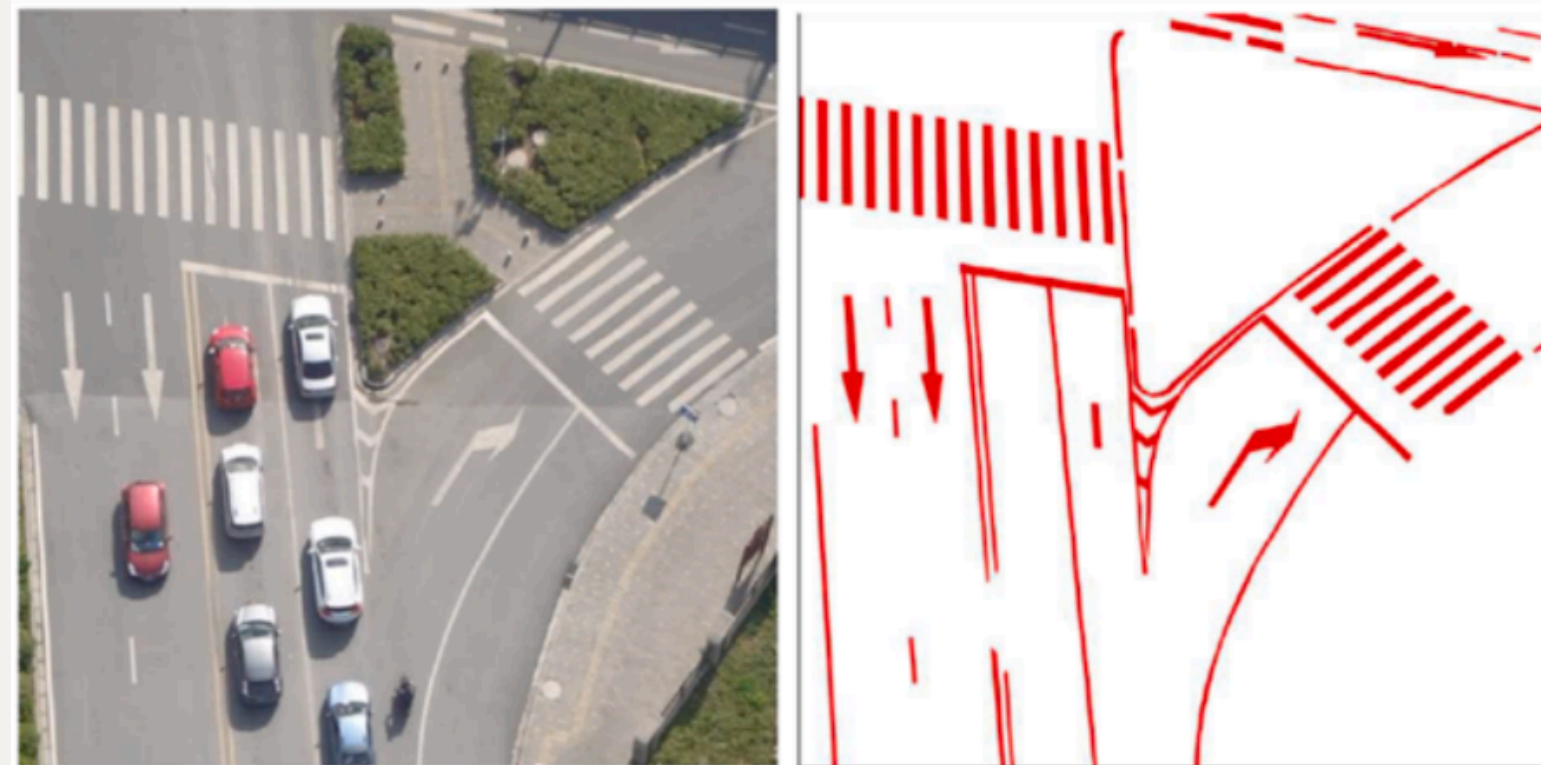
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# Problem Statement

Road marking detection presents significant challenges due to factors such as faded markings, occlusions, shadows, and low-contrast images. Most existing models are trained on foreign datasets, limiting their effectiveness in Indian road conditions. This project aims to evaluate and adapt segmentation-based models using UAV imagery to enhance their performance in detecting road markings under Indian conditions.



# Literature Survey

Paper	Approach	Limitations
Road marking extraction in UAV imagery using attentive capsule feature pyramid network	Capsule Networks + Attention: Uses vector neurons in capsule networks to capture spatial hierarchies and transformations, making it highly robust to variations in lane markings. Relevant for complex road scenes with occlusions and irregular patterns.	Computationally Expensive compared to CNN, False positives are high.  senisitive to image quality and noise.
Lane segmentation using Wavelet-Enhanced Cost-sensitive Fully Convolutional Neural Networks	Wavelet Transform + Cost-Sensitive Loss: Integrates DWT to preserve high-frequency details, improving the segmentation of small lane markings. The cost-sensitive loss reduces the impact of class imbalance, making it relevant for small object segmentation in aerial imagery	Faded Markings are difficult for the model to recognise.  Markings in shadowed regions are difficult to distinguish.
Advancements in Road Lane Mapping: Comparative Fine-Tuning Analysis of Deep Learning-based Semantic Segmentation	Transformer vs. CNN Benchmarking: Comprehensive evaluation of 12 models reveals that transformers outperform CNNs in lane marking segmentation. Helpful in identifying the best-performing architecture for HD map creation.	Occlusion by plants, poles or other objects make it harder to detect.  High computation cost for transformers.
A Dense Feature Pyramid Network-Based Deep Learning Model for Road Marking Instance Segmentation	Dense Feature Pyramid + Focal Loss: Combines FPN with DFPN for multi-level feature extraction and uses focal loss to emphasize hard-classified samples. Relevant for precise instance segmentation of complex and irregular road markings.	Misclassification in complex patterns such as Box Junction.Struggles with incomplete boundary extraction.

# Dataset Description

## AU Drone Dataset:

- UAV (drone) images capturing Indian road markings
- Includes RGB road images and segmentation masks
- Multi-class masks for different road markings

## Dataset Splits:

- Train (75%) – Used for model training
- Valid (10%) – For hyperparameter tuning
- Test (15%) – For final performance evaluation

## File Format:

- Images: .jpg/.png (RGB aerial images)
- Masks: .png (colored annotations)



Fig.1 UAV image

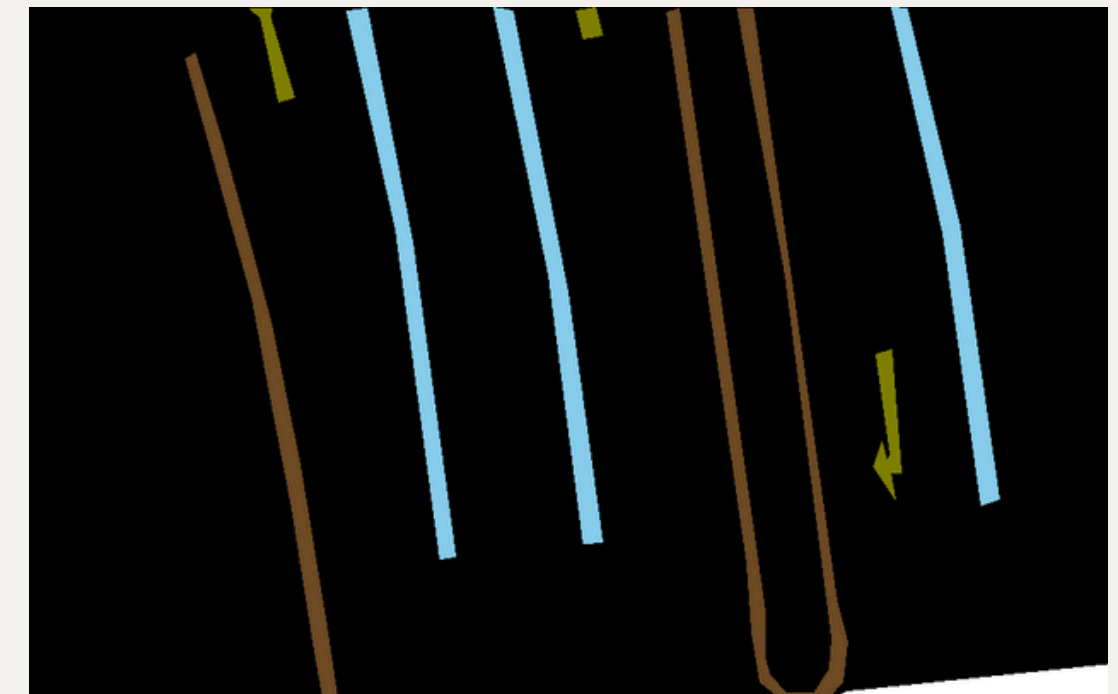


Fig.2 Segmentation masks



# Segmentation Masks & Challenges

- **Black (0,0,0) – Background (non-road markings)**
- **White (255,255,255) – Lane markings or pedestrian crossings**
- **Brown (139,69,19 or similar) – Possibly road dividers, lane boundaries, or special markings**
- **Blue (Varied shades) – Could indicate bike lanes, speed breakers, or other traffic markings**

## Challenges:

- **Different Road Types – Urban, rural, highways.**
- **Lighting & Weather Variations – Shadows, night-time images, rainy conditions.**
- **Obstructions – Vehicles, pedestrians, and debris affecting visibility.**
- **Faded or Irregular Markings – Inconsistent road signs across regions.**

# Approach and Future Work

## PreProcessing:

- Apply data augmentation like rotation flipping and scaling as images have large coverage area.
- Map colours to Class ID ( since masks are already colour coded, and its has multiple classes).

## Model Improvement:

- DeepLabV3+ or U-Net as a baseline
- Use Dice loss + Cross Entropy to address class imbalance.
- Utilise multi scale training.
- Evaluation on IoU and F1 score.

# References

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**Thank You!**