Road Extraction from Satellite Images using DeepLabV3+

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1. PROBLEM STATEMENT

Efficient road network mapping is essential for urban planning, disaster management, and navigation systems.

Traditional methods for road extraction from satellite images are time-intensive, labor-intensive, and prone to inaccuracies.

The challenge is to develop an automated, accurate, and scalable solution for road segmentation and extraction from satellite imagery.

2. INTRODUCTION

- This project leverages **DeepLabV3+**, a state-of-the-art deep learning model, for road segmentation from high-resolution satellite images.
- The goal is to produce binary masks that accurately identify road pixels, enabling rapid and precise road network mapping.
- By automating the process, this solution supports a wide range of applications, including urban development, navigation systems, and disaster recovery.

3. LITERATURE SURVEY

Paper 1: Road Extraction From Satellite Images Using Attention-Assisted UNet

- **Summary**: Enhances the UNet model with attention mechanisms to better detect and extract roads from satellite images.
- **Solution**: Uses attention modules to focus on important features, improving road detection.
- **Drawbacks**: Needs high computational power and large datasets.
- **Future Advancements**: Develop lighter attention modules for faster processing and real-time use.

Paper 2: Challenging AI for Sustainability: What Ought It Mean?

- **Summary**: Discusses the ethical and environmental impact of using AI for sustainability.
- **Solution**: Offers a framework for responsible AI applications in sustainable development.
- **Drawbacks**: Lacks specific technical solutions or AI models.
- **Future Advancements**: Create energy-efficient AI models to reduce carbon footprint in real-world applications.

Paper 3: BL-YOLO v8: An Improved Road Defect Detection Model Based on YOLOv8

- **Summary**: Improves YOLO v8 for detecting road defects like potholes and cracks, focusing on small defects.
- **Solution**: Enhances YOLO v8 layers to improve detection accuracy for small defects.
- **Drawbacks**: May struggle with low-resolution images or poor lighting.
- **Future Advancements**: Use data augmentation to improve robustness in diverse conditions.

Paper 4: Dual-Attention-Guided Multiscale Feature Aggregation Network for Remote Sensing Image Change Detection

- **Summary**: Introduces a dual-attention mechanism for better change detection in satellite images.
- **Solution**: Combines dual-attention and multiscale features to capture more details.
- **Drawbacks**: Computationally intensive, not ideal for real-time use with large datasets.
- **Future Advancements**: Optimize for faster processing and use in real-time infrastructure monitoring.

4.METHODOLOGY:

11.Dataset Preparation

- **Input Data**:
  - High-resolution satellite images serve as input.
  - Ground truth labeled masks are provided to identify road regions (binary: road vs. non-road).
- **Preprocessing**:
  - Images are resized to ensure consistency in dimensions.
  - Data augmentation techniques such as rotation, flipping, scaling, and color jittering are applied to increase dataset variability and prevent overfitting.
- **Splitting**:
  - The dataset is split into training, validation, and testing sets to ensure robust evaluation.

2. Model Selection

Model Architecture:

- **DeepLabV3+** is chosen for its superior performance in semantic segmentation tasks.
- Encoder-decoder structure:
  - Encoder: ResNet-50 backbone pre-trained on ImageNet for feature extraction.
  - Decoder: Upsamples feature maps to generate fine-grained segmentation masks.

3. Training Process

- **Loss Function**:
  - **Dice Loss**: Handles class imbalance by focusing on overlap between predicted and actual road regions.
  - **Cross-Entropy Loss**: Provides robust multi-class segmentation where necessary.
- **Optimizer**:
  - Adam optimizer with a learning rate of 0.00008 for efficient weight updates.
- **Learning Rate Scheduler**:
  - Cosine Annealing Warm Restarts to adjust the learning rate dynamically for better convergence.
- **Hardware**:
  - Training performed on GPUs (e.g., NVIDIA) to handle computationally intensive tasks.

4.**Metrics**:

- **Intersection over Union (IoU)**: Measures overlap between predicted and ground truth road pixels.
- **Accuracy**: Proportion of correctly classified pixels.
- **Precision/Recall/F1-Score**: Evaluates balance between true positives and false positives/negatives.

Testing:

- Evaluate on unseen satellite images to test generalizability.
- Visual comparison: Overlay predicted road masks on original images to assess qualitative performance.

THANK YOU