

# Proposal for Road Network Extraction from Satellite Imagery

**Institution:** Saskatchewan Polytechnic

**Course:** Capstone Project

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### I. INTRODUCTION

The extraction of road networks from satellite imagery plays a vital role in urban planning, navigation, and autonomous vehicle operations. Traditional road mapping techniques are labor-intensive and prone to errors, making automated methods highly desirable. Advances in deep learning have provided an opportunity to enhance road network detection, improving both accuracy and efficiency.

#### 1. Project Overview

This project aims to develop a deep learning-based model for accurate road network detection from high-resolution satellite imagery with the following goals:

- **Efficiency:** Automate road mapping to reduce processing time by at least 50% compared to manual methods.
- **Accuracy:** Achieve >90% precision in road detection, minimizing false positives and negatives.
- **Scalability:** Develop an open-source model adaptable for various terrains and satellite data sources.
- **Real-World Application:** Support disaster management, infrastructure planning and navigation with real-time updates.
- **Reliability:** Ensure consistent and up-to-date road maps for crisis-affected regions.

#### 2. Problem Statement

Accurate and up-to-date road maps are essential for transportation, disaster response, and urban planning. However, maintaining reliable road network data remains a significant challenge due to various factors:

- In many regions, road networks frequently change due to urbanization, natural disasters, and infrastructure development, making existing maps outdated.
- Traditional road extraction methods, such as manual digitization and semi-automated techniques, are time-consuming, resource-intensive, and lack real-time adaptability.
- This project aims to overcome these limitations by developing a deep learning-based model capable of automatically identifying and extracting road networks from satellite imagery with high accuracy.

#### 3. Research Questions/Hypotheses

Several research questions and hypotheses have been given as below:

- **Research Question 1:** How accurately can a deep learning model extract road networks from satellite images compared to traditional methods?
- **Research Question 2:** What are the optimal deep learning architectures (e.g., U-Net, DeepLabV3) for road extraction in terms of precision, recall, and computational efficiency?
- **Research Question 3:** How well does the model generalize across different regions and terrains present in the DeepGlobe dataset?

- **Hypothesis 1:** A deep learning model trained on high-resolution satellite imagery can achieve > 90% precision in road detection.
- **Hypothesis 2:** Transfer learning and data augmentation techniques improve model generalization across diverse landscapes.

## II. LITERATURE REVIEW

Below is a summary of relevant literature, key findings, and gaps in existing research:

### Road Extraction Techniques

Traditional road extraction methods rely on edge detection, thresholding, and morphological operations. These methods, while effective in some cases, struggle with complex urban layouts and occlusions. More recent approaches incorporate machine learning and deep learning techniques to improve accuracy and adaptability.

### Deep Learning for Road Extraction

Deep learning models, particularly convolutional neural networks (CNNs), have revolutionized image segmentation. Models such as U-Net, SegNet, and DeepLabV3+ have demonstrated significant improvements in extracting road networks from satellite images. Studies comparing these models indicate that DeepLabV3+ offers superior accuracy and efficiency due to its ability to capture multiscale contextual information.

### Existing Research and Benchmarks

- **DeepGlobe Challenge (2018):** Introduced a standardized dataset for road extraction and benchmarked several deep learning models.
- **IEEE Research (2021, 2024):** Explored variations of CNN architectures and their performance on different satellite imagery datasets.
- **Comparative Studies on PyTorch vs. TensorFlow:** Discussed framework efficiency, ease of implementation, and computational performance in training deep learning models for image segmentation.

## III. PROJECT METHODOLOGY

This project follows a structured deep learning-based approach for automated road extraction from satellite imagery. The methodology consists of the following key phases:

### 1. Dataset Collection

Utilize the **DeepGlobe Road Extraction Dataset**, which contains high-resolution satellite images and corresponding road masks (<https://www.kaggle.com/datasets/balraj98/deepglobe-road-extraction-dataset/data>).

2. Data Analysis

- Analyze dataset statistics (e.g., image resolution, class distribution).
- Visualize sample images and road masks to understand data quality.
- Identify potential issues (e.g., imbalanced classes, missing labels).

3. Data Preprocessing

- Image resizing for standardization.
- Normalization to enhance contrast.
- Data augmentation techniques (flipping, rotation, cropping) for diversity.
- Noise reduction to improve image clarity.

4. Model Selection & Training

- **Deep Learning Model:** With the need for high segmentation accuracy on large datasets with multi-scale object handling, **DeepLabV3+** is the best choice compared with SegNet and U-Net.

Criteria	SegNet	DeepLabV3+	U-Net
Accuracy	☆☆☆	☆☆☆☆☆	☆☆☆☆
Training Speed	☆☆☆☆	☆☆☆	☆☆☆☆
Memory Efficiency	☆☆☆☆☆	☆☆☆	☆☆☆☆
Handles Complex Road Networks	☆☆	☆☆☆☆☆	☆☆☆☆
Best for Small Roads & Occlusions	☆☆	☆☆☆☆☆	☆☆☆

- **Framework: PyTorch** for flexible model development when compared with TensorFlow.

Step	PyTorch	TensorFlow
Pre-Trained Model	✔ Yes	✔ Yes
Custom Training	✔ Yes	✔ Yes
Flexibility	✔ Better	✘ Less Flexible
Deployment (Edge, Mobile, Web)	✘ Limited	✔ Better

- **Libraries:** OpenCV, NumPy, Pandas, Matplotlib, Scikit-learn.

5. Training and Evaluation

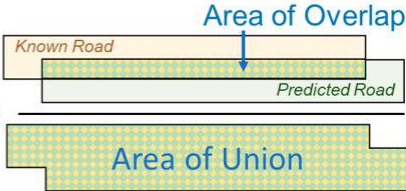
5.1. Training

- Supervised learning using the labeled dataset.

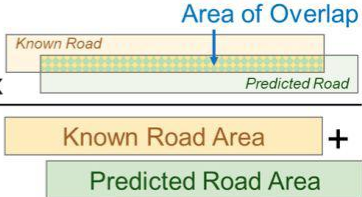
- Optimized with techniques like learning rate scheduling and batch normalization.

### 5.2. Evaluate Metrics

- **Intersection over Union (IoU):** Measures overlap between predicted and ground truth segmentation.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$


- **F1-Score:** Balances precision and recall to assess model accuracy.

$$\text{F1 Score} = \frac{\text{Area of Overlap} \times 2}{\text{Total Area}} = \frac{2 \times \text{Area of Overlap}}{\text{Known Road Area} + \text{Predicted Road Area}}$$


## 6. Deployment

PyTorch provides **TorchScript** for converting models to a format that can be run independently of Python, which is useful for deployment.

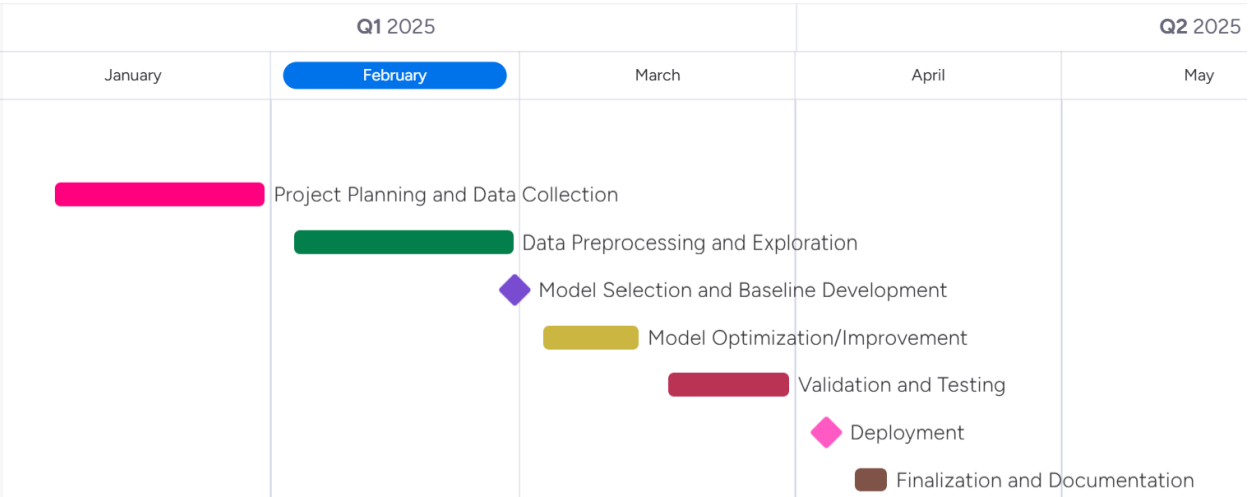
## 7. Project Timeline and Deliverables

All following items will be delivered at the final delivery stage before launching to Production:

### 7.1. Project Timeline

The project will be implemented in 3 months divided into 2 milestones:

- **Milestone 1:** Baseline Model Development.
- **Milestone 2:** Model Optimization Deployment.



7.2. Project Deliverables

- **Preprocessed Dataset:** Cleaned, augmented, and split dataset.
- **Trained Models:**
  - Baseline model
  - Optimized/Advanced model
- **Evaluation Metrics:** IoU, F1-score, and visualizations of predictions.
- **Project Report and Presentation:** Comprehensive documentation and summary

IV. CONCLUSION

This project aims to develop a high-accuracy deep learning model using DeepLabV3+ for automated road network extraction from satellite imagery. By implementing a structured methodology encompassing data preprocessing, model training, and evaluation, we strive to create an efficient, scalable, and adaptable solution for real-time road mapping. The proposed model has the potential to significantly enhance urban planning, disaster response, and transportation systems by providing up-to-date and reliable road networks.

V. REFERENCE

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