
Computer Vision

Project Presentation

*Road Extraction from RoadNet-based Satellite Imagery
Using Classical Computer Vision Techniques*

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Introduction

- ❖ **What is Road Extraction?**
- ❖ **Why is it Important?**
- ❖ **Challenges with Deep Learning**
- ❖ **Project Goal**

Problem Statement & Objectives

Objective: Extract road networks from satellite images using classical computer vision.

Challenges:

- Ensuring **road connectivity** despite occlusions (shadows, buildings, vegetation).
- Managing **noise and variability** in satellite images.
- Handling **edge discontinuities** and parameter sensitivity.

Techniques Used:

- **Noise reduction** (bilateral filtering, anisotropic diffusion).
- **Feature enhancement** for better road extraction.

Final Goal:

- Develop a **structured, efficient, and interpretable** alternative to deep learning for road extraction.



Related work

Early Road Extraction Methods:

- Handcrafted pipelines using **morphological operations, edge detection, and connectivity analysis**.
- **Mena & Gamba (2007)**: Used **mathematical morphology** to extract road segments, refining them with connectivity constraints.

Machine Learning Approaches:

- **Moderate ML techniques**: Support Vector Machines (SVMs) and Decision Trees improved adaptability.
- **Ensemble methods (Random Forest)**: Combined multiple weak learners to handle complex cityscapes.

Feature-Based Approaches:

- **RoadNet (Chen et al., 2016)**: Used contrast adjustment and line detection for road extraction.
- **Challenges**: Traditional methods struggle with **parameter sensitivity, fragmented roads, and occlusions**.

Methodology - Overview

Dataset & Preprocessing

- 20 high-resolution satellite images from the **Ottawa dataset**
- Variations in format, resolution, and zoom levels
- Processed using **OpenCV** and **NumPy**

Pipeline Approach

- **Image enhancement** to improve road visibility
- **Edge detection & morphological operations** to refine connectivity
- **Hough Transform** for detecting linear road structures

Performance Evaluation

- **Intersection over Union (IoU)** as the primary metric
- **Visual inspection** for qualitative validation

Project Objective

- Develop a **computationally efficient** and **interpretable** road extraction method
- Provide an **alternative to deep learning** for road detection

Methodology - Image Processing

Dataset Challenges

- Images of **varying sizes**, requiring **normalization** for consistency
- **Lighting variations** mitigated with **gray-world white balancing**

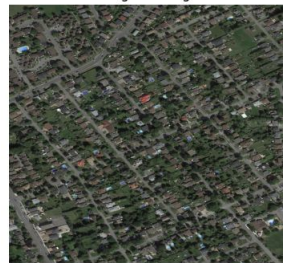
Preprocessing Techniques

- **Grayscale conversion** to focus on intensity variations
- **Histogram equalization & CLAHE** to enhance contrast
- **Anisotropic diffusion & bilateral filtering** to reduce noise while preserving road structures

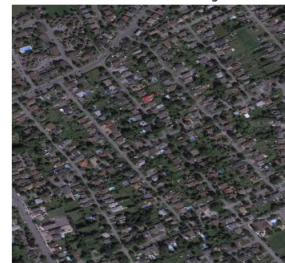
Objective of Preprocessing

- Ensure **clean and well-defined images**
- Improve **accuracy of edge detection** and road extraction

Original image



White-balanced image



Grayscaled image after W-B



Grayscaled image after W-B & H-E



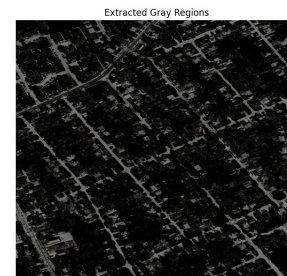
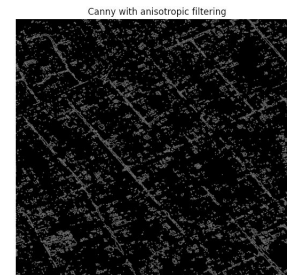
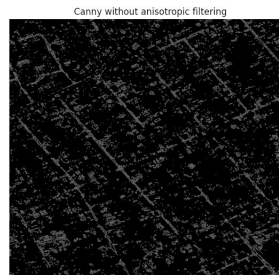
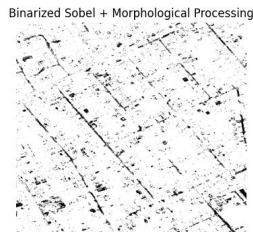
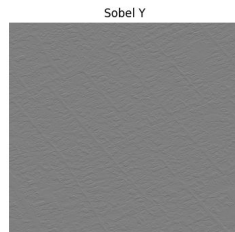
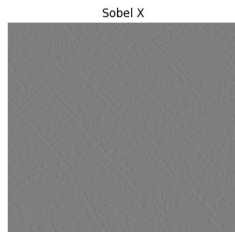
Methodology - Road Feature Extraction

Edge Detection Techniques

- **Sobel Filter:** Highlights strong brightness changes to approximate road edges.
- **Canny Edge Detection:** Refines contours for thin and well-defined road boundaries.
- **Gabor Filter:** Tested for detecting elongated features but struggled with differentiation from rooftops.

Masking Techniques

- **HSV Color Space:** Used to isolate grayscale road regions while filtering out vegetation and water bodies.
- **House Detection Mask:** Applied to remove buildings and reduce false positives in road detection.



Methodology - Road Network Refinement

Hough Transform for Road Continuity

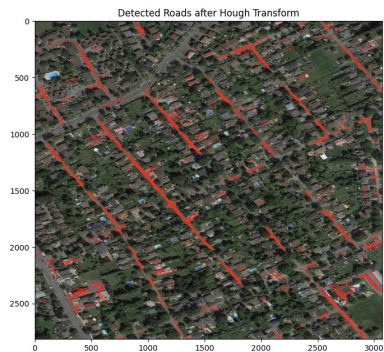
- Reinforced linear structures to ensure road segments remained connected.
- Connected fragmented road edges from the **Canny detector** using Hough Transform.
- Used **Probabilistic Hough Transform (HoughLinesP)** to remove irrelevant lines while preserving meaningful roads.

Final Refinement

- Applied **grayscale and house detection masks** to eliminate non-road elements.
- **Challenges:** Parameter sensitivity and the lack of global contextual understanding in classical methods.

Future Improvements

- Implementing **adaptive thresholding** for better edge detection.
- Exploring **graph-based connectivity refinements** to improve road continuity.



Machine Learning Approaches

Machine Learning Approaches for Road Detection

- Explored both **supervised** and **unsupervised** methods for detecting roads in satellite imagery.
- Standardized dataset and split into **75% training / 25% testing**, treating each pixel as a separate data point.

Supervised Learning

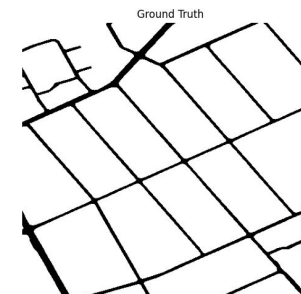
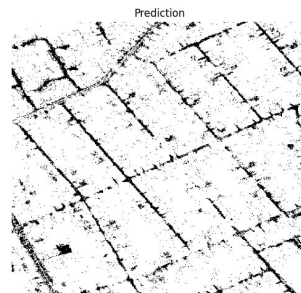
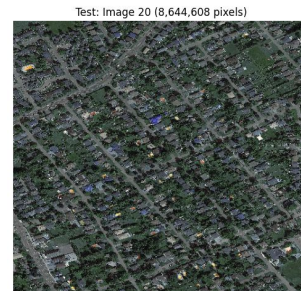
- Tested **Random Forest, SVM, and XGBoost** models.
- **Random Forest** achieved the **best performance**, balancing accuracy and computational efficiency.

Unsupervised Learning

- Used **DBSCAN** and **Mean Shift** to detect road structures without labeled data.
- Identified patterns in pixel distributions to cluster road-like features.

Results & Conclusion

- **Supervised models** relied on ground truth data for learning, leading to better accuracy.
- **Random Forest** was the **most effective**, outperforming other models in both precision and speed.



Performance Evaluation

Qualitative Assessment

- Visually inspected **extracted road masks** overlaid on satellite images.
- Roads **aligned well with ground truth**, but **misalignment occurred in low-contrast regions**.

Quantitative Evaluation

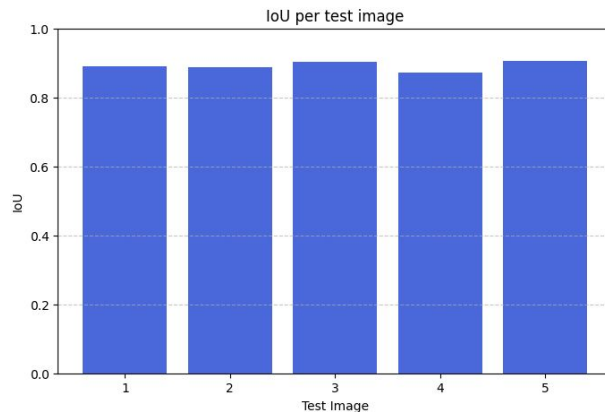
- Used **Intersection over Union (IoU)** as the main metric.
- **Most test images achieved an IoU close to 0.9**.
- The **mean IoU was 0.8923**, indicating strong agreement between predictions and ground truth.

Challenges & Limitations

- **Occlusions, shadows, and parameter sensitivity** affected performance.
- Different image conditions required **careful tuning of preprocessing and detection parameters**.

Conclusion

- Despite challenges, the **pipeline proved effective**, demonstrating the feasibility of **classical vision techniques** for road extraction.



Conclusion & Future Work

- Classical vision extracts roads from satellite images efficiently.
- Uses **preprocessing, edge detection, morphological ops, and Hough Transform**.
- **Interpretable & low-resource friendly** but sensitive to parameters.
- **Future work**: Adaptive thresholding, graph-based refinements, lightweight ML.
- **Balanced approach** between efficiency, interpretability, and accuracy.

References & Acknowledgments

- The methodology was inspired by previous work on traditional road extraction and machine learning approaches.
- Key references include studies by Chen et al. (2016), Mena & Gamba (2007), and Syed & Naeem (2014).
- The Ottawa dataset was used for evaluation, with ground truth annotations providing a benchmark for performance assessment.
- Special thanks to our instructors and mentors for their guidance throughout the project.
- Our findings contribute to ongoing research in computationally efficient road extraction methods.

We hope that you enjoyed our presentation.

Thank you!