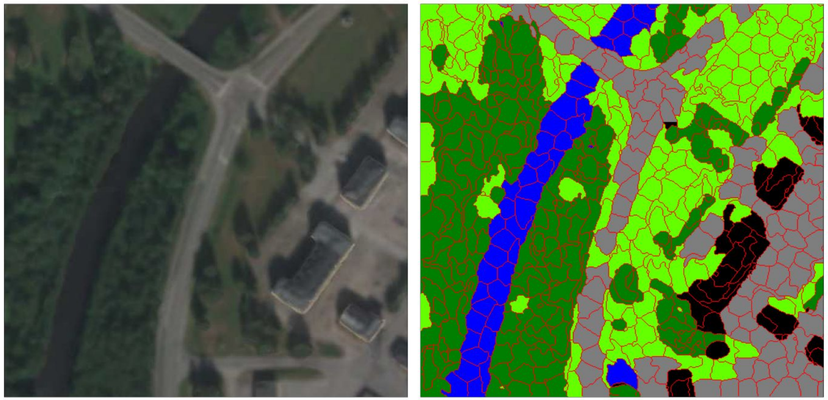
Satellite Image Segmentation

Advanced Image Processing - 22/01/2026

Colin Manyri



Project Overview and Objectives

<u>Project Objectives</u>

- Implement and compare multiple image segmentation methods. (thresholding, histograms, CNN)

- Challenges of optimizing computational complexity (low-power computer).
- Focus on methodology over absolute performance metrics

I. Dataset Presentation and Feature Extraction
II. Multiples image segmentations techniques
III. Inference, Post-Processing, and Predictions
IV. Results and Performances
V. Conclusion and Perspectives

Presentation of the Dataset

Land Cover from Aerial Imagery - LandCover.ai

A dataset for mapping of buildings, woodlands, water and roads from AIs.

Dataset structure

https://landcover.ai.linuxpolska.com/

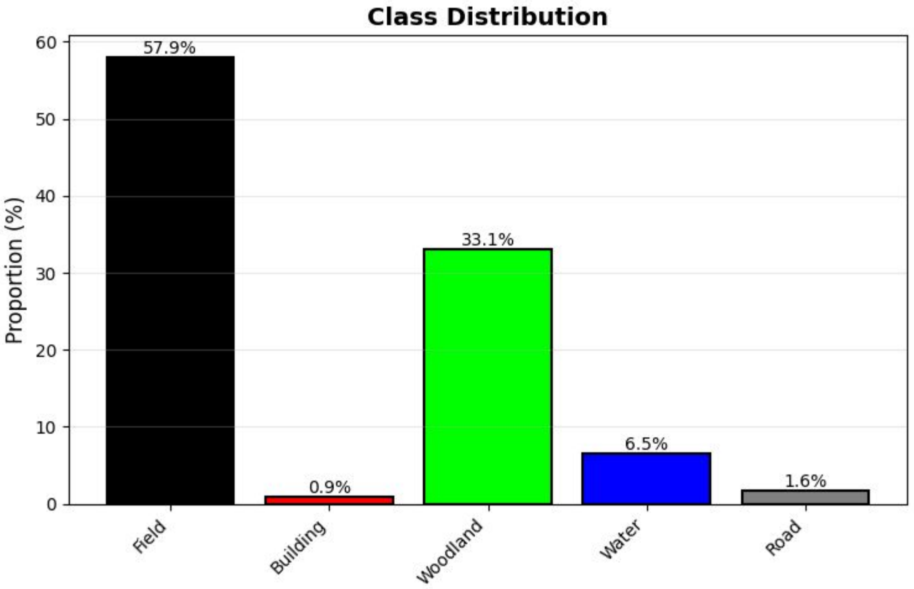
- **Images**: Around 10,000 satellite images, with a resolution of 512 × 512, stored in *.jpg* format.
- **Masks (Labels)**: Each image is associated with a **monochannel** segmentation mask, used as ground truth and stored in *.png* format.

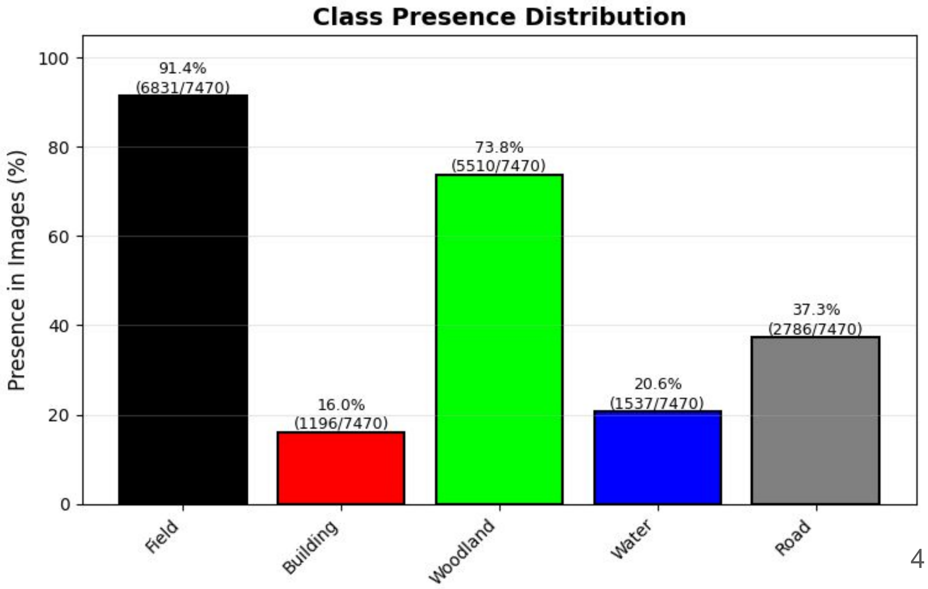
- **Data Splits**: The dataset is divided into ***Train, Val and Test*** subsets for model development and evaluation.
- **Classes**: The segmentation task includes 5 semantic classes: *Field, Woodland, Building, Water, and Road.*

About the classes

Class imbalance: lots of *Field*, few *Buildings* and *Roads*.

- **Accuracy is misleading:** high accuracy ≠ good classification.
- **Focus on minority classes:** monitor recall and consider alternative metrics (F1, IoU).
- **Use data augmentation or class weighting** to help underrepresented classes.





Feature choice

The current observation

- Heterogeneous dataset
- Images vary in intensity, texture, etc…
- **Hard to know a priori which features are most discriminative.**

The best solution

- Extracting a broad set of features (color, texture, geometry, multi-scale context) ensures all possible discriminative cues are captured.
- Dimensionality reduction (PCA) or feature selection can be applied later.

Color / Spectral
RGB, HSV

Intensity / Context:
Grayscale, Multi-scale Blur

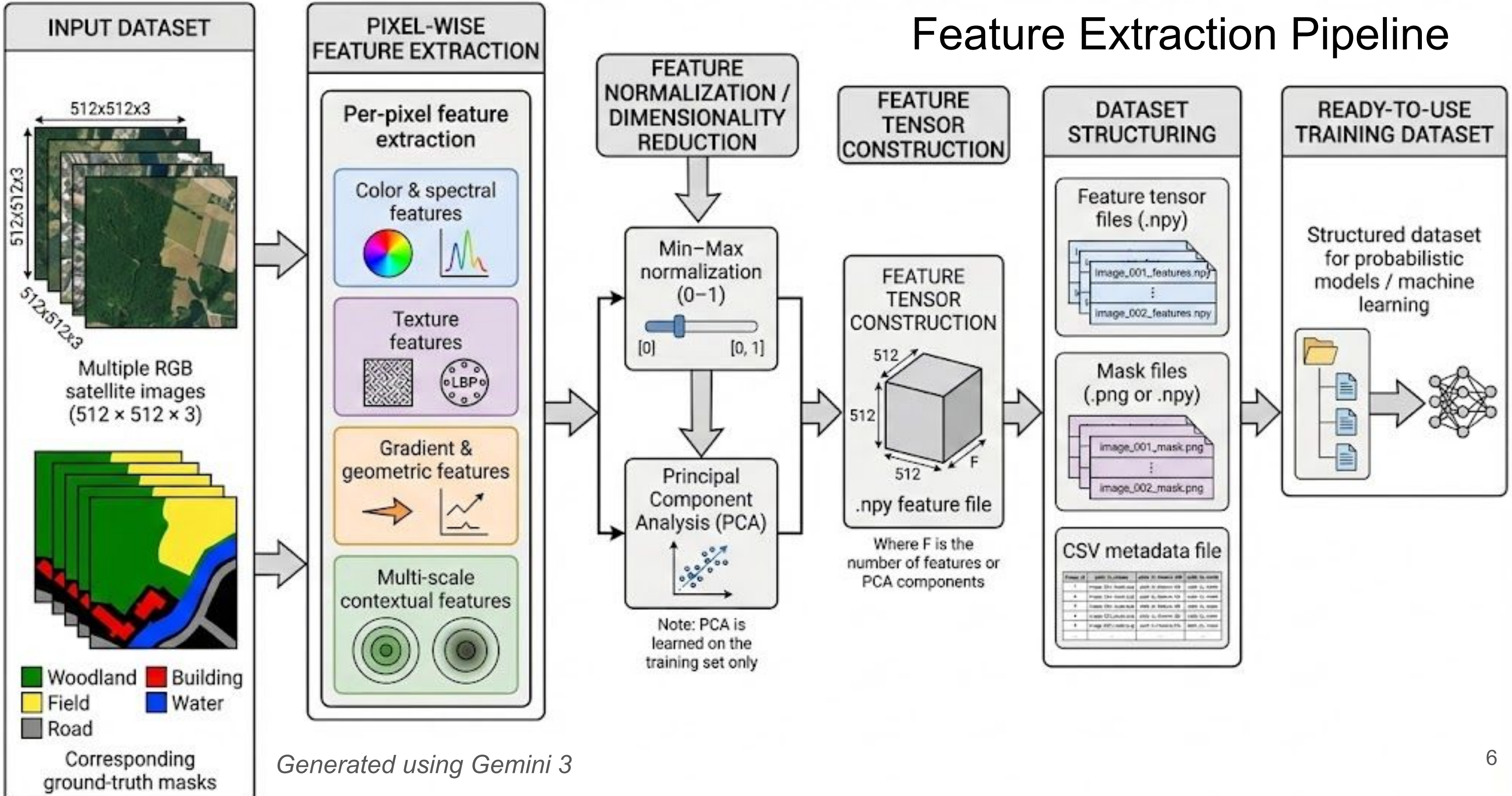
Gradient / Geometry
Gradient, Anisotropy

Texture
Variance, Entropy, LBP

Indices
NDVI, Water

Robustness for probabilistic models : Ensures that all relevant patterns can be captured by histogram-based or learning-based models.

Feature Extraction Pipeline



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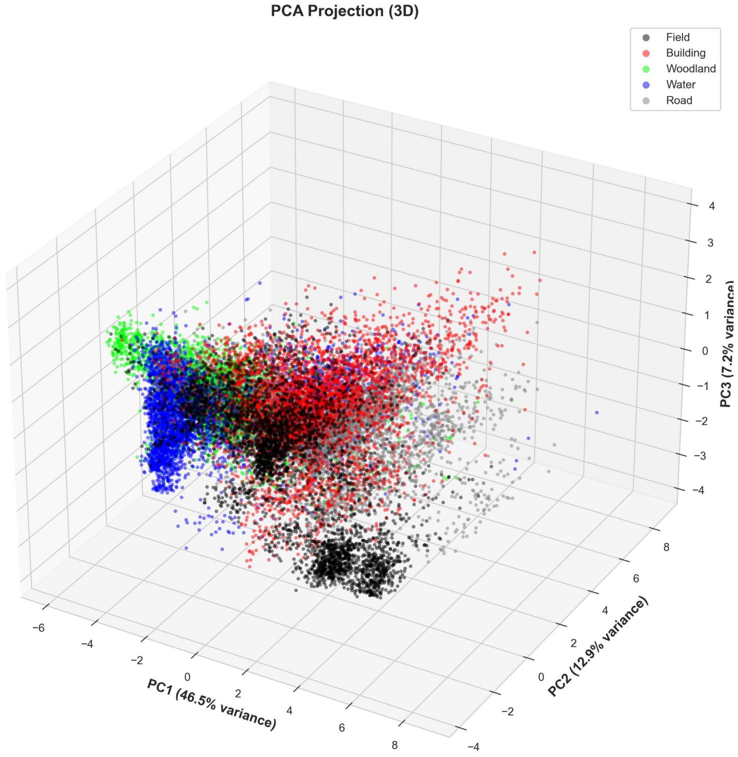
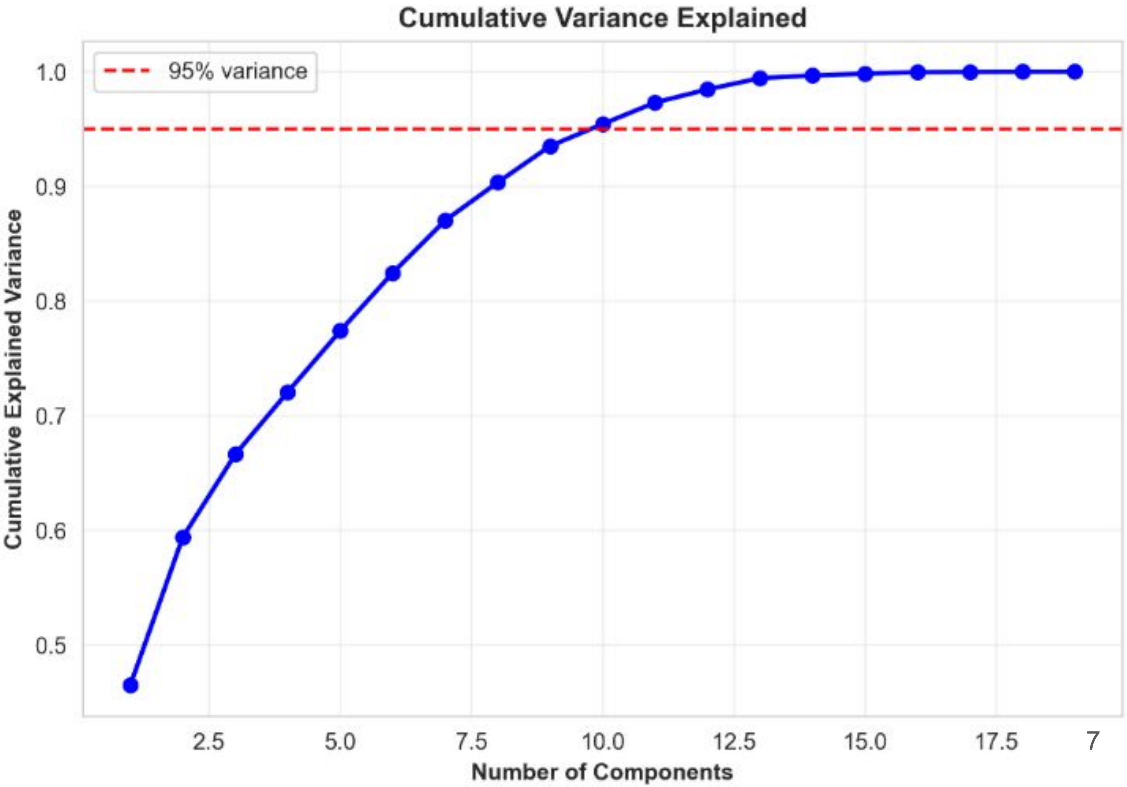
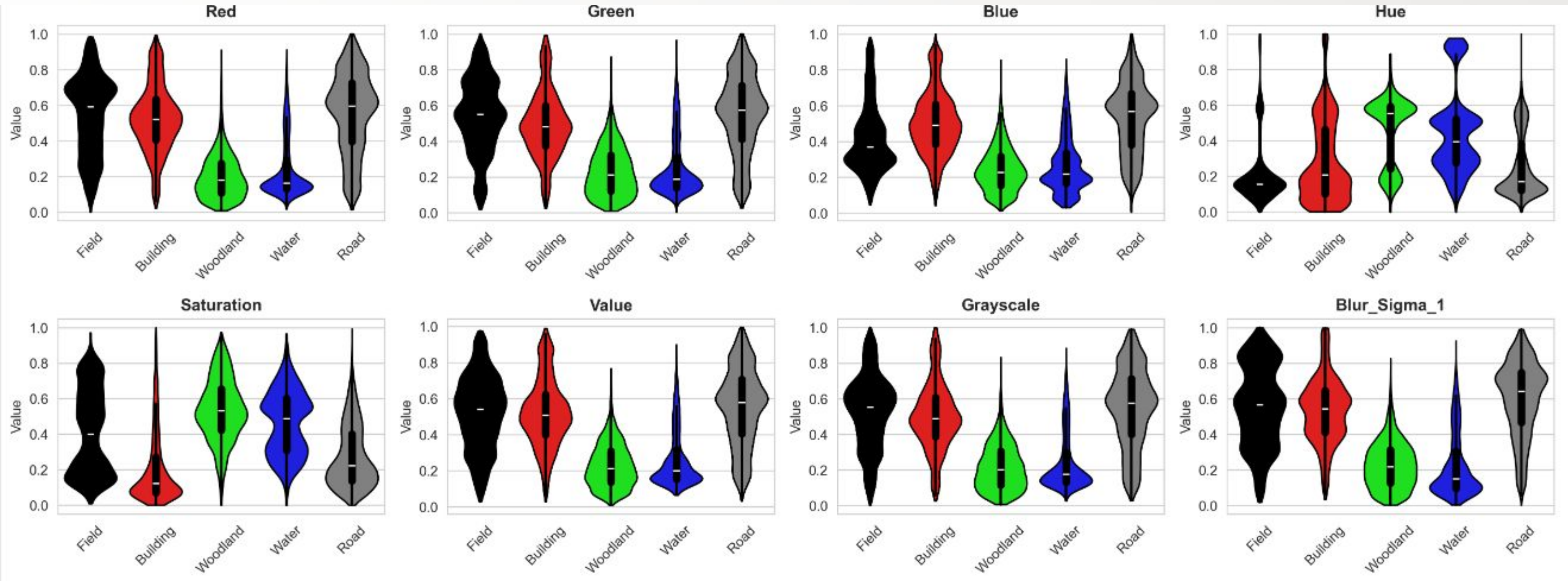
Selected Feature analysis





Selected Feature analysis



Histogram-Based Probabilistic Segmentation

- Each pixel is represented by a **feature vector** x∈ℝ^F
- For each class c, a **feature distribution** is learned using **histograms**
- Segmentation is performed by assigning each pixel to the most probable class:

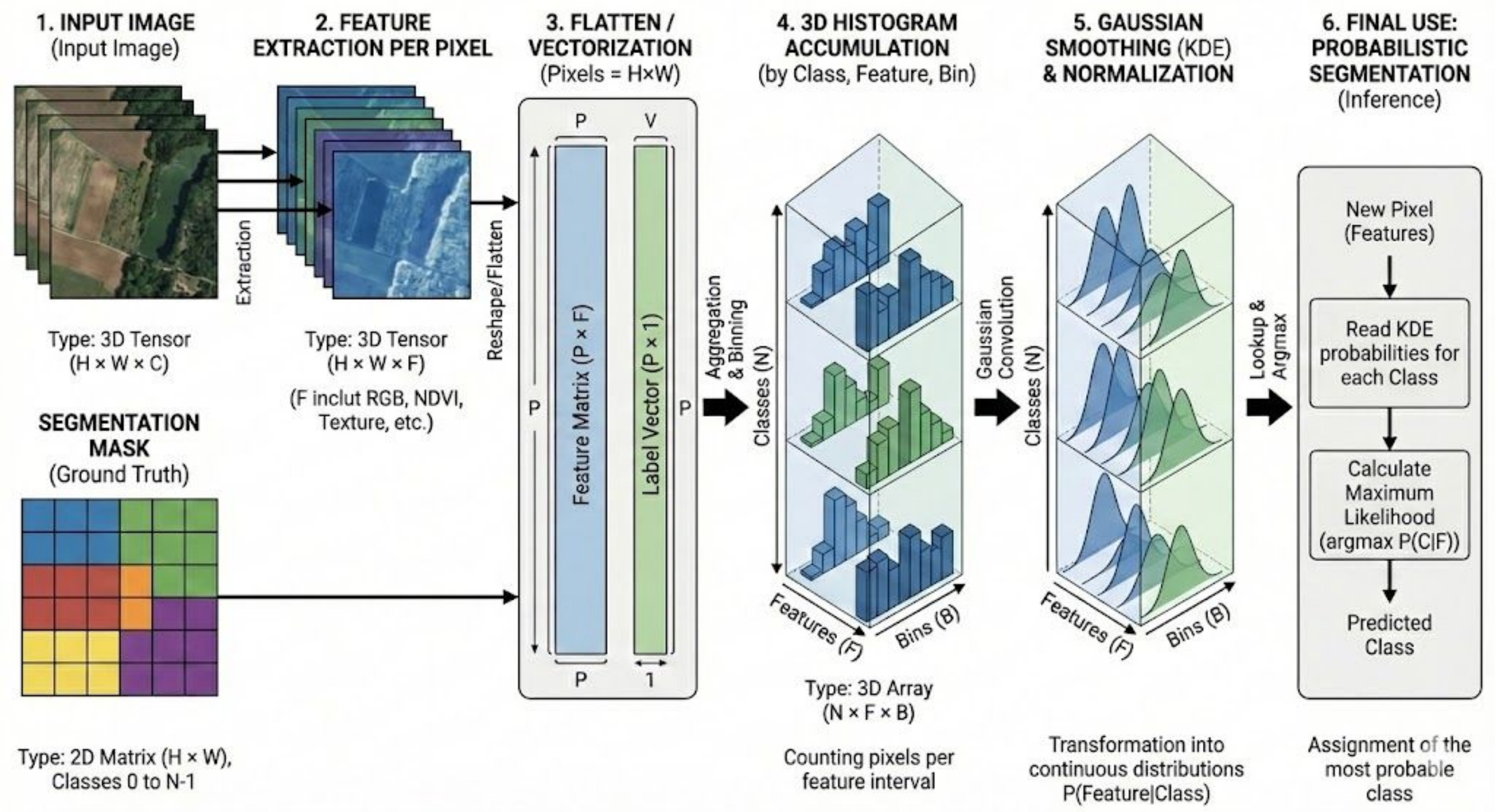
$$\hat{c} = \arg\max_{c} \; P(\mathbf{x} \mid c)$$

- Feature space is discretized into bins
- For each class ccc, a histogram estimates the density:

$$P(\mathbf{x} \mid c) \approx \frac{N_{c,\mathrm{bin}(\mathbf{x})}}{N_c}$$

Aspect	Multi-thresholding	Histogram-based Segmentation
Decision type	Hard, binary decision	Soft, probabilistic decision
Feature usage	Single or few features	Multi-dimensional feature vectors
Decision boundary	Fixed thresholds	Data-driven decision surfaces
Handling uncertainty	Not modeled	Explicitly modeled
Class overlap	Poorly handled	Naturally handled
Robustness to noise	Low	Higher

Histogram-Based Probabilistic Segmentation



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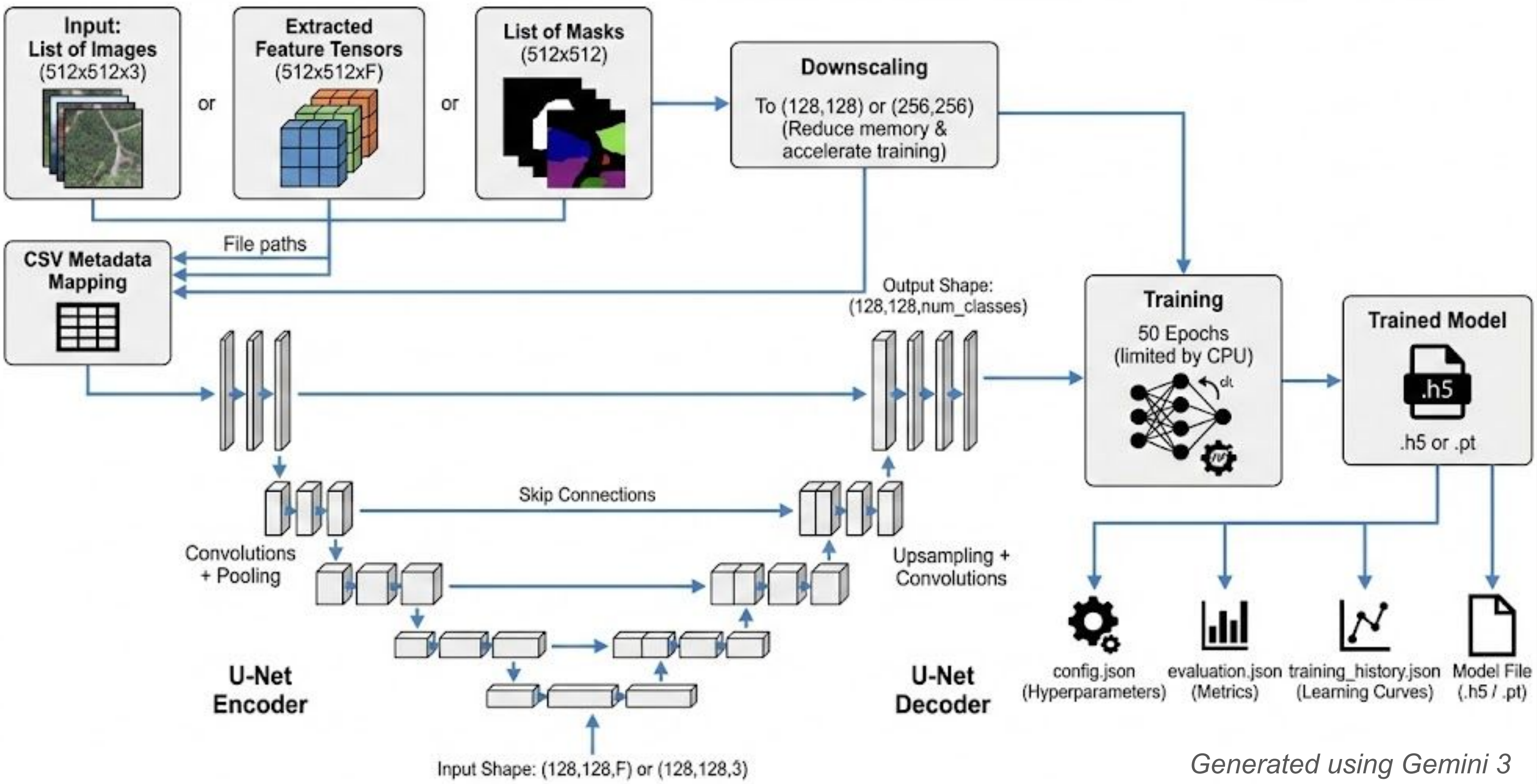
Another Technique: CNN Pipeline using U-Net



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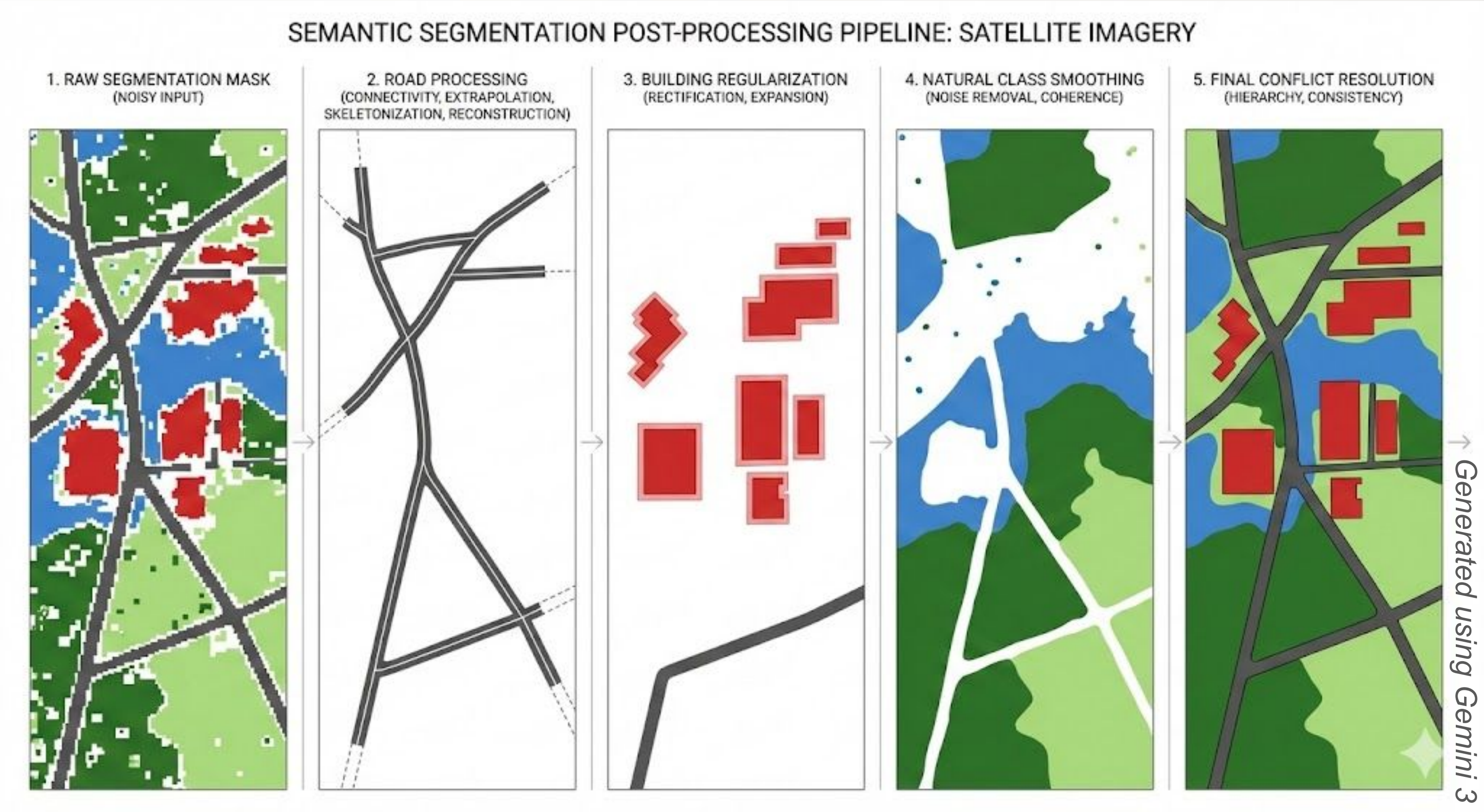
Post-Processing : *Main Ideas*



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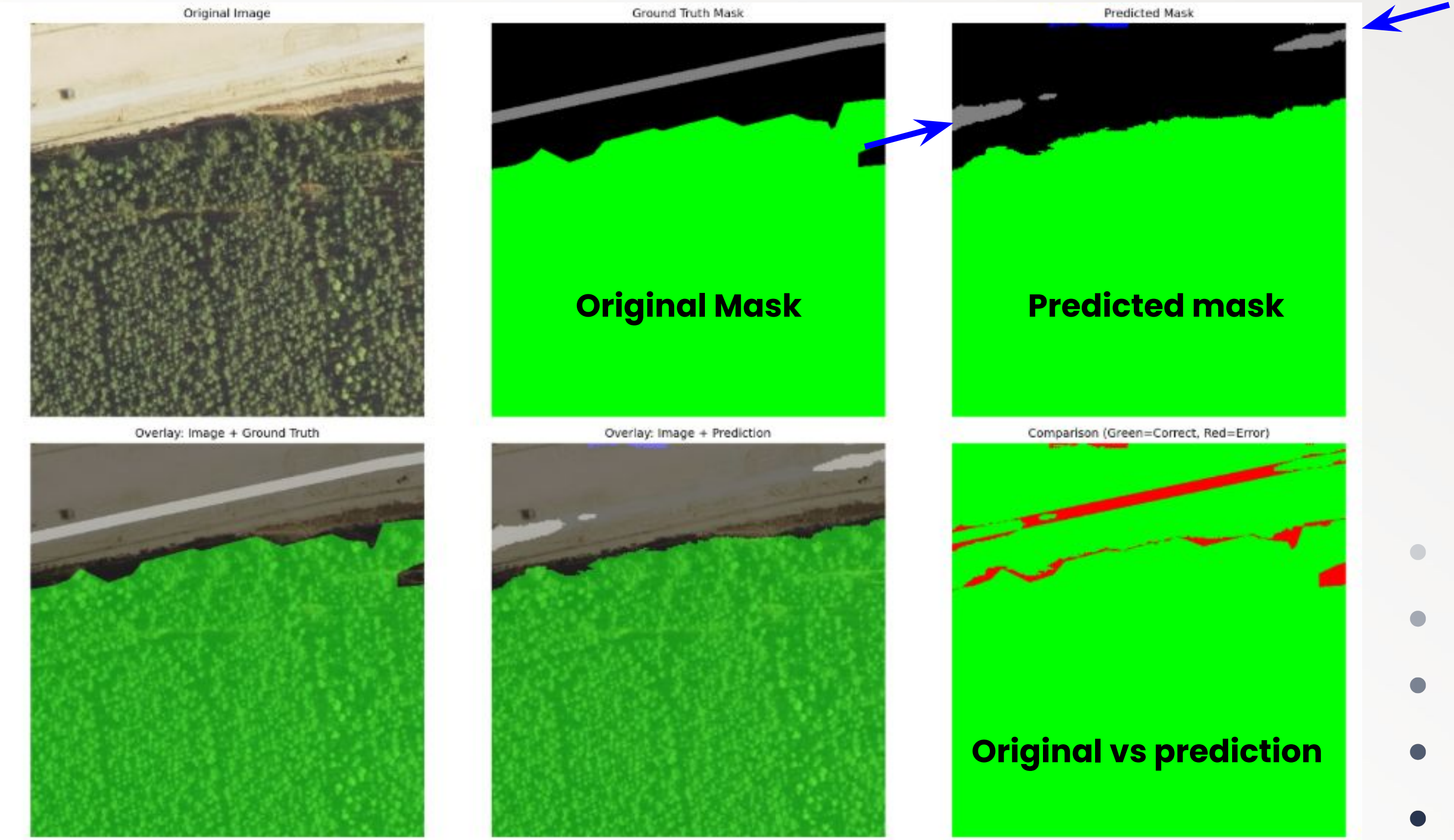
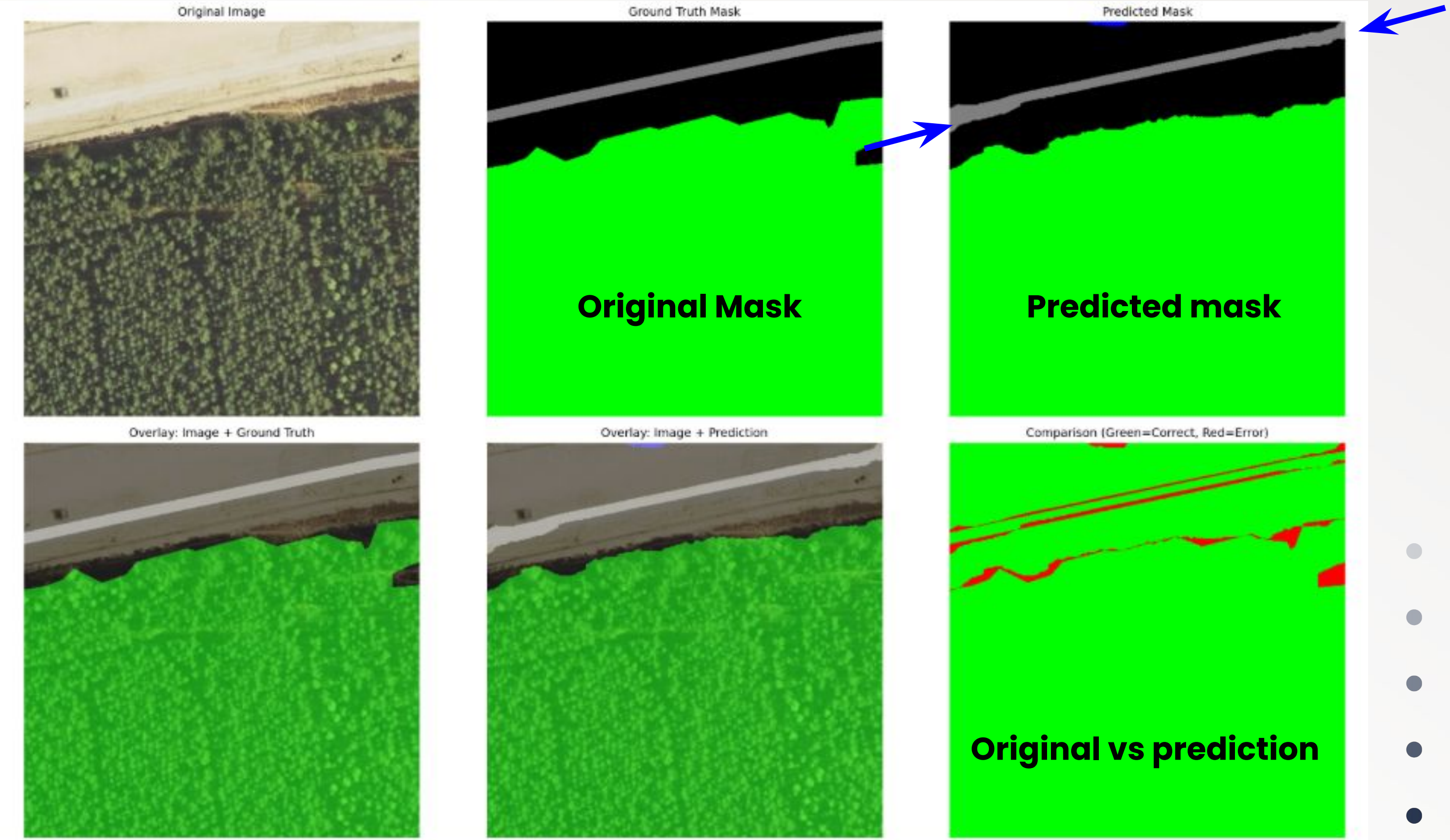
Post-Processing Example : *Before*



Post-Processing Example : *After*



Choice of Evaluation Metrics

Dice Coefficient

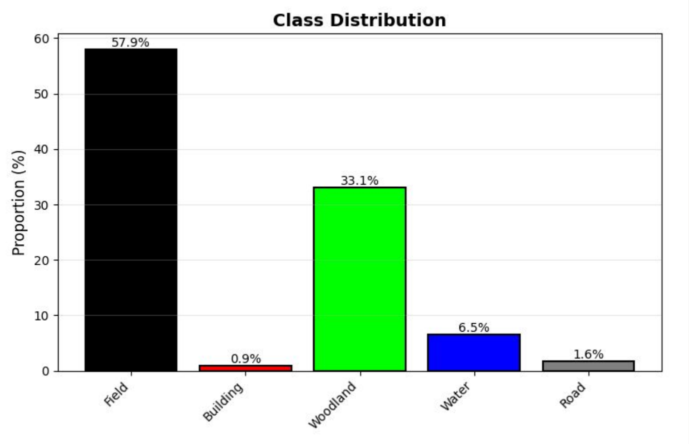
- Measures **spatial overlap** between prediction and ground truth
- Sensitive to **false negatives and false positives**, unlike accuracy
- Ideal for **imbalanced classes**

$$\text{Dice} = \frac{2TP}{2TP + FP + FN}$$

- *TP (True Positives)*
- *FP (False Positives)*
- *FN (False Negatives)*

Why not Accuracy

- Large class imbalance in satellite images
- accuracy can be **misleadingly high**



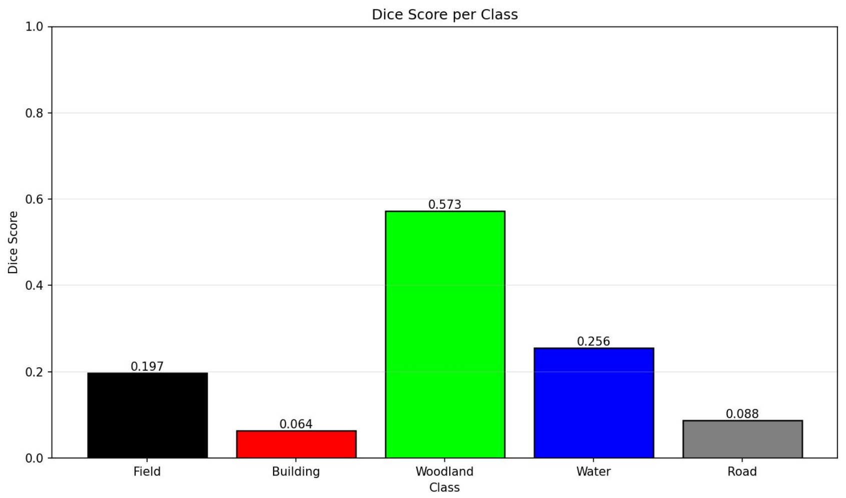
Class-specific strategy

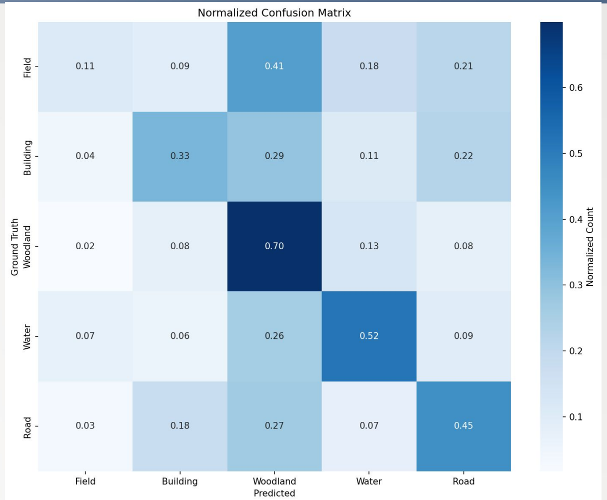
- **Roads and Buildings**: prioritize **high recall**
- Slight over-prediction (FP) is acceptable

Results

Histogram

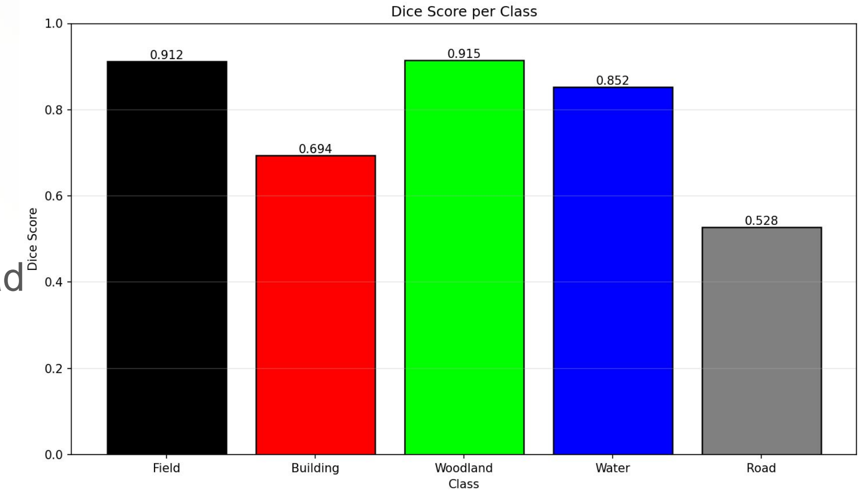
Very bad results
for now

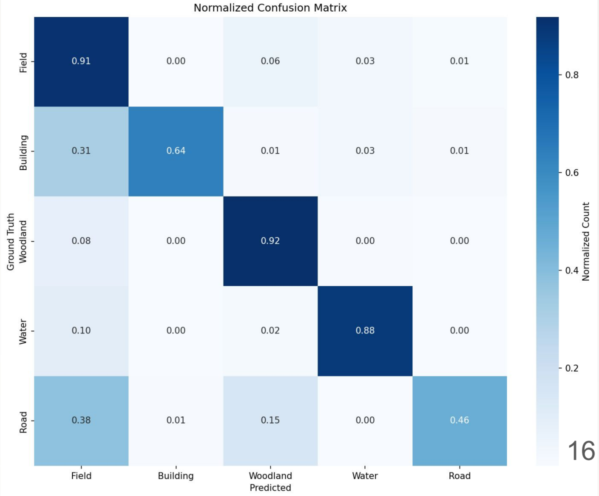




Unet

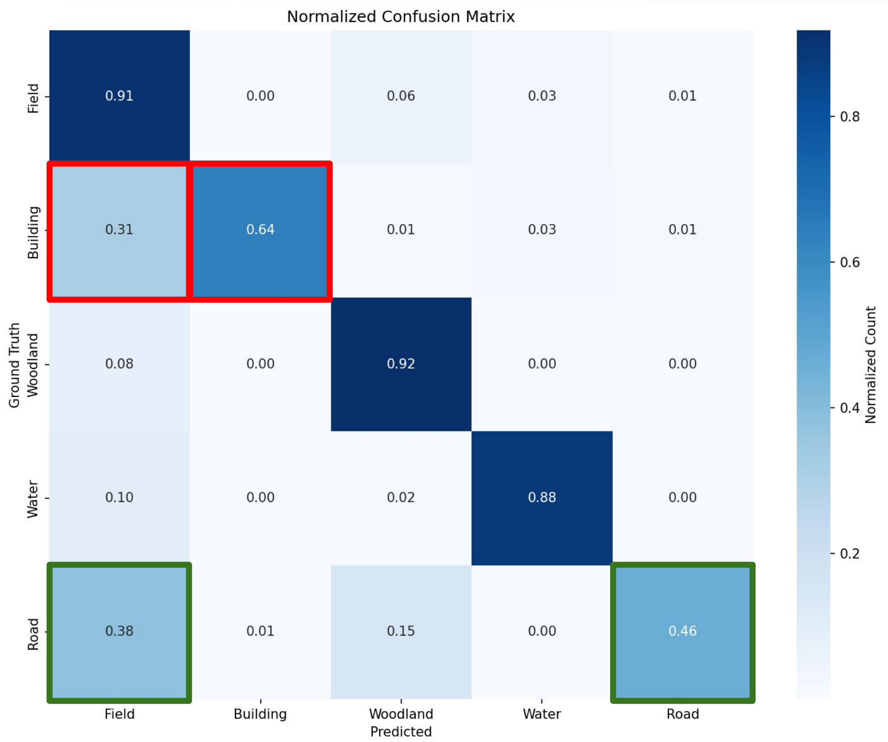
Good results
Moderate Dice
on Building and Road



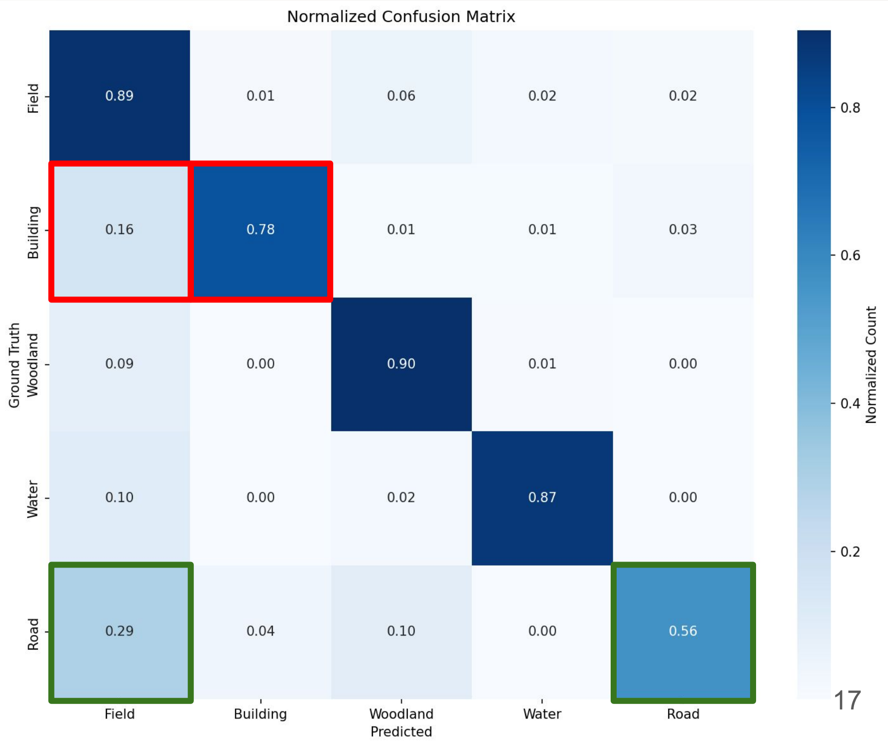


Post-Processing Impact

Before Post-Processing

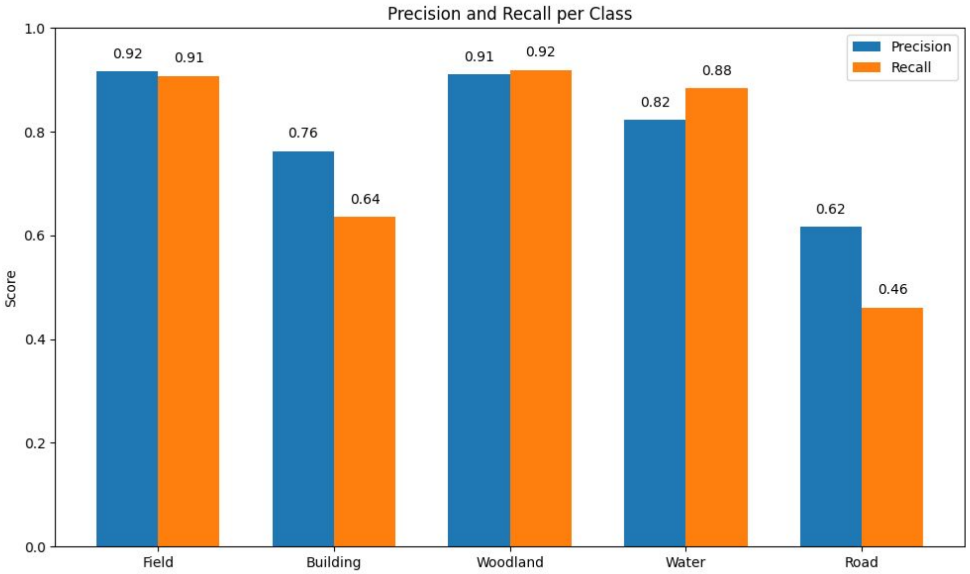


After Post-Processing

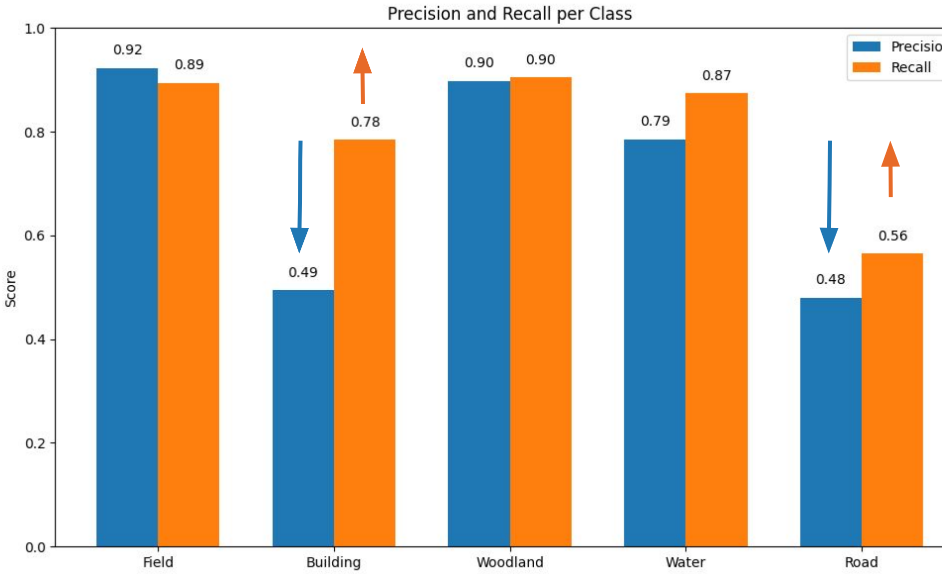


Post-Processing Impact

Before Post-Processing



After Post-Processing



Conclusion : Improvement Perspectives

Learning & Actions Taken

- **Built a pipeline** for feature extraction, preprocessing, training, and evaluation
- **Achieved good U-Net segmentation results**, while handling class imbalance and prioritizing recall for small structures
- Learned the importance of selecting relevant features for effective segmentation

Perspectives / Future Work

- **Improve computation efficiency**, code robustness
- **Explore better histogram-based methods** and additional or more relevant features
- **Improve Post-Processing pipeline** for better performances

References :

First image: https://www.mdpi.com/2072-4292/8/4/329
Dataset Official Link: https://landcover.ai.linuxpolska.com/
Dataset Kaggle Link: https://www.kaggle.com/datasets/aletbm/land-cover-from-aerial-imagery-landcover-ai

GitHub Repository