Tree Detection, Counting & Classification from Satellite Imagery

# Project Overview

This project focuses on detecting, counting, and classifying individual trees from high-resolution satellite imagery using deep learning models. The goal was to support ecological monitoring and environmental planning by automating the identification and analysis of vegetation from space.

# Objective

- Detect and localize individual trees in satellite images.

- Count the number of trees accurately.

- Classify different types of vegetation based on spatial and visual features.

- Support large-scale forest monitoring and management using AI.

# Tools & Technologies Used

- Python

- PyTorch, TensorFlow

- YOLOv8, Faster R-CNN

- OpenCV, Roboflow

- Google Colab

- LabelImg, Roboflow Annotate

- Evaluation: IoU, mAP, F1-score

# Workflow & Methodology

1. Dataset Collection:

- Acquired satellite images from SentinelHub and Google Earth Engine.

2. Data Annotation:

- Annotated trees using LabelImg and Roboflow Annotate.

3. Data Preprocessing:

- Resized images, applied augmentations, split data.

4. Model Training:

- Trained YOLOv8 and Faster R-CNN using Colab GPU.

- Hyperparameters tuned for optimal accuracy.

5. Evaluation:

- Used IoU, mAP, F1-score to assess performance.

6. Tree Counting:

- Counted trees from YOLOv8 outputs using bounding boxes.

7. Classification (Optional):

- Fine-tuned ResNet18 for species-level classification.

8. Visualization:

- Plotted detection results and generated reports.

# Results

| Model | mAP@0.5 | F1 Score | Tree Count Accuracy |

|--------------|---------|----------|----------------------|

| YOLOv8 | 0.87 | 0.91 | ±95% accuracy |

| Faster R-CNN | 0.89 | 0.93 | ±97% accuracy |

# Key Learnings

- Small object detection requires high-quality data and annotations.

- YOLOv8 is fast and reliable for real-time applications.

- Data augmentation enhances model generalization.

- Faster R-CNN provides better results in complex environments.

# 🌍 Impact

- Enables scalable and automated forest monitoring.

- Useful in biodiversity, green cover tracking, and post-disaster recovery.

- Can be adapted for agriculture or urban green analysis.

Spatial-Temporal Tree Change Detection

## Summary

Analyzed multi-year satellite data to map changes in tree cover over time using deep learning models. The objective was to monitor deforestation, reforestation, and overall ecological trends using spatial-temporal analysis.

## Skills & Tools Used

- Image Segmentation  
- Roboflow  
- QGIS  
- Python, OpenCV  
- Multi-temporal Satellite Imagery  
- Deep Learning (UNet, YOLOv8)

## Process Overview

1. Collected satellite images from different years for the same geographic region.  
2. Used Roboflow and manual annotation to label tree regions.  
3. Trained segmentation models (U-Net) to extract vegetation masks.  
4. Performed change detection by comparing segmented masks across years.  
5. Visualized changes using QGIS and generated spatial reports.  
6. Quantified tree loss or gain per region using pixel-level analysis.

## Key Highlights

- Enabled visual comparison of tree cover across years.  
- Detected patterns of deforestation and reforestation.  
- Contributed to land-use planning and forest conservation efforts.