Faster RCNN for Forest Fire Detection

Object Detection

A dive into the FASTer-RCNN architecture and applications

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Wildfire Detection Challenges

WildFire Detection

Every year, wildfires devastate an average of **6-7 million acres** of land—destroying homes, displacing wildlife, and endangering lives. But **What if we could detect them sooner?**

What is a Wildfire and Why is it Dangerous?

A wildfire is an uncontrolled blaze fueled by wind and heat, growing more frequent and intense due to climate change **causing:**

🔥 **Environmental:**
Deforestation, wildlife loss, and air pollution.

💰 **Economic:**
Billions in damages, high firefighting costs, and business disruptions.

🏠 **Human:**
Displacement, health risks, and loss of lives.

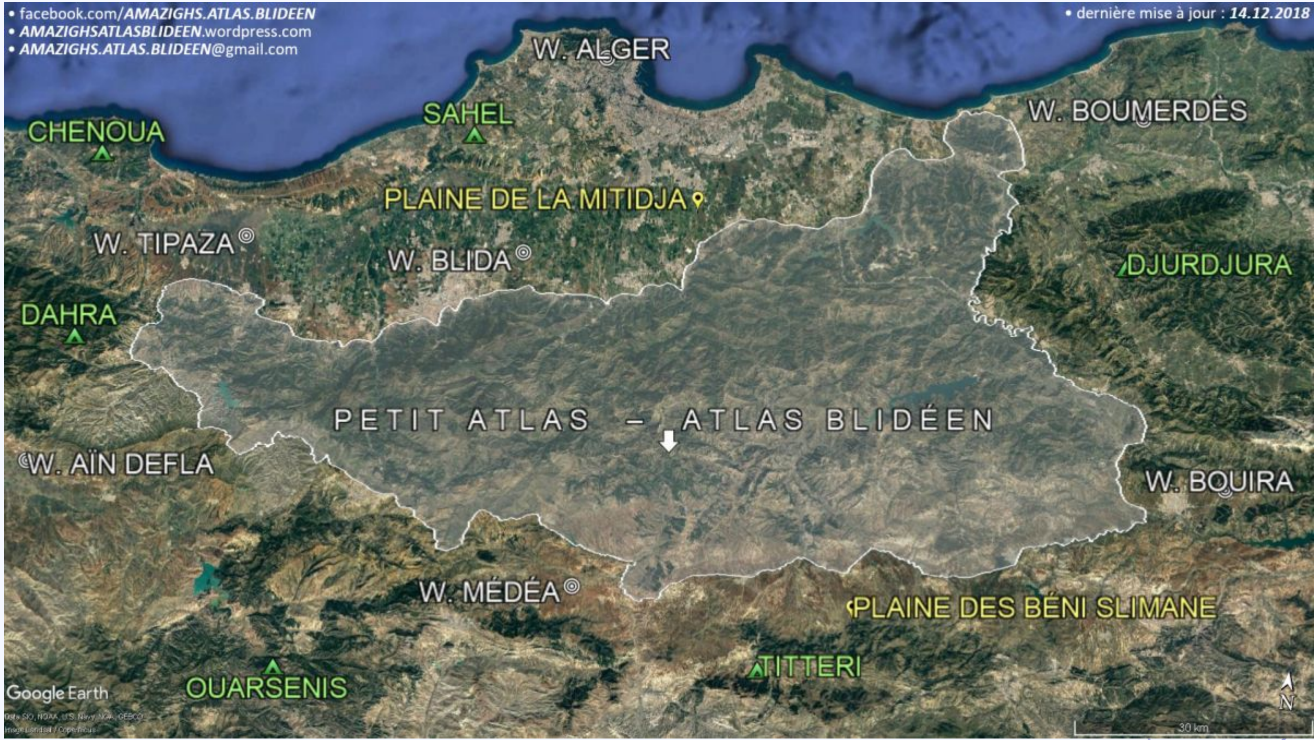
Traditional Methods vs. Satellite Imagery

Traditional Methods	Satellite Imagery
Relies on human observation (watchtowers, patrols)	Automatically detects fires from space
Drones (high cost, limited coverage)	Monitors vast areas in real-time
Firefighters depend on public reports	Operates 24/7, even in remote locations

Proposed solution

Source: European Union, Copernicus Sentinel-3 imagery

Our solution leverages satellite imagery and advanced deep learning techniques—specifically **Faster R-CNN**—to detect wildfires at an early stage, helping mitigate damage before it's too late.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How Region-Based Models Work ?

Region Proposals

first generate region proposals — potential areas in the image where objects might be present.

Feature Extraction per Region

Each proposed region is then resized and passed through a Convolutional Neural Network (CNN) to extract feature representations.

Classification and Bounding Box Regression

Each region's features are classified to determine what object it contains.
A bounding box is also generated or refined to closely outline the detected object.

Why Faster-RCNN ?

02

Data Collection and Preprocessing

Dataset sources

We merge **11** different datasets from roboflow

- **Wildfire N12RK**
- **Wildfire Satellite**
- **Wildfire YH86L**
- **Fire Forest New**
- **Fire Forest Gen**
- **12345-su5ee**
- **640x640 XDhu3**
- **Fire Detection2 Wayva**
- **DLR**
- **Volcano NZTT3**
- **Wildfire Detection Satellite**

Preprocessing:

1. 🧹 **Cleaning:**
Removed low-quality, duplicate, and corrupted images.

2. 📏 **Resizing:**
Standardized image resolution.

3. 📊 **Normalization:**
Scaled pixel values for stable training.

4. 🚫 **Augmentation:**
Not applied due to computational constraints.

Challenges Faced 🚧

🖼️ **Irrelevant Images:**
Some dataset images were unrelated to fires, requiring manual filtering.

🌀 **Augmented Data:**
Pre-existing augmentation affected data consistency.

💻 **High Computational Needs:**
Faster R-CNN demands significant processing power.

Data Reduction and Splitting

The dataset was reduced by **54.5%** To fit Kaggle’s memory limits.

📚 **Train:**
19,407 files **(87.1%)** for Model learning.

⚙️ **Valid:**
1,623 files **(7.3%)** for Hyperparameter tuning.

🧪 **Test:**
1,251 files **(5.6%)** for Final evaluation.

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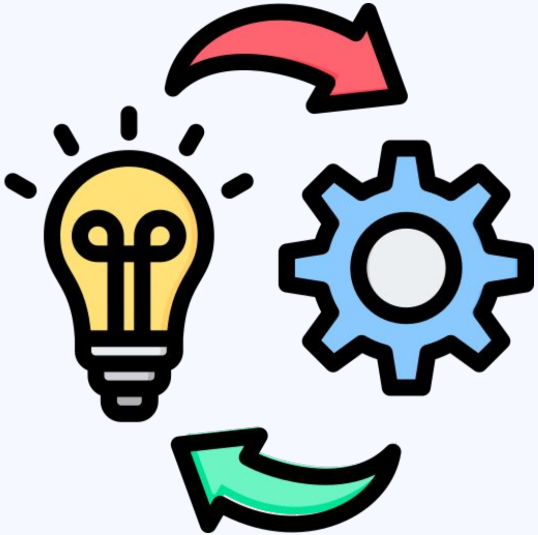
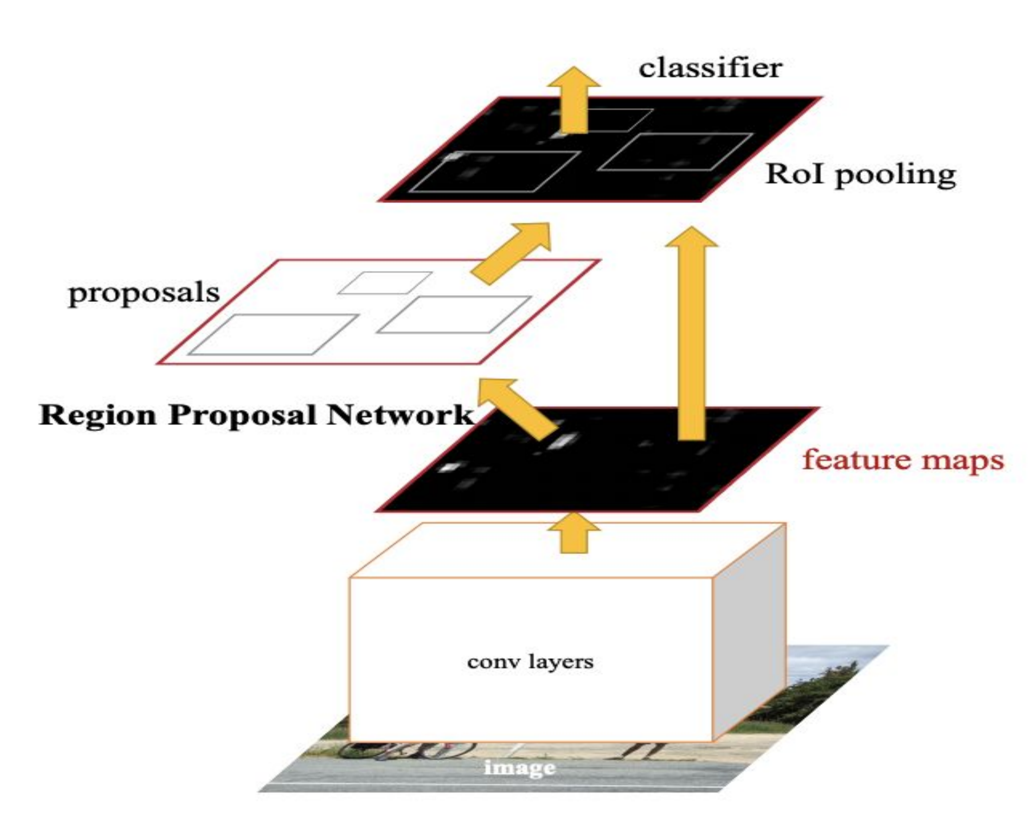
Faster R-CNN: Architecture and Training



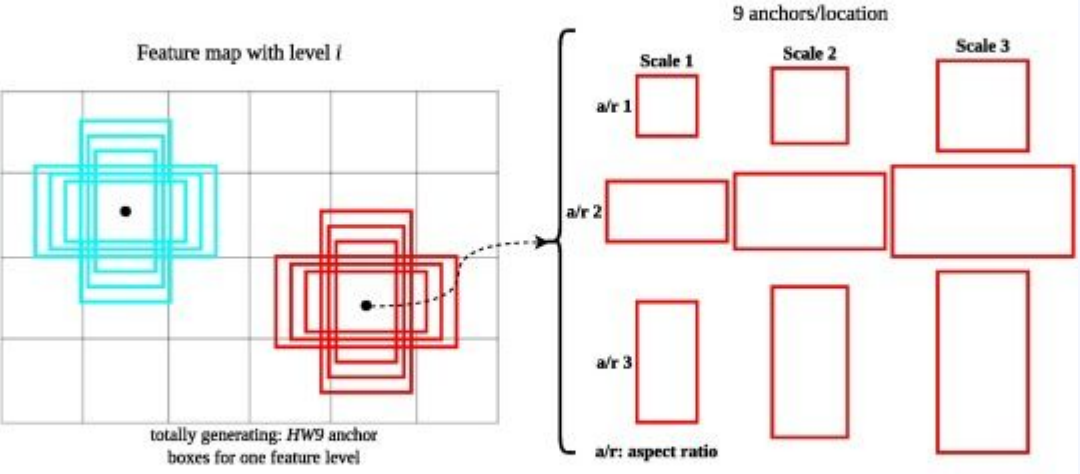
Faster rcnn architecture

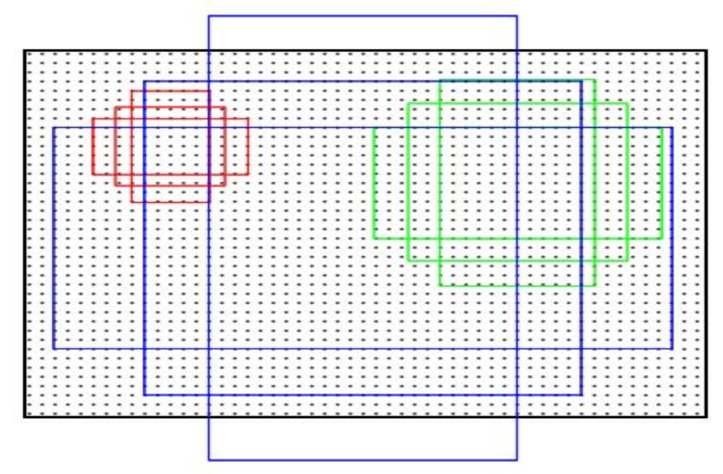
- We'll dive into:
  Region proposal network
  Region of Interest



Region proposal network

- The RPN generates **Region of Interest (RoI)** proposals, which are potential bounding boxes where objects might exist. This module significantly speeds up the process compared to earlier methods

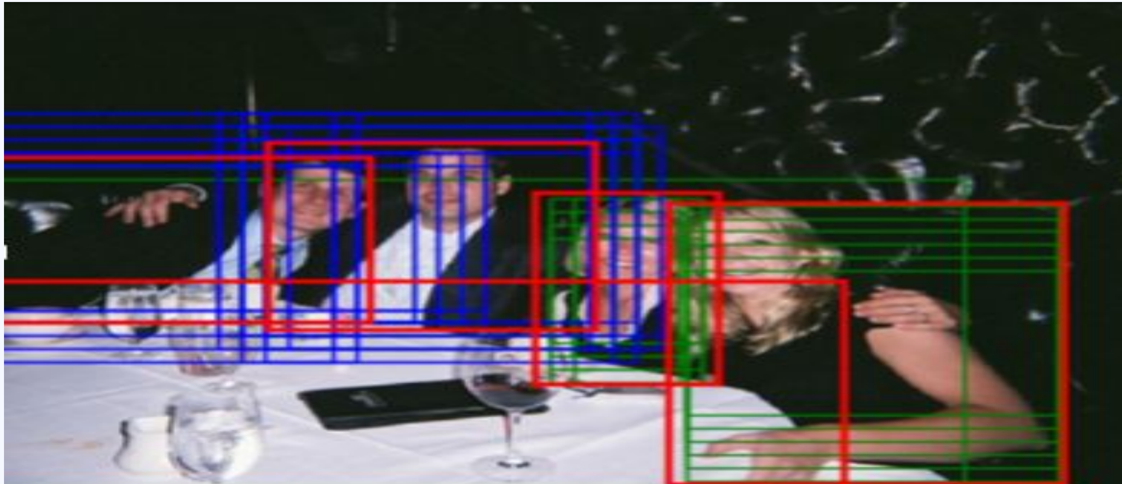


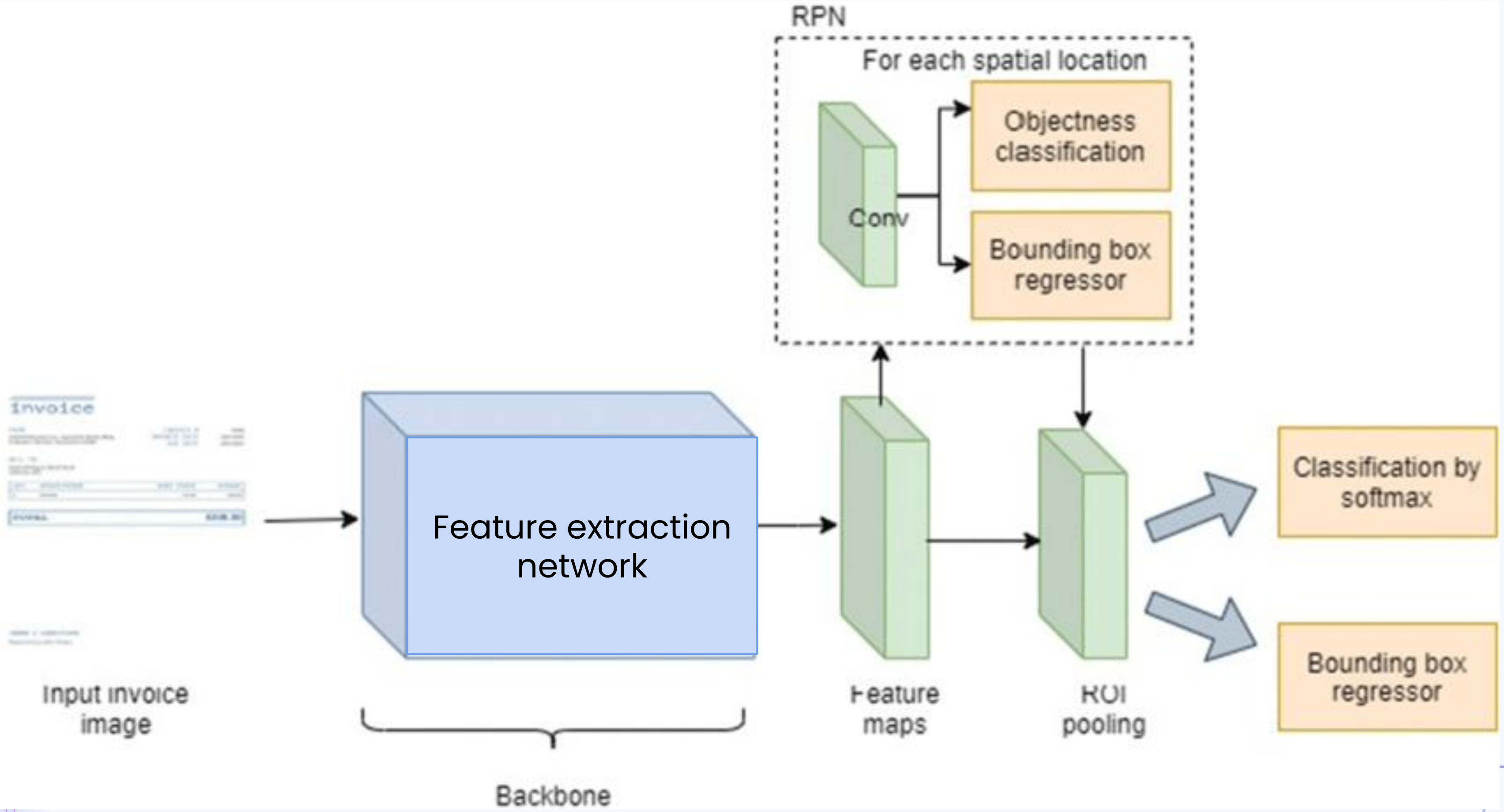


Region proposal network

- The image with the anchor boxes in every grid goes through the RPN which is a fully convolutional network (FCN)
- The region proposal neural network output to different vectors
- The first one tackle the classification problem
- The second one has the coordinate of the bounding box

  - We classify every anchor into ***object if the iou*** >= 0.7
  - ***background if the iou*** <= 0.3
  - ***mix*** if it's neither positive or negative




RPN
For each spatial location
Conv
Objectness classification
Bounding box regressor
Feature extraction network
Input invoice image
Backbone
Feature maps
ROI pooling
Classification by softmax
Bounding box regressor

Backbone Selection

	ResNet 50	EfficientNet_B3	ResNet 101
Model Depth	50 layers	233 layers	101 layers
Accuracy	High (competes well with many models)	Higher accuracy for fewer parameters	very High
Inference Speed	Moderate	Faster than ResNet-50 (in many cases)	Less efficient
Computational Efficiency	Moderate	Very efficient (fewer parameters)	computationally heavier

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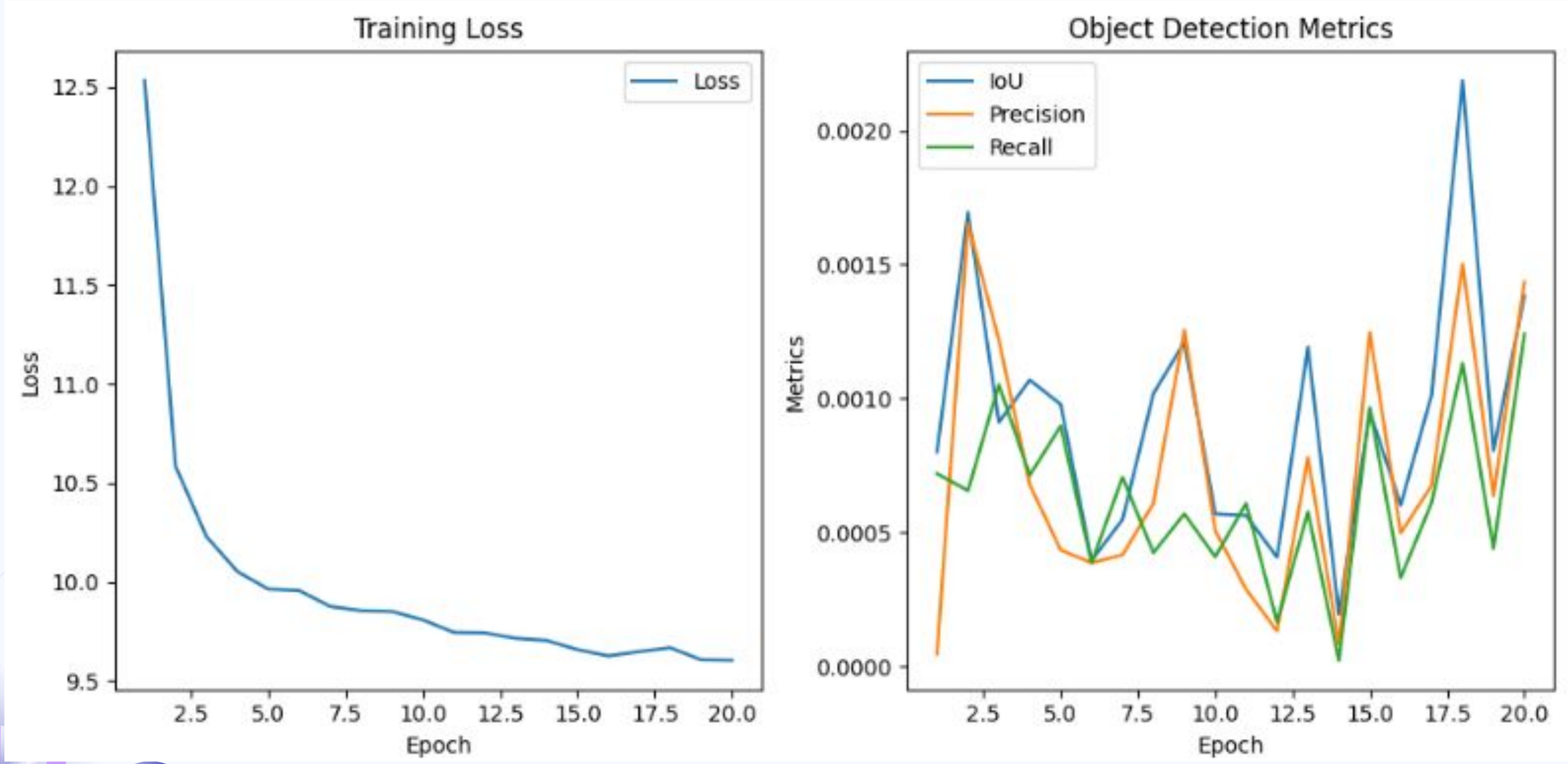
Performance Evaluation and Future Prospects

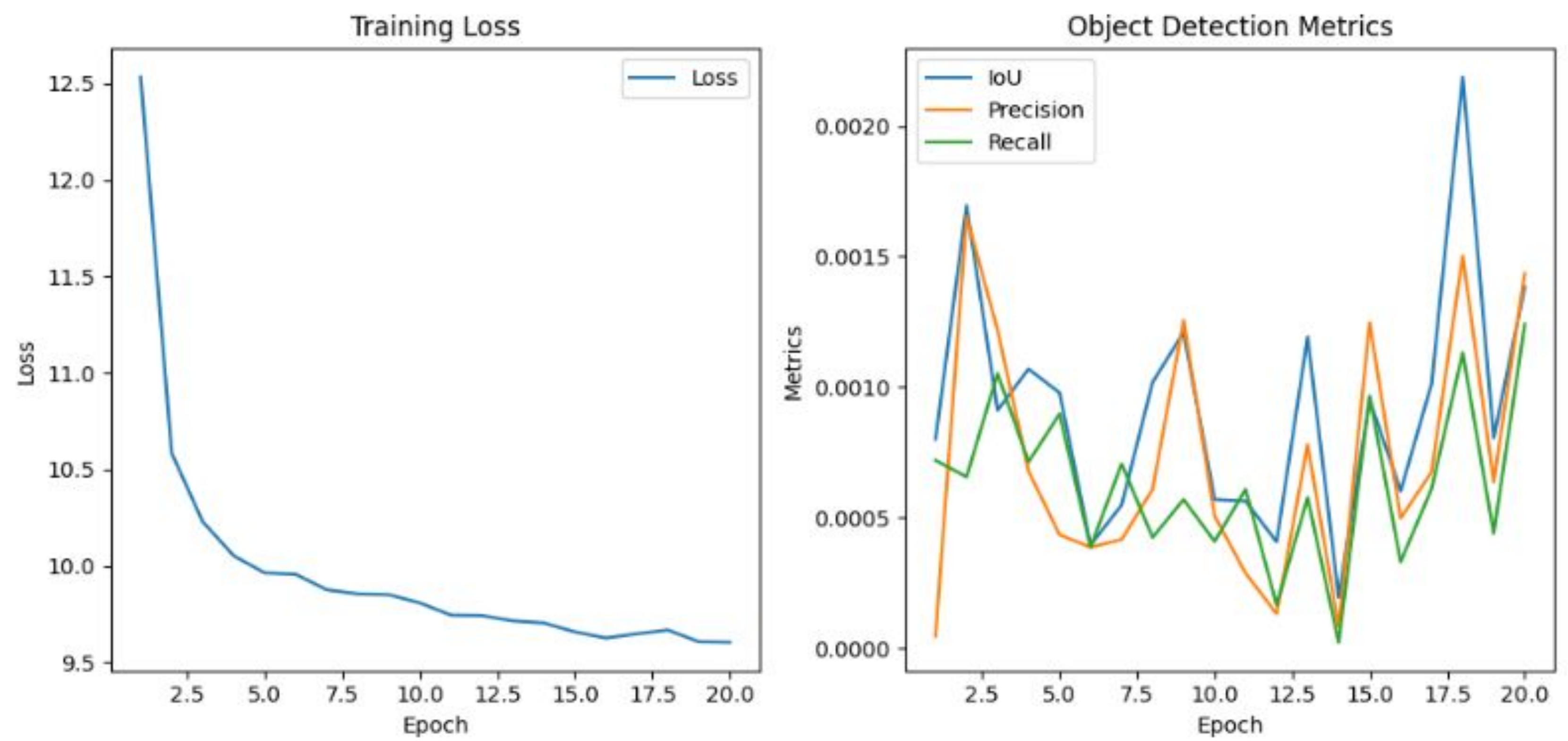
Results

EfficientNet_B3



Results

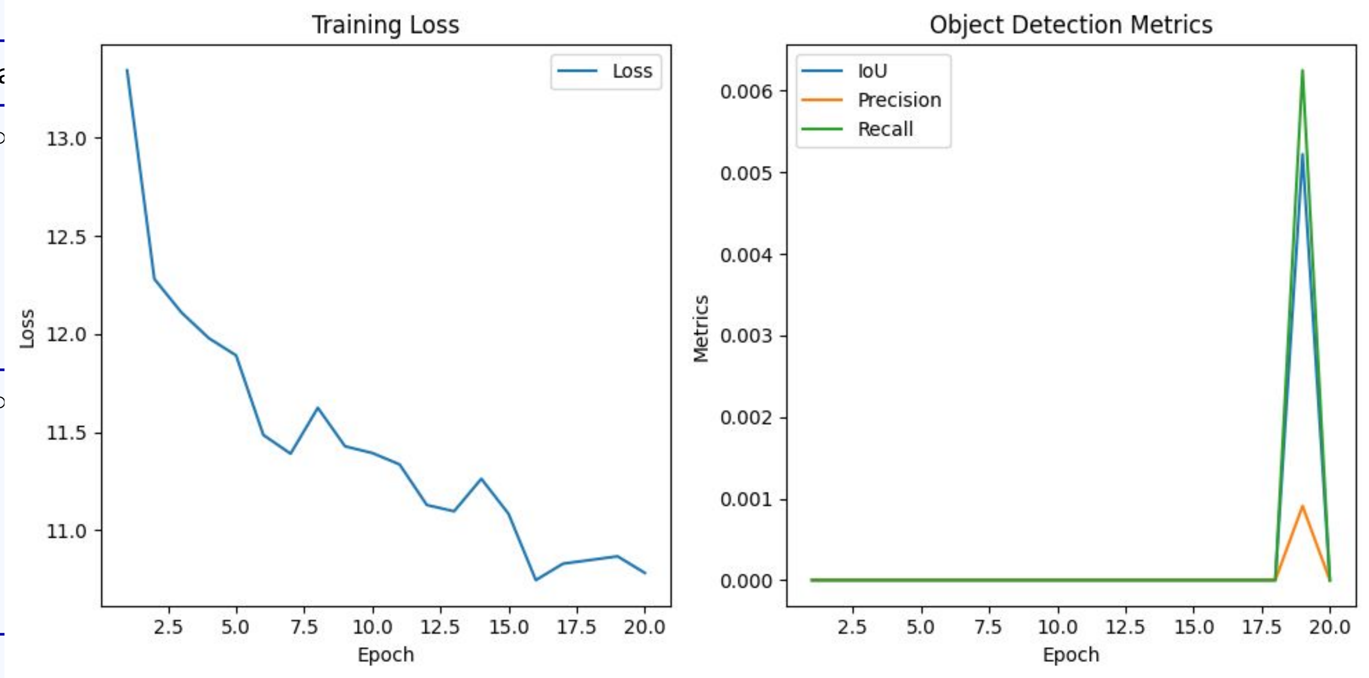
ResNet 101



Results

ResNet 50

	Tra	: 40
first epoch	Ep	its)"
last epoch	Ep	its)"



Analysis of Results

Model Performance:

01

🥇 ResNet-101

02

🥈 EfficientNet-B3

03

🥉 ResNet-50

Metric	Faster R-CNN 🥈 (EfficientNet)	Faster R-CNN 🥉 (ResNet-50)	Faster R-CNN (ResNet-101) 🥇
IoU	0.0023	0.0019	**0.0049**
mAP	0.0014	0.0001	**0.0040**
Precision	0.0010	0.0004	**0.0030**
Recall	0.0019	0.0013	**0.0031**
F1-score	0.0013	0.0004	**0.0028**

Future Perspectives

🌀 **Real-Time Deployment:**
Implementing the model for real-time wildfire detection and automated alert systems.

💻 **Performance Optimization:**
Reducing inference time and memory consumption to improve efficiency, particularly for real-time applications on edge devices.

🖼️ **Data Augmentation and Expansion:**
Increasing dataset diversity through advanced augmentation techniques to enhance generalization across different environmental conditions.

📹 **Integration with Surveillance Systems:**
Deploying the model in drone-based and satellite-based fire monitoring systems to enhance early detection.

Conclusion

The results show that the tested **Faster R-CNN** models **did not achieve satisfactory performance** in terms of **IoU** and **mAP**, likely due to an insufficient **number of epochs,** suboptimal architecture for the problem, or lack of computing power. Among the tested architectures, **ResNet-101** on the X-Large dataset showed the best overall performance, but it remained low.

To improve these results, adjustments such as increasing the **number of epochs**, **using a better GPU**, tuning hyperparameters, and exploring alternative architectures may be necessary

Thanks !