RUINS TO RECOVERY:
MACHINE LEARNING FOR DISASTER BUILDING DETECTION

Ruthik Kale (GRA – ITOS)

01

INTRODUCTION

Introduction

- Rapid and accurate building detection is critical for effective disaster response and resource allocation.
- Existing methods are often overwhelmed by the scale and urgency of post-disaster needs.
- This project introduces machine learning solutions, specifically tailored to enhance speed and accuracy in building detection under disaster conditions.

02

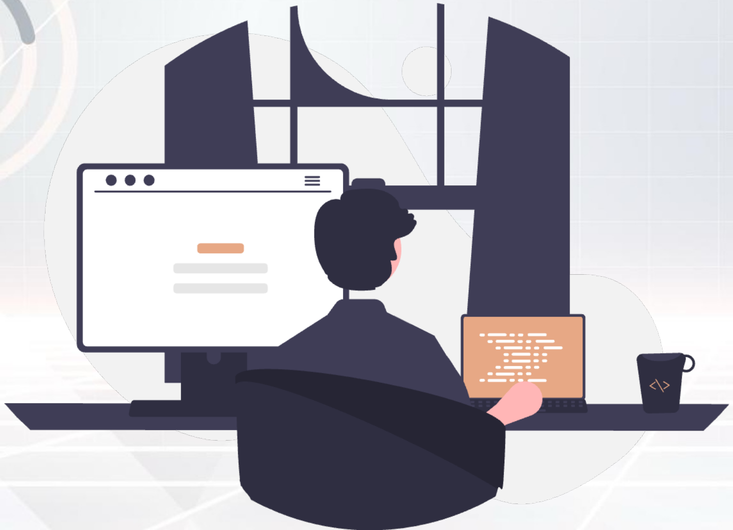
BACKGROUND & RELATED WORK

Background & Related Work

- Conventional building detection methods are manual and slow, struggling to meet the demands of timely disaster response.
- Recent advancements in CNNs have shown promise in remote sensing but are underutilized in disaster scenarios.
- Our study builds on existing knowledge and introduces machine learning architectures tailored for post-disaster building detection.

03

METHODOLOGY OVERVIEW




Data Collection
Data Preparation
Model Training
Model Evaluation
Results

04

DATA PREPARATION

Data Preparation

- High-resolution satellite images are segmented into 1024x1024 pixel chunks using rasterio and PIL, optimized for efficient processing.

- GeoPandas is employed to create precise building masks from shapefiles, essential for accurate model training.

- Images and masks are converted into TensorFlow-compatible TFRecord files, enhancing the model's training efficiency.

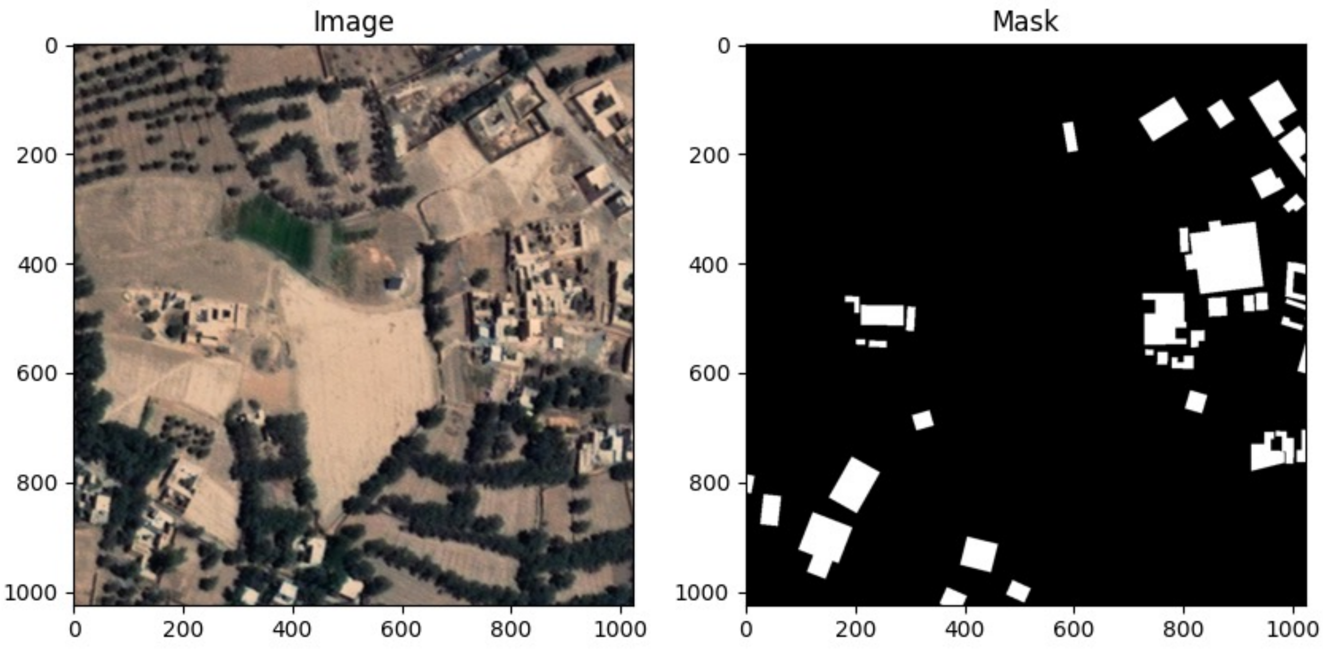


Image
Mask
0
200
400
600
800
1000

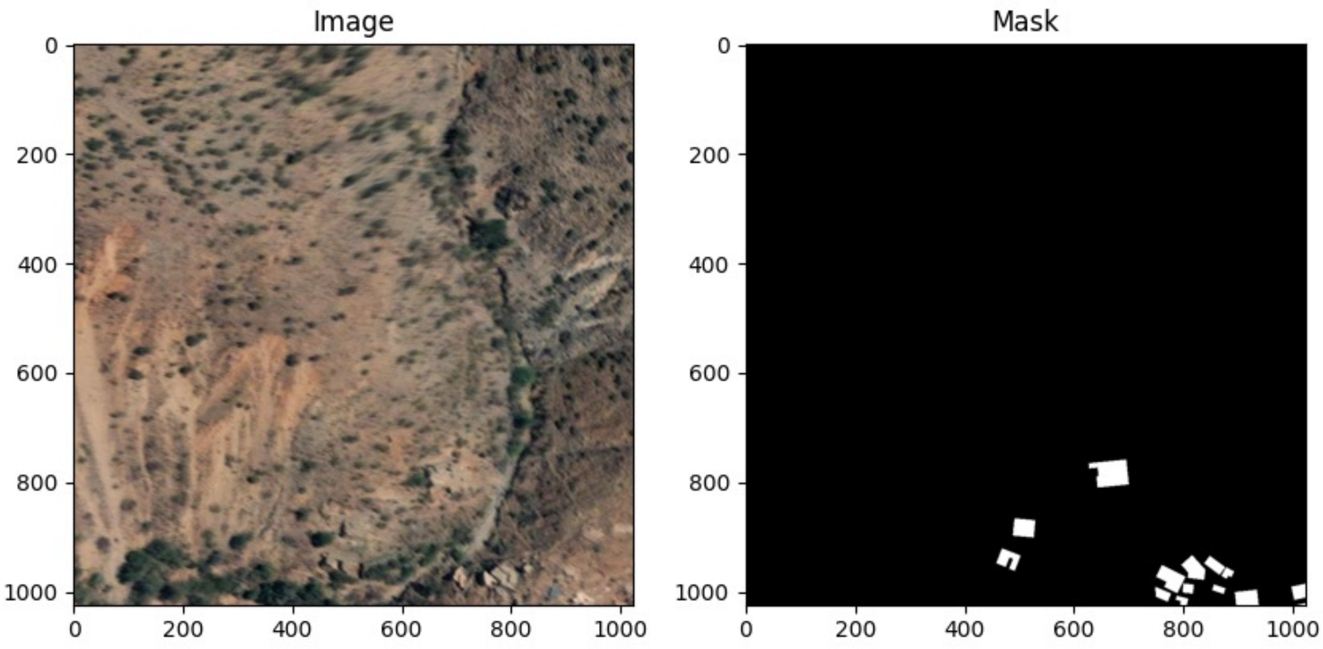


Image
Mask
0
200
400
600
800
1000
0
200
400
600
800
1000

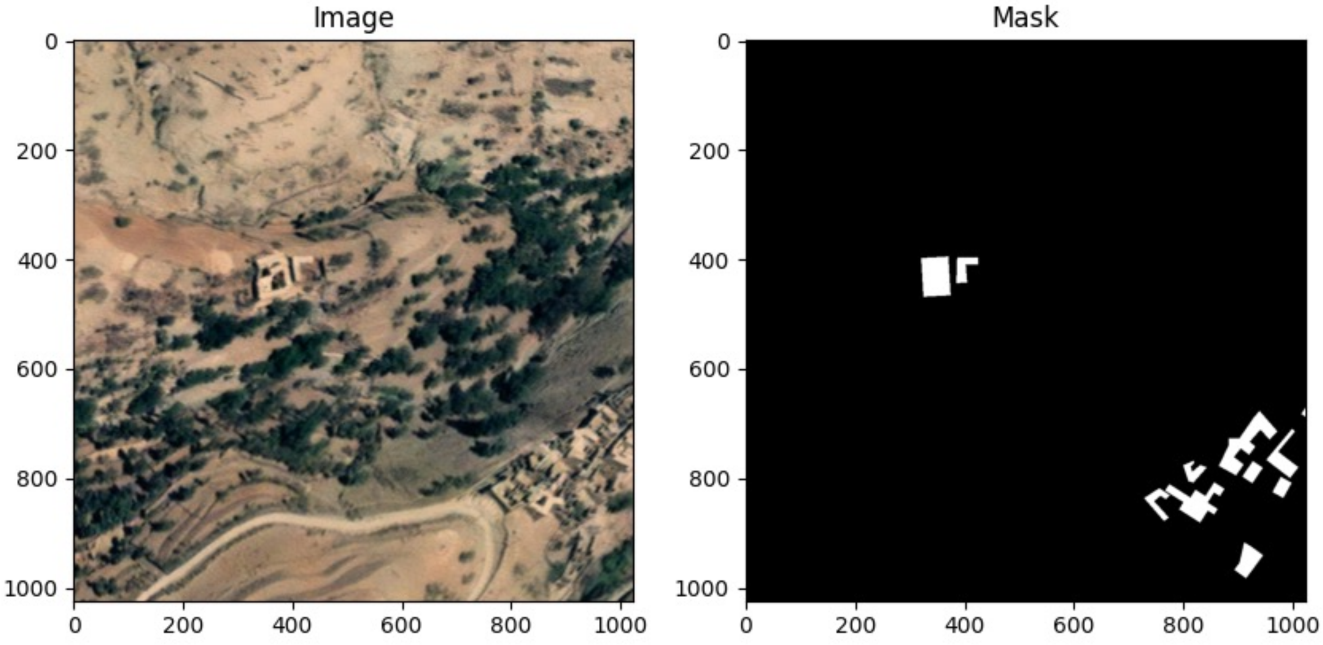


Image
Mask
0
200
400
600
800
1000
0
200
400
600
800
1000
0
200
400
600
800
1000
0
200
400
600
800
1000

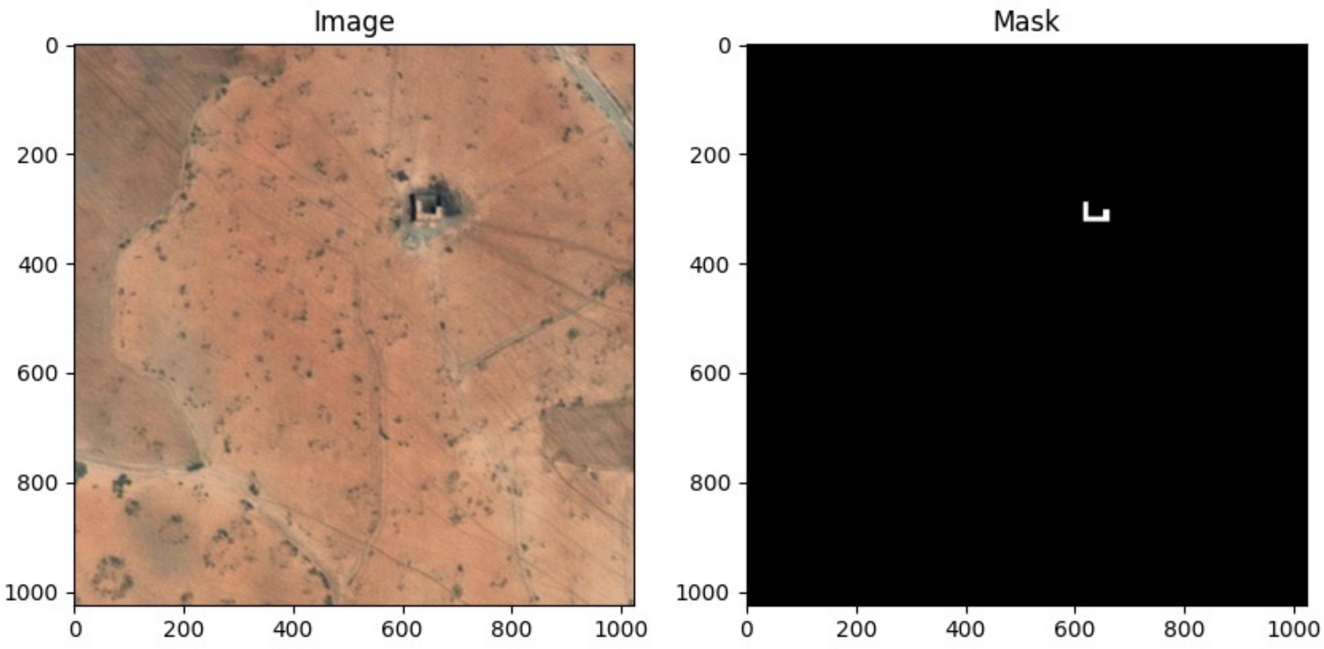
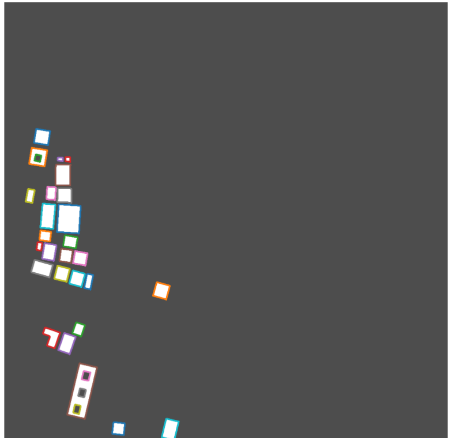


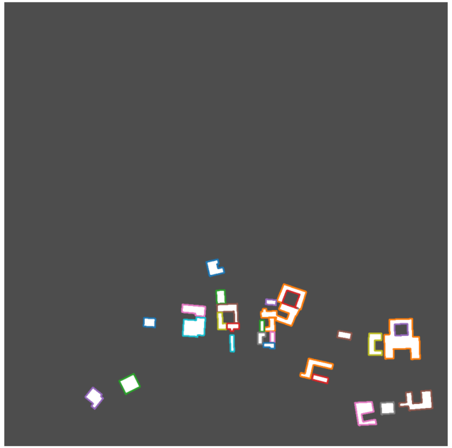
Image
Mask
0
200
400
600
800
1000
0
200
400
600
800
1000

Verified Contours

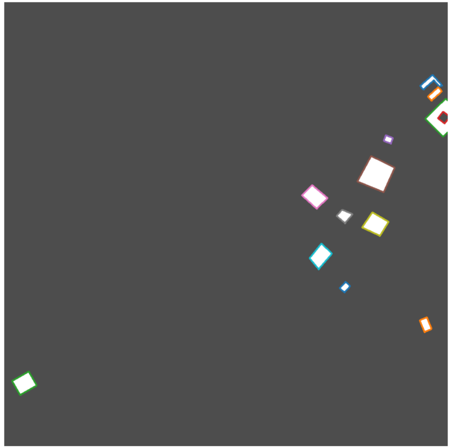


Verified Contours

Verified Contours



Verified Contours



05

MODEL TRAINING

Model Training

- The Mask R-CNN Inception ResNet V2 1024x1024 model is trained using NVIDIA A100 GPUs, enabling high-speed computations.

- Extensive testing of various hyperparameters, such as learning rates and batch sizes, is conducted to find the optimal model settings.

- Training is performed on Sapelo2's high-performance computing resources, allowing for robust model development.

```
        warmup_steps: 400  # Consistent with increased training complexity
      }
    }
    momentum_optimizer_value: 0.9
  }
  use_moving_average: false
}
gradient_clipping_by_norm: 10.0
fine_tune_checkpoint: "/home/rk42218/Building_Detection/garden_garden/mask_rcnn_inception_resnet_v2_1024x1024_coco17_gpu-8/
checkpoint/ckpt-0"
fine_tune_checkpoint_type: "detection"
from_detection_checkpoint: true
load_all_detection_checkpoint_vars: false
fine_tune_checkpoint_version: V2
data_augmentation_options {
  random_horizontal_flip {
  }
  random_adjust_brightness {
    max_delta: 0.2
  }
  random_adjust_contrast {
    min_delta: 0.8
    max_delta: 1.2
  }
  random_adjust_saturation {
    min_delta: 0.8
    max_delta: 1.2
  }
  random_adjust_hue {
    max_delta: 0.02
  }
  random_distort_color {
    color_ordering: 1
  }
 }
}
```

```
        warmup_steps: 400  # Increased warmup period
      }
    }
    momentum_optimizer_value: 0.9
  }
  use_moving_average: false
}
gradient_clipping_by_norm: 10.0
fine_tune_checkpoint: "/home/rk42218/Building_Detection/garden_garden/mask_rcnn_inception_resnet_v2_1024x1024_coco17_gpu-8/
checkpoint/ckpt-0"
fine_tune_checkpoint_type: "detection"
from_detection_checkpoint: true
load_all_detection_checkpoint_vars: false
fine_tune_checkpoint_version: V2
  data_augmentation_options {
    random_crop_image {
      min_object_covered: 0.3
      min_aspect_ratio: 0.75
      max_aspect_ratio: 1.33
      min_area: 0.5
      max_area: 1.0
    }
  }
}
```

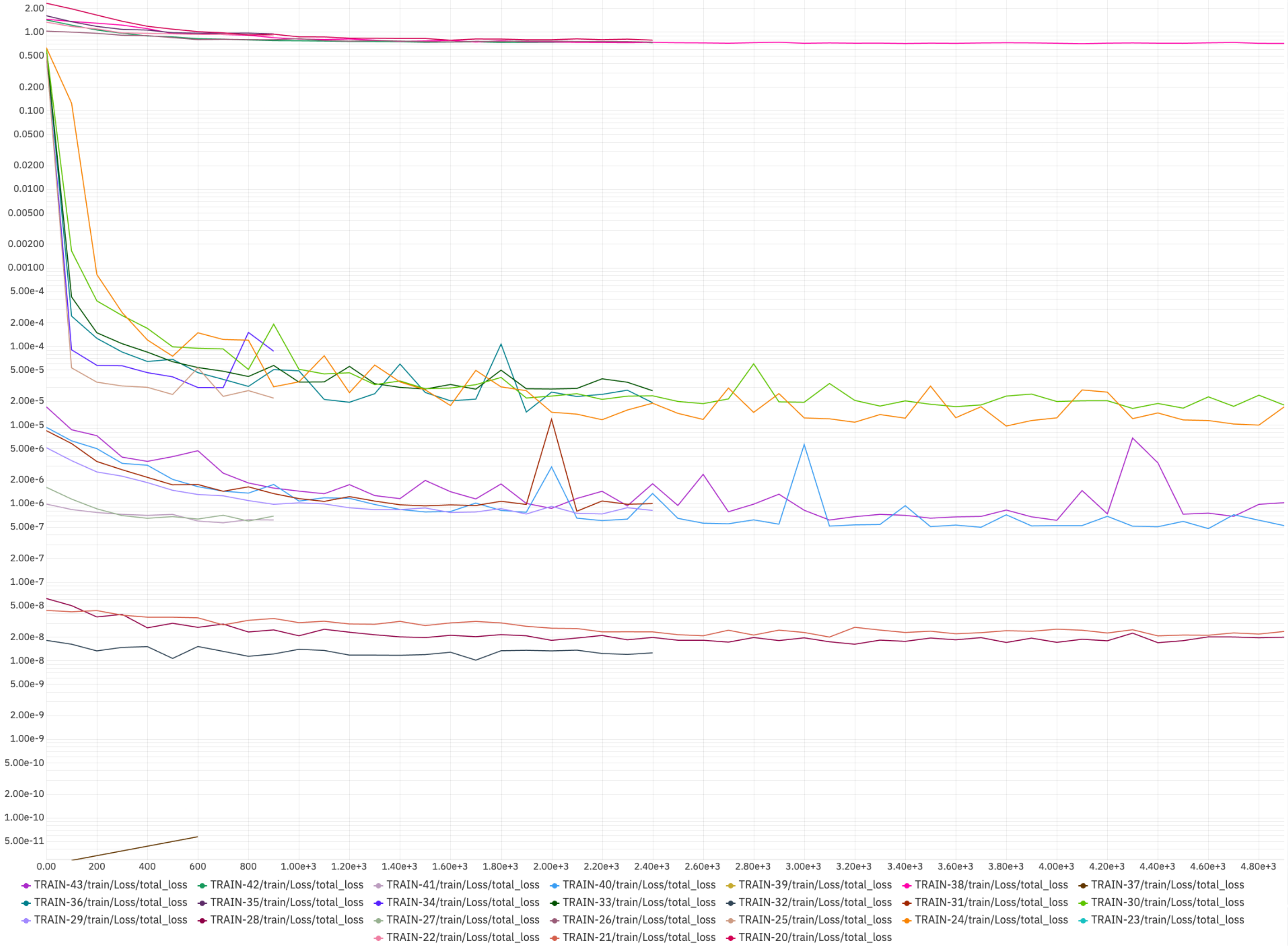
06

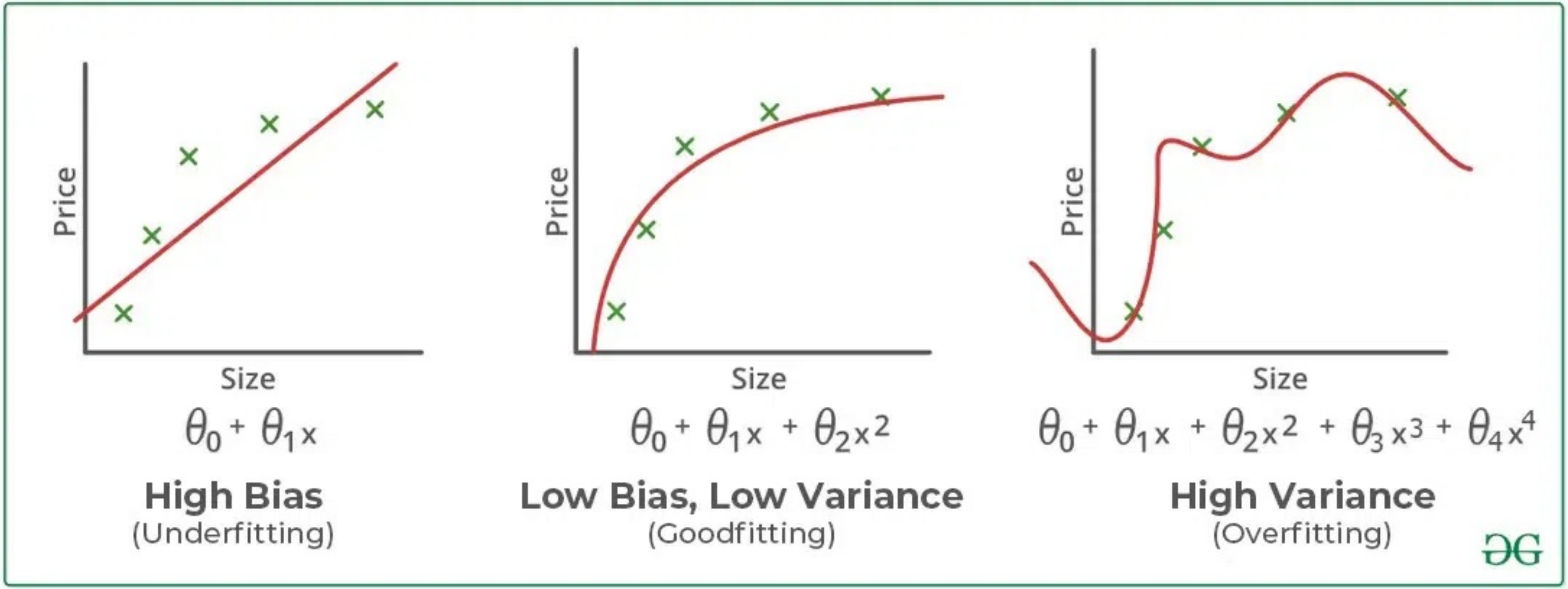
MODEL EVALUATION

Model Evaluation

- Model performance is assessed using precision, recall, and Intersection over Union (IoU) metrics.
- These metrics provide critical insights into the model's ability to identify and accurately delineate buildings from satellite imagery.

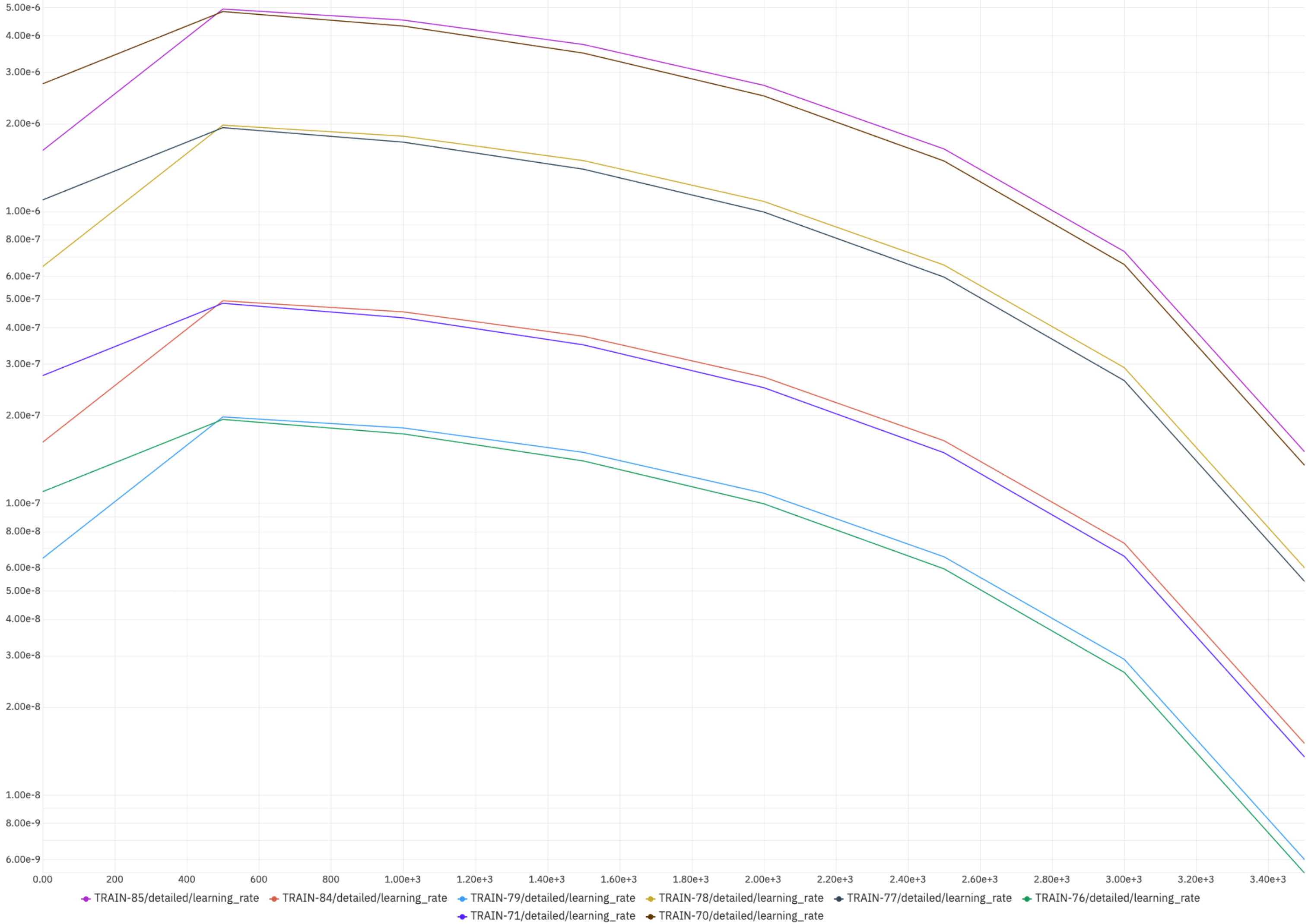
TOTAL LOSS


2.00
1.00
0.500
0.200
0.100
0.0500
0.0200
0.0100
0.00500
0.00200
0.00100
5.00e-4
2.00e-4
1.00e-4
5.00e-5
2.00e-5
1.00e-5
5.00e-6
2.00e-6
1.00e-6
5.00e-7
2.00e-7
1.00e-7
5.00e-8
2.00e-8
1.00e-8
5.00e-9
2.00e-9
1.00e-9
5.00e-10
2.00e-10
1.00e-10
5.00e-11
0.00
200
400
600
800
1.00e+3
1.20e+3
1.40e+3
1.60e+3
1.80e+3
2.00e+3
2.20e+3
2.40e+3
2.60e+3
2.80e+3
3.00e+3
3.20e+3
3.40e+3
3.60e+3
3.80e+3
4.00e+3
4.20e+3
4.40e+3
4.60e+3
4.80e+3
TRAIN-43/train/Loss/total_loss
TRAIN-42/train/Loss/total_loss
TRAIN-41/train/Loss/total_loss
TRAIN-40/train/Loss/total_loss
TRAIN-39/train/Loss/total_loss
TRAIN-38/train/Loss/total_loss
TRAIN-37/train/Loss/total_loss
TRAIN-36/train/Loss/total_loss
TRAIN-35/train/Loss/total_loss
TRAIN-34/train/Loss/total_loss
TRAIN-33/train/Loss/total_loss
TRAIN-32/train/Loss/total_loss
TRAIN-31/train/Loss/total_loss
TRAIN-30/train/Loss/total_loss
TRAIN-29/train/Loss/total_loss
TRAIN-28/train/Loss/total_loss
TRAIN-27/train/Loss/total_loss
TRAIN-26/train/Loss/total_loss
TRAIN-25/train/Loss/total_loss
TRAIN-24/train/Loss/total_loss
TRAIN-23/train/Loss/total_loss
TRAIN-22/train/Loss/total_loss
TRAIN-21/train/Loss/total_loss
TRAIN-20/train/Loss/total_loss

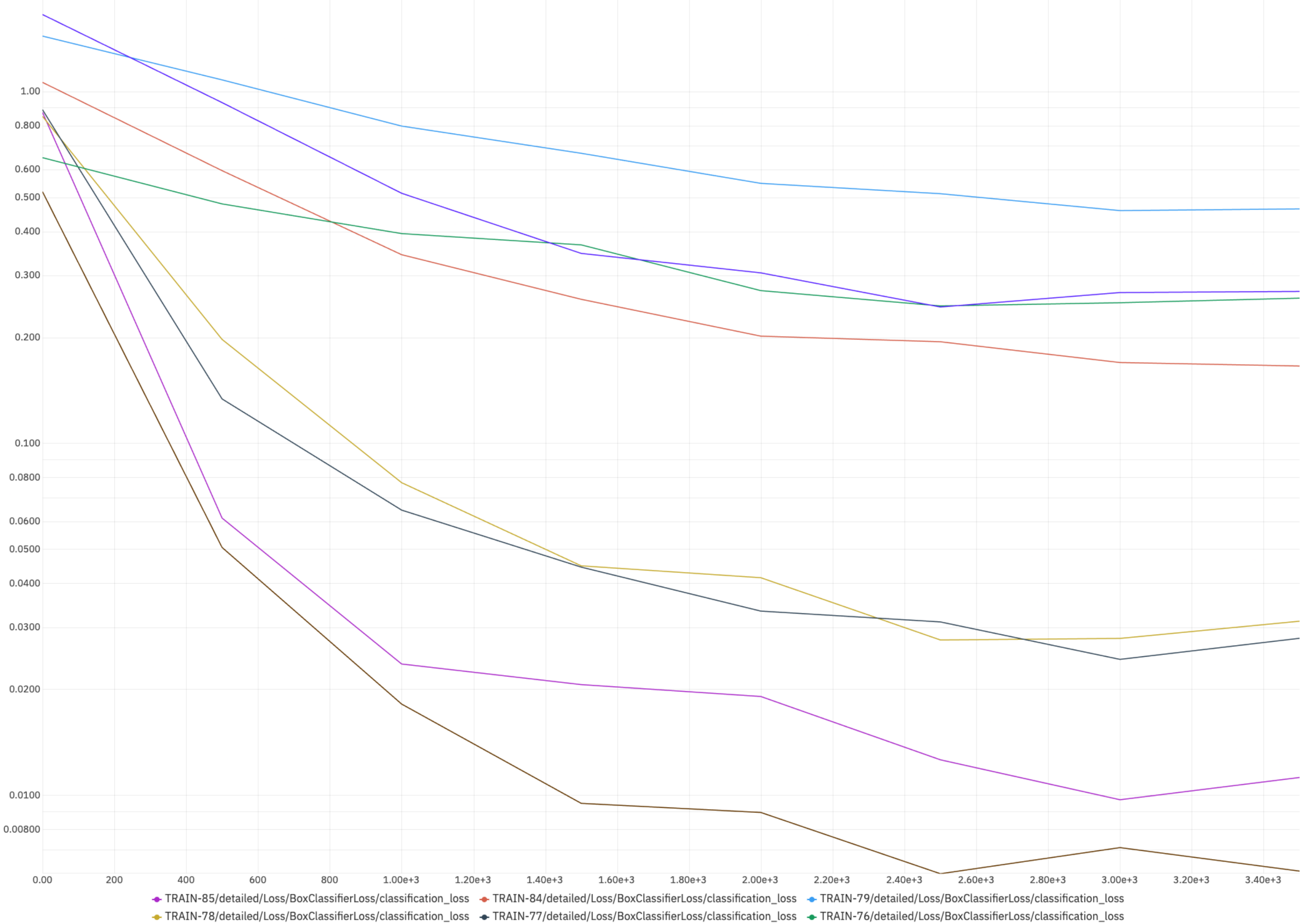


https://www.geeksforgeeks.org/underfitting-and-overfitting-in-machine-learning/

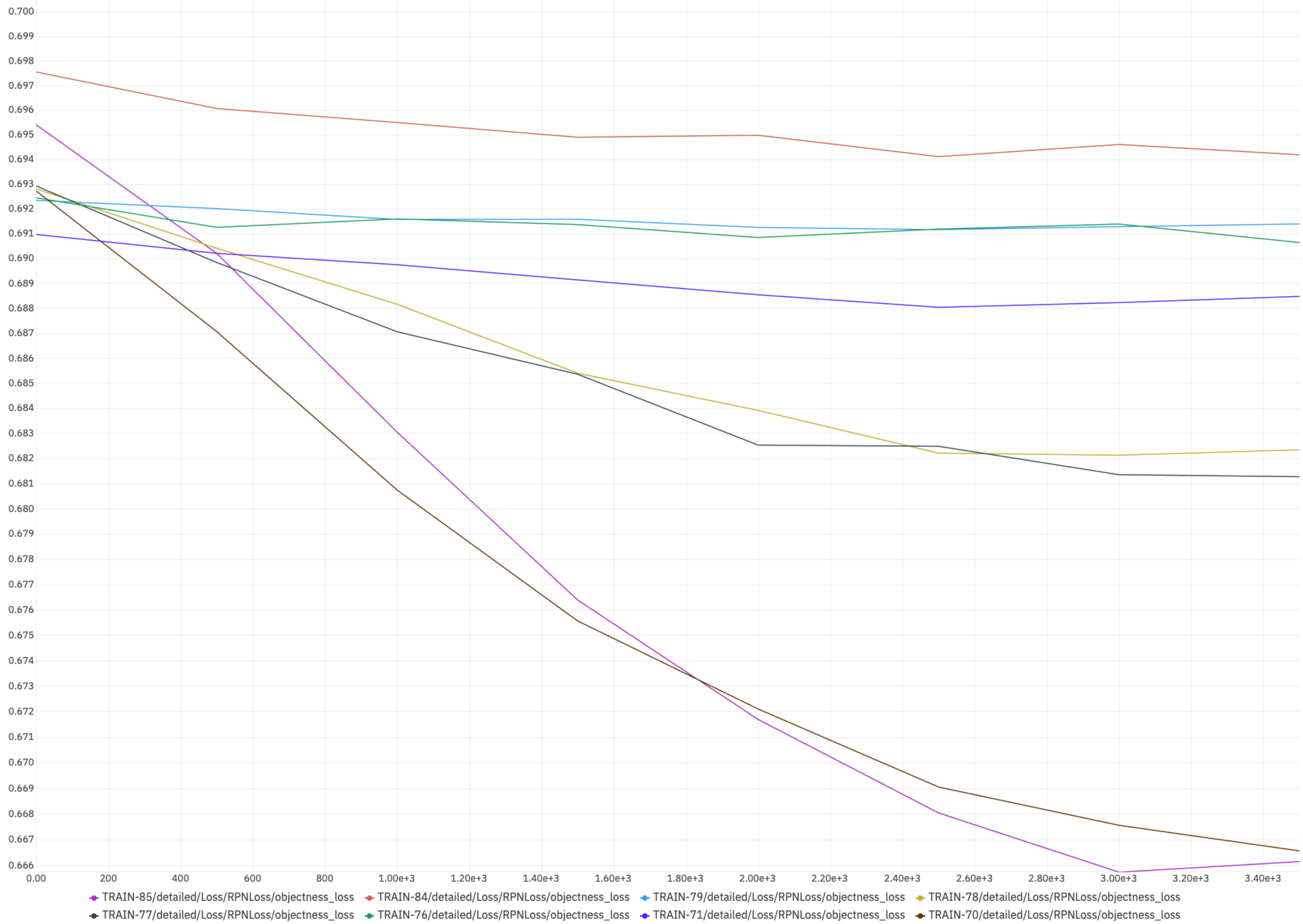
LEARNING RATE

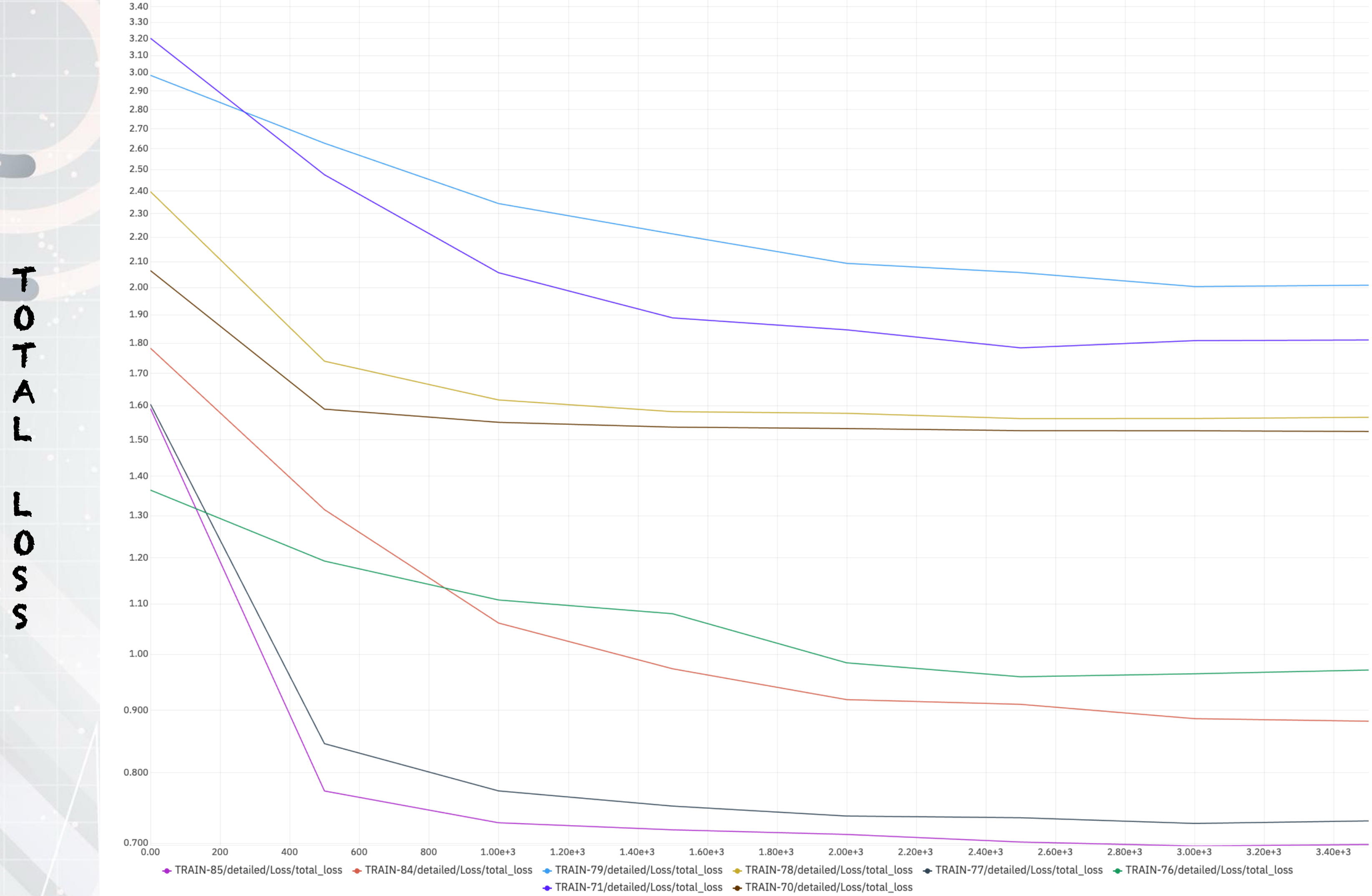


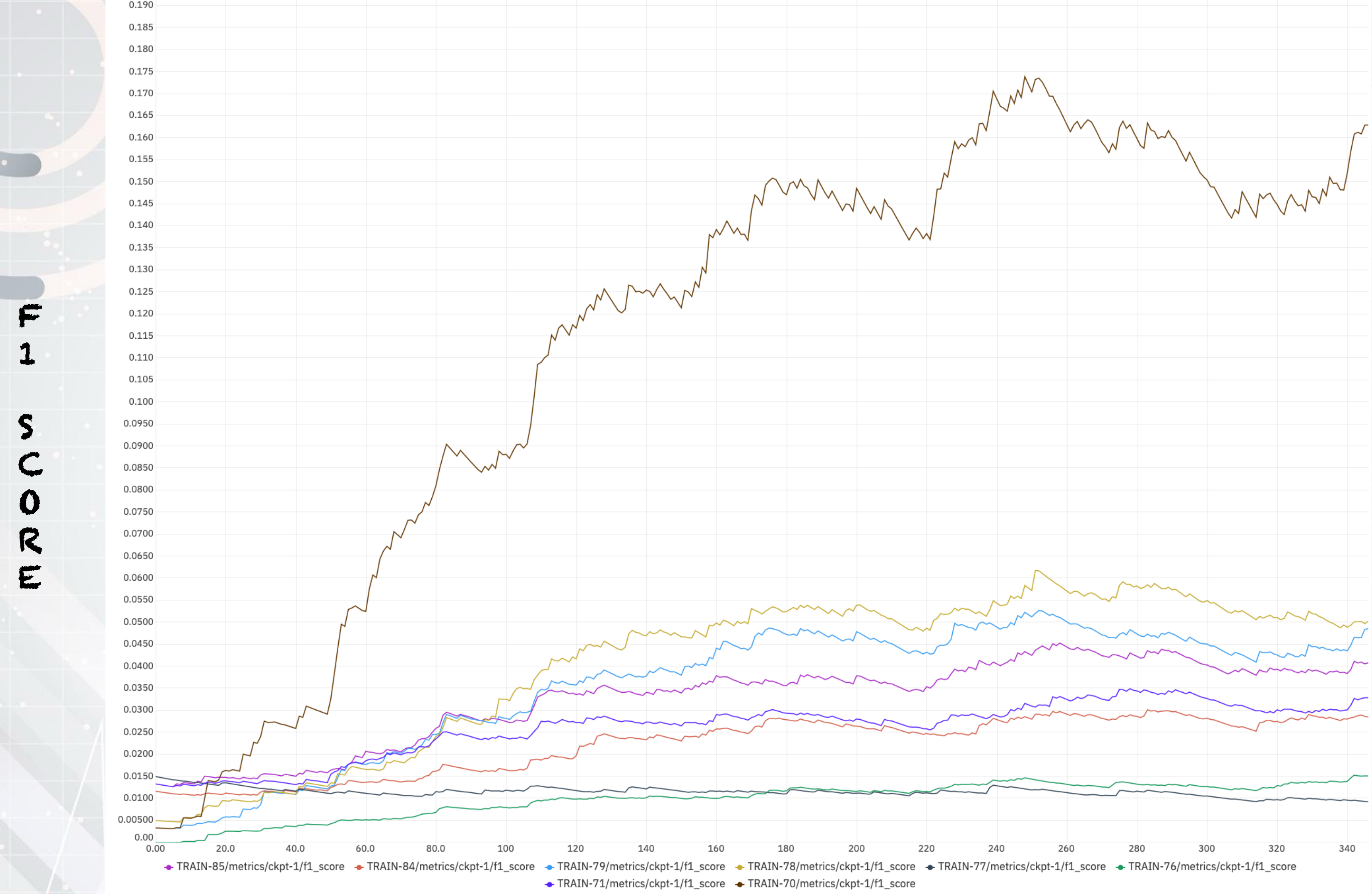
CLASSIFICATION LOSS



OBJECTNESS LOSS

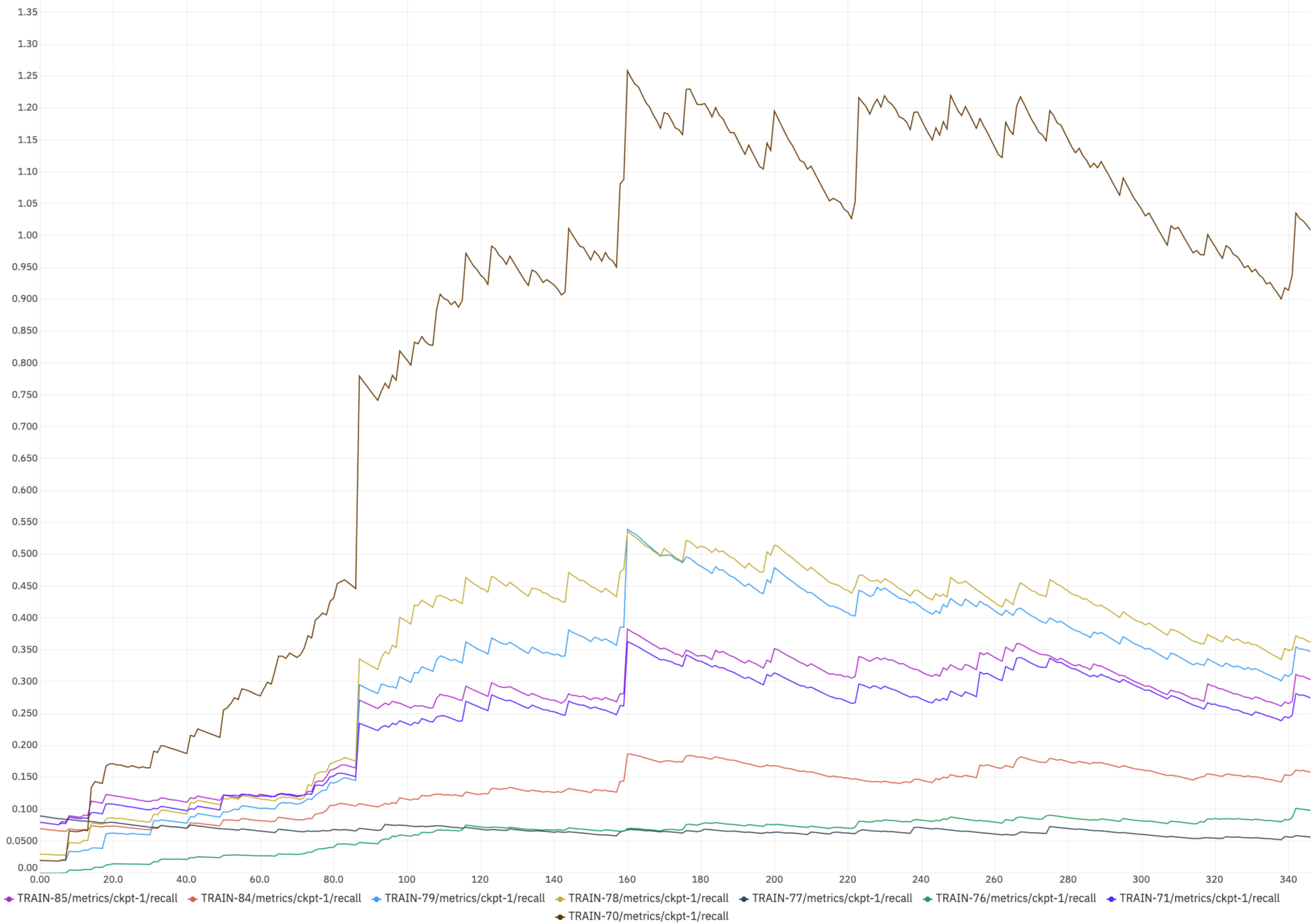


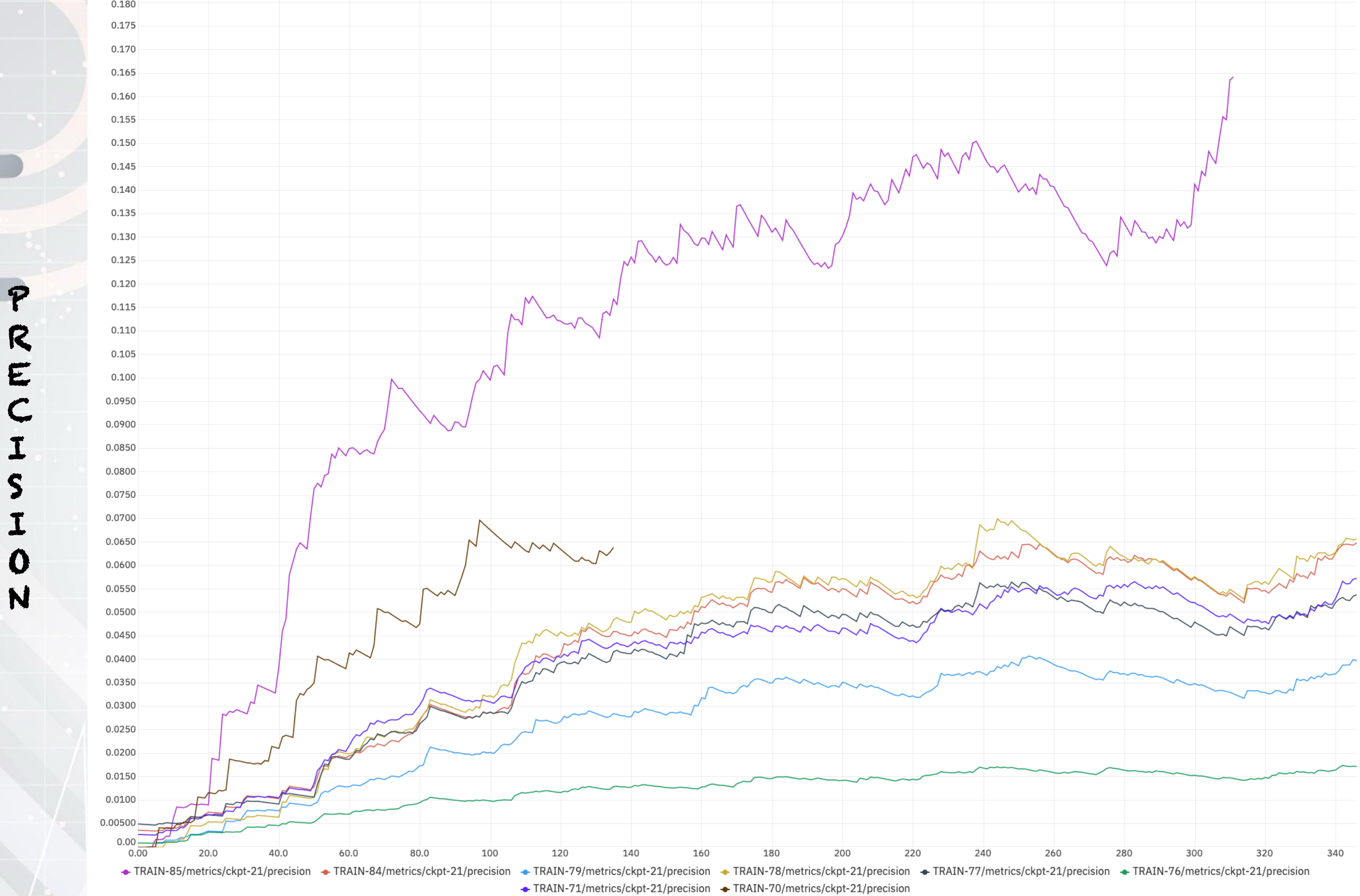

TOTAL LOSS
3.40
3.30
3.20
3.10
3.00
2.90
2.80
2.70
2.60
2.50
2.40
2.30
2.20
2.10
2.00
1.90
1.80
1.70
1.60
1.50
1.40
1.30
1.20
1.10
1.00
0.900
0.800
0.700
0.00
200
400
600
800
1.00e+3
1.20e+3
1.40e+3
1.60e+3
1.80e+3
2.00e+3
2.20e+3
2.40e+3
2.60e+3
2.80e+3
3.00e+3
3.20e+3
3.40e+3
TRAIN-85/detailed/Loss/total_loss
TRAIN-84/detailed/Loss/total_loss
TRAIN-79/detailed/Loss/total_loss
TRAIN-78/detailed/Loss/total_loss
TRAIN-77/detailed/Loss/total_loss
TRAIN-76/detailed/Loss/total_loss
TRAIN-71/detailed/Loss/total_loss
TRAIN-70/detailed/Loss/total_loss



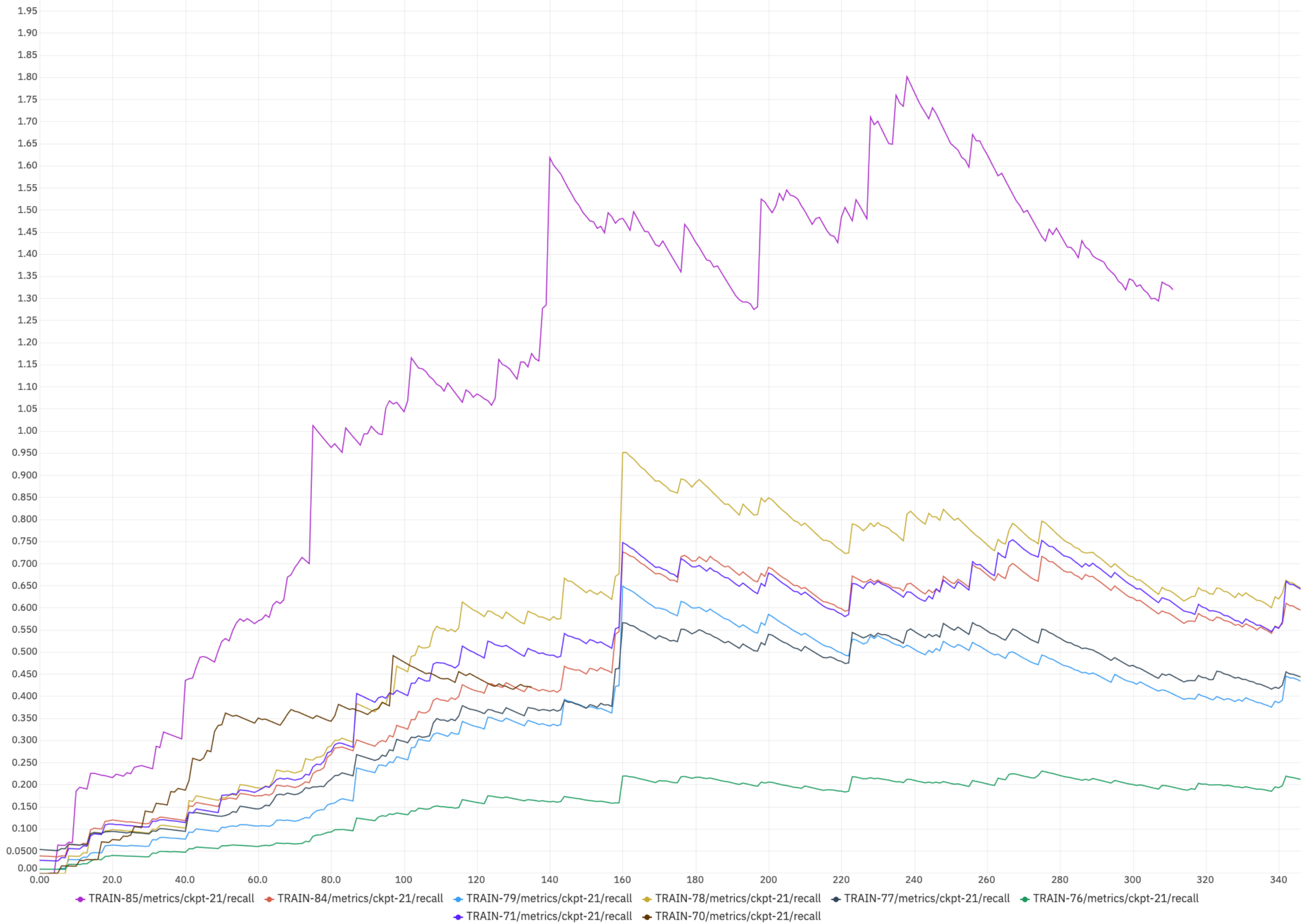
F1 SCORE
0.190
0.185
0.180
0.175
0.170
0.165
0.160
0.155
0.150
0.145
0.140
0.135
0.130
0.125
0.120
0.115
0.110
0.105
0.100
0.0950
0.0900
0.0850
0.0800
0.0750
0.0700
0.0650
0.0600
0.0550
0.0500
0.0450
0.0400
0.0350
0.0300
0.0250
0.0200
0.0150
0.0100
0.00500
0.00
0.00
20.0
40.0
60.0
80.0
100
120
140
160
180
200
220
240
260
280
300
320
340
TRAIN-85/metrics/ckpt-1/f1_score
TRAIN-84/metrics/ckpt-1/f1_score
TRAIN-79/metrics/ckpt-1/f1_score
TRAIN-78/metrics/ckpt-1/f1_score
TRAIN-77/metrics/ckpt-1/f1_score
TRAIN-76/metrics/ckpt-1/f1_score
TRAIN-71/metrics/ckpt-1/f1_score
TRAIN-70/metrics/ckpt-1/f1_score

RECALL


1.35
1.30
1.25
1.20
1.15
1.10
1.05
1.00
0.950
0.900
0.850
0.800
0.750
0.700
0.650
0.600
0.550
0.500
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.0500
0.00
0.00
20.0
40.0
60.0
80.0
100
120
140
160
180
200
220
240
260
280
300
320
340
TRAIN-85/metrics/ckpt-1/recall
TRAIN-84/metrics/ckpt-1/recall
TRAIN-79/metrics/ckpt-1/recall
TRAIN-78/metrics/ckpt-1/recall
TRAIN-77/metrics/ckpt-1/recall
TRAIN-76/metrics/ckpt-1/recall
TRAIN-71/metrics/ckpt-1/recall
TRAIN-70/metrics/ckpt-1/recall


PRECISION
0.180
0.175
0.170
0.165
0.160
0.155
0.150
0.145
0.140
0.135
0.130
0.125
0.120
0.115
0.110
0.105
0.100
0.0950
0.0900
0.0850
0.0800
0.0750
0.0700
0.0650
0.0600
0.0550
0.0500
0.0450
0.0400
0.0350
0.0300
0.0250
0.0200
0.0150
0.0100
0.00500
0.00
0.00
20.0
40.0
60.0
80.0
100
120
140
160
180
200
220
240
260
280
300
320
340
TRAIN-85/metrics/ckpt-21/precision
TRAIN-84/metrics/ckpt-21/precision
TRAIN-79/metrics/ckpt-21/precision
TRAIN-78/metrics/ckpt-21/precision
TRAIN-77/metrics/ckpt-21/precision
TRAIN-76/metrics/ckpt-21/precision
TRAIN-71/metrics/ckpt-21/precision
TRAIN-70/metrics/ckpt-21/precision

RECALL



1.95
1.90
1.85
1.80
1.75
1.70
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
1.25
1.20
1.15
1.10
1.05
1.00
0.950
0.900
0.850
0.800
0.750
0.700
0.650
0.600
0.550
0.500
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.0500
0.00
0.00 20.0 40.0 60.0 80.0 100 120 140 160 180 200 220 240 260 280 300 320 340
TRAIN-85/metrics/ckpt-21/recall
TRAIN-84/metrics/ckpt-21/recall
TRAIN-79/metrics/ckpt-21/recall
TRAIN-78/metrics/ckpt-21/recall
TRAIN-77/metrics/ckpt-21/recall
TRAIN-76/metrics/ckpt-21/recall
TRAIN-71/metrics/ckpt-21/recall
TRAIN-70/metrics/ckpt-21/recall

07

EXPERIMENTS

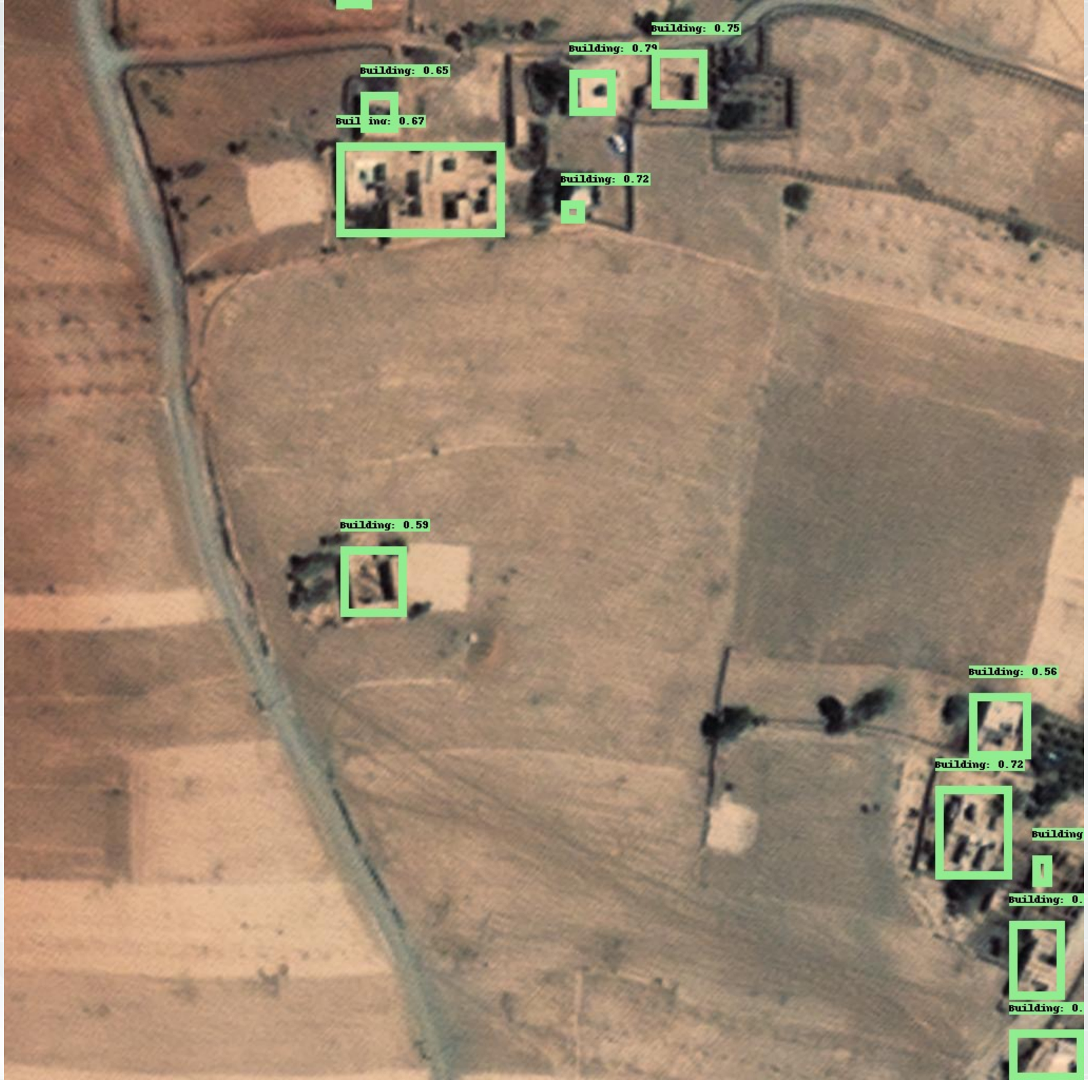
& RESULTS

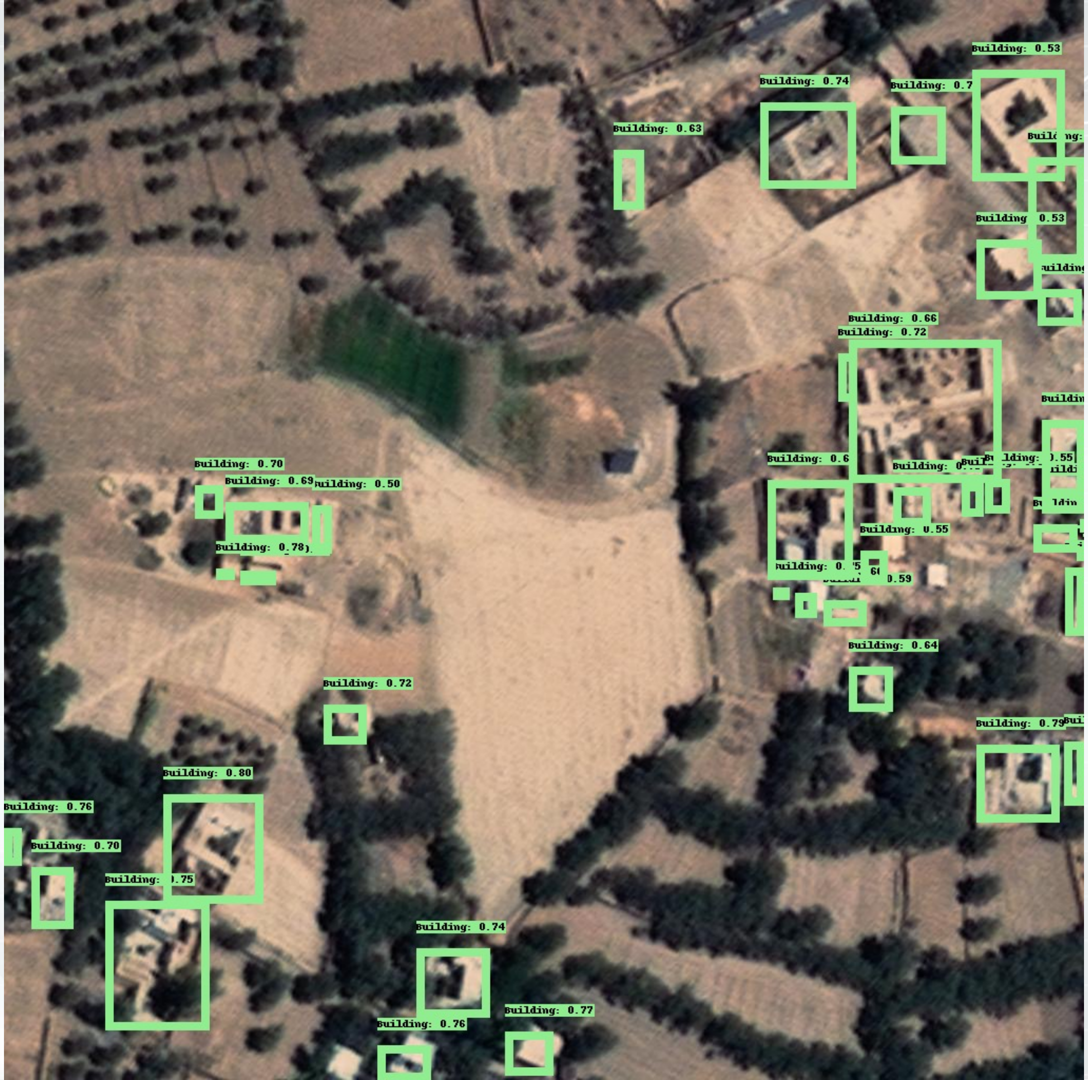
Experiments & Results

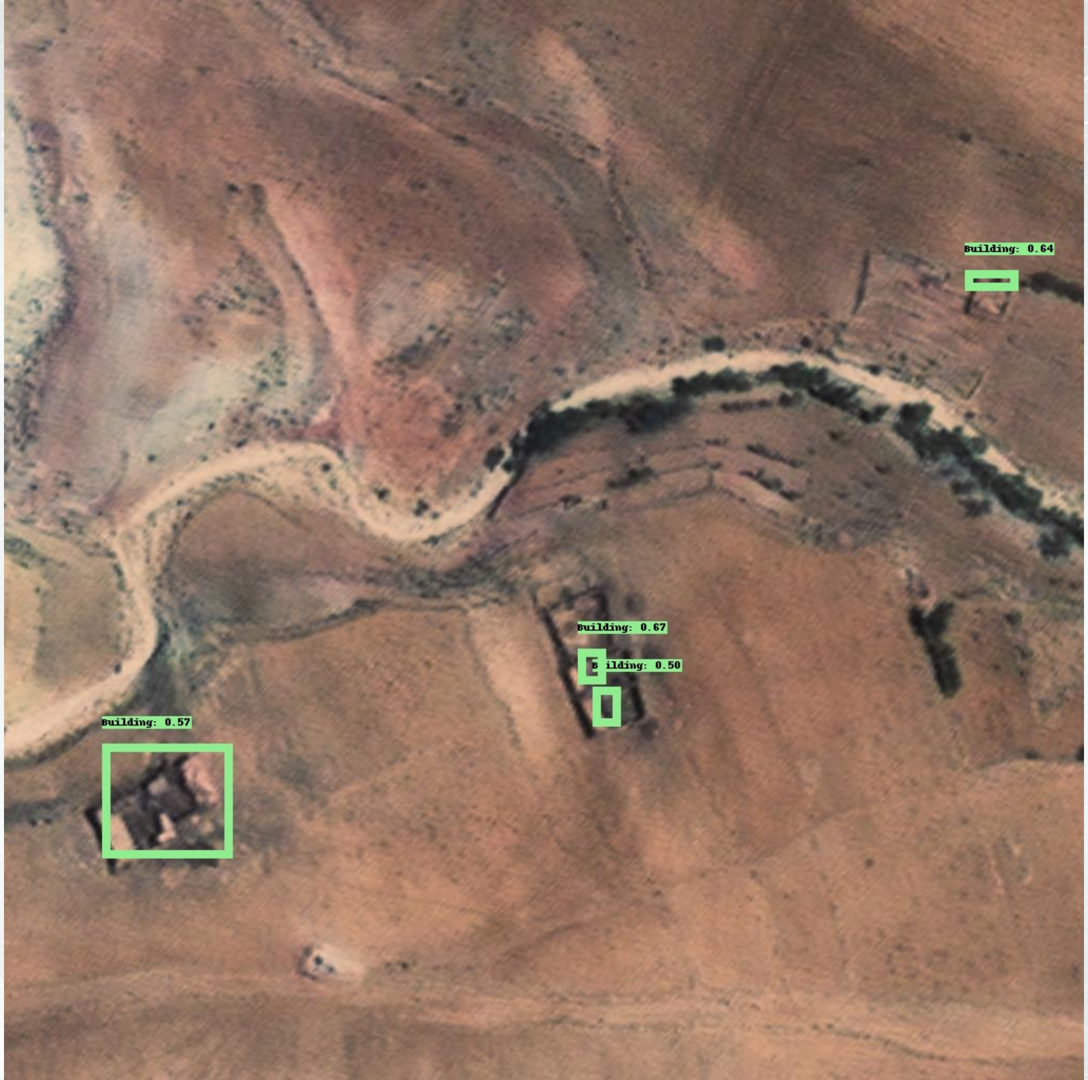
- The evaluation phase involves rigorous testing across different model configurations and extensive data sets.
- Results show that our machine learning model significantly outperforms traditional methods, demonstrating high levels of precision and recall.
- Detailed analysis of performance metrics is facilitated by Neptune, which tracks each iteration of model training.

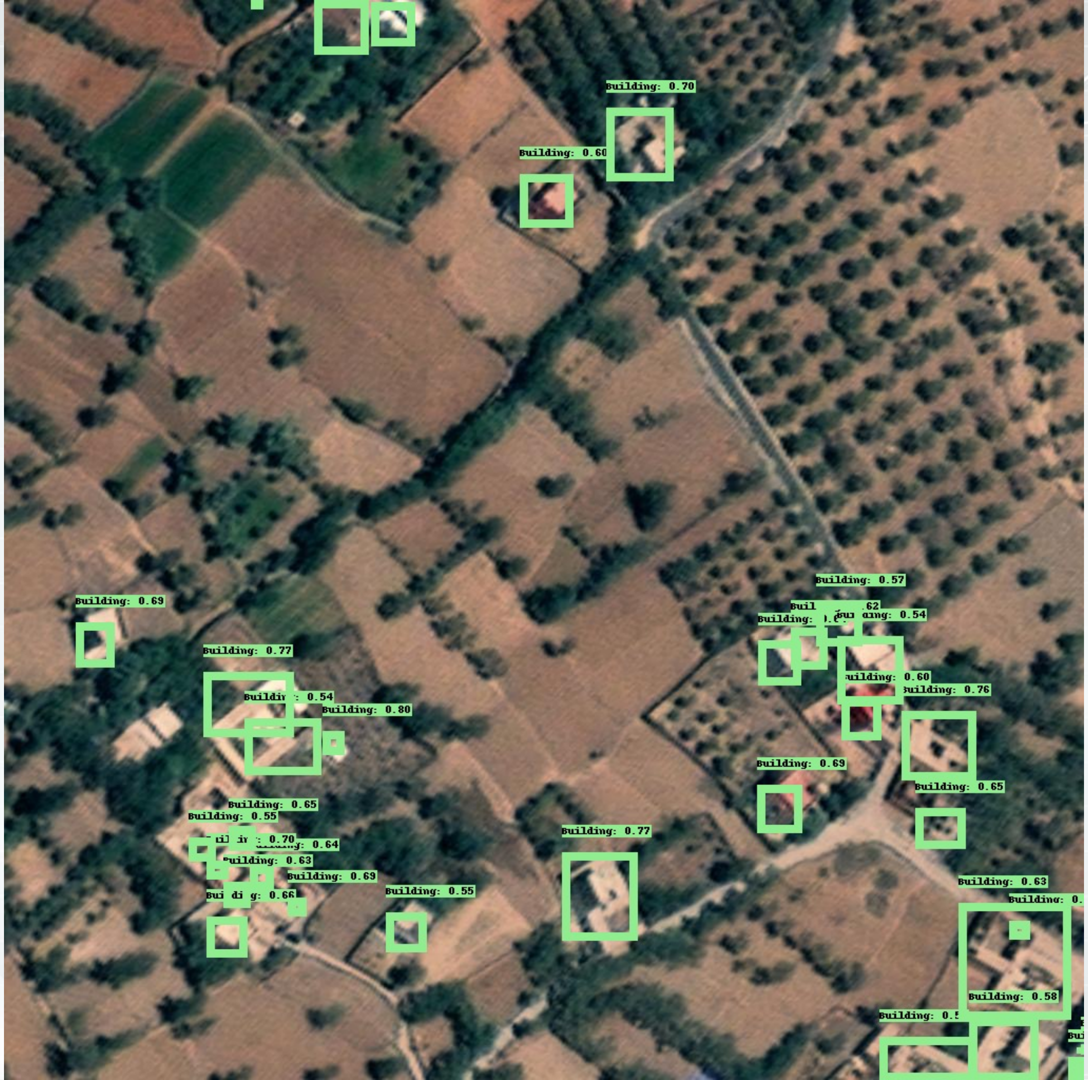

building: 59%
building: 62%
building: 60%


Building: 0.63
Building: 0.72
Building: 0.80
Building: 0.76


Building: 0.75
Building: 0.79
Building: 0.65
Buil ing: 0.67
Building: 0.72
Building: 0.59
Building: 0.56
Building: 0.72
Building
Building: 0.
Building: 0.


Building: 0.53
Building: 0.74
Building: 0.63
Building: 0.53
Building: 0.66
Building: 0.72
Building: 0.70
Building: 0.69
Building: 0.50
Building: 0.78
Building: 0.55
Building: 0.59
Building: 0.64
Building: 0.72
Building: 0.79
Building: 0.80
Building: 0.76
Building: 0.70
Building: 0.75
Building: 0.74
Building: 0.77
Building: 0.76


Building: 0.64
Building: 0.67
Building: 0.50
Building: 0.57



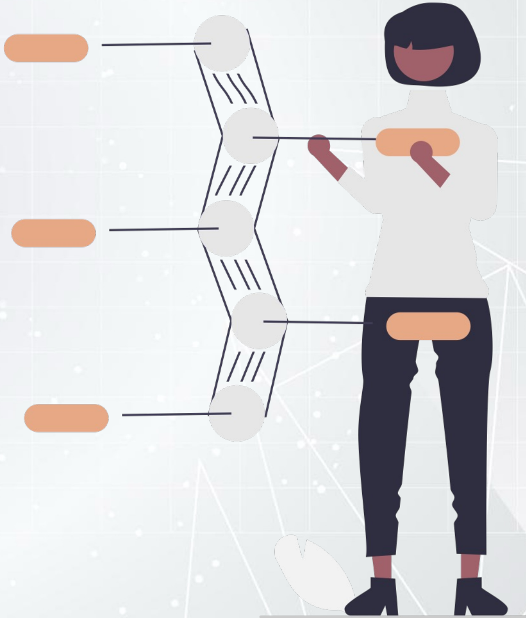
Building: 0.70
Building: 0.60
Building: 0.57
Building: 0.54
Building: 0.69
Building: 0.77
Building: 0.54
Building: 0.80
Building: 0.60
Building: 0.76
Building: 0.69
Building: 0.65
Building: 0.65
Building: 0.55
Building: 0.64
Building: 0.63
Building: 0.69
Building: 0.66
Building: 0.55
Building: 0.77
Building: 0.63
Building: 0.58

08

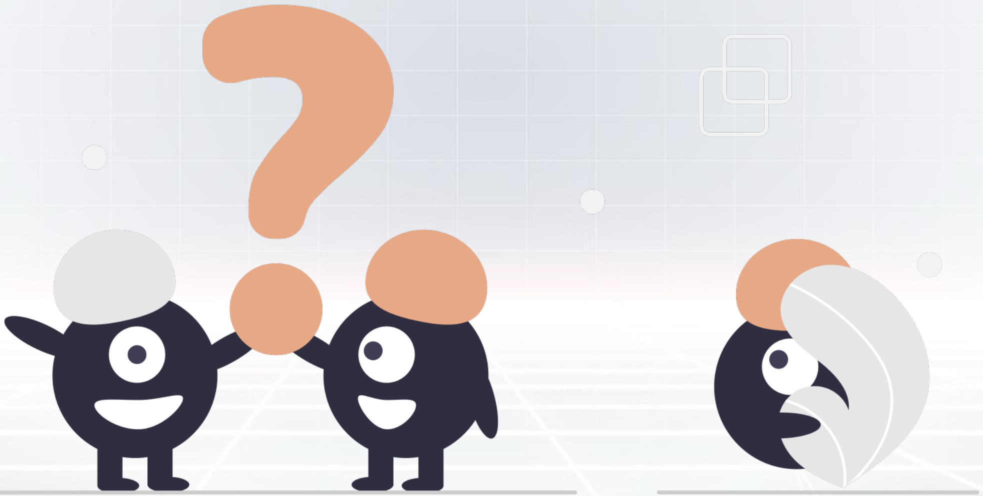
CONCLUSION & FUTURE WORK

Conclusion & Future Work

- The project demonstrates the viability of using advanced machine learning techniques to enhance building detection in disaster-stricken areas.
- Future improvements will focus on integrating real-time satellite imagery to provide immediate assessments post-disaster.
- Plans include expanding the model's scalability to different geographical settings and incorporating continuous learning mechanisms to adapt to new data.



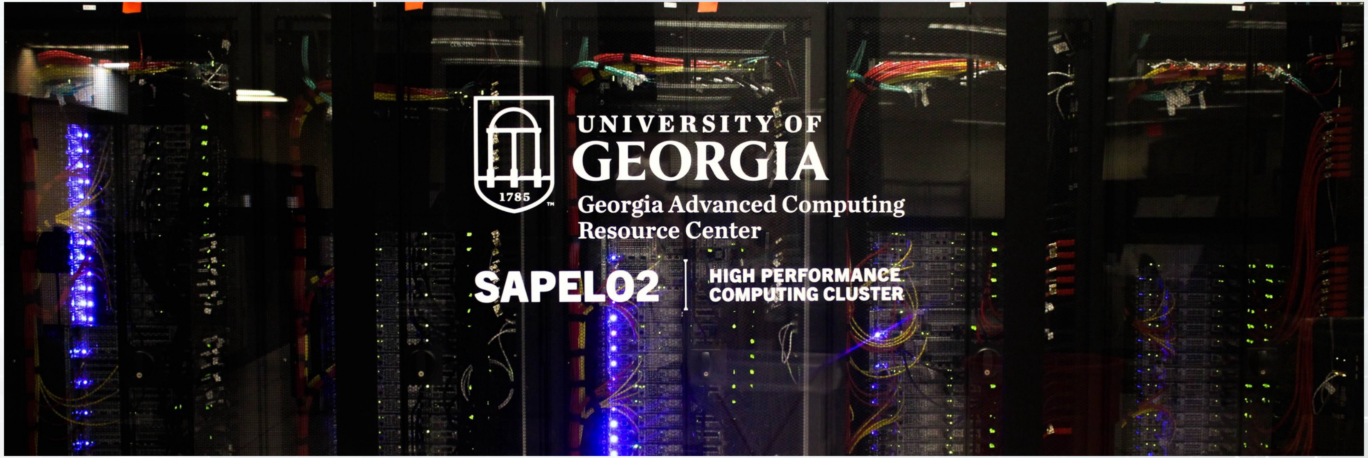
QUESTIONS?



ACKNOWLEDGEMENTS

Carl Vinson
Institute of Government
UNIVERSITY OF GEORGIA

Georgia Advanced Computing
Resource Center
UNIVERSITY OF GEORGIA



References ☺

xView2

GitHub - DIUx-xView/xView2_baseline: Baseline localization and classification models for the xView 2 challenge.

GitHub - vdurnov/xview2_1st_place_solution: 1st place solution for "xView2: Assess Building Damage" challenge.

https://services5.arcgis.com/0JofV0ocsiMyrWAn/arcgis/rest/services/Morocco_Al_Haouz_Province_West_Structures_and_Buildings_first_edition/FeatureServer

Machine Learning and Disaster Management

•Y. Yuan and F. Lin. "Machine learning in visual object recognition: A survey." IEEE Transactions on Neural Networks and Learning Systems, vol. 29, no. 9, pp. 3920-3939, 2018.

Convolutional Neural Networks (CNNs)

•A. Krizhevsky, I. Sutskever, and G. E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems, 2012.

Remote Sensing and Disaster Response

•M. K. Peters, et al. "Remote sensing technologies for enhancing forest inventories: A review." Canadian Journal of Remote Sensing, vol. 42, no. 5, pp. 619-641, 2016.

Mask R-CNN and Its Applications

•K. He, G. Gkioxari, P. Dollár, and R. Girshick. "Mask R-CNN." Proceedings of the IEEE international conference on computer vision, 2017.

Use of AI in Post-Disaster Scenarios

•L. G. Shapiro and G. C. Stockman. "Computer Vision." Prentice-Hall, Inc., 2001.

Performance Metrics for Object Detection

•R. Padilla, S. L. Netto, and E. A. B. da Silva, "A Survey on Performance Metrics for Object-Detection Algorithms," in IEEE Access, vol. 8, pp. 85327-85342, 2020.