

YOLOv5s-Fire

— Forest Fire Detection and Severity Assessment
Using Improved YOLOv5 on Satellite Imagery

Oxford Brookes University in collaboration with Chengdu University of Technology, BSc
Computer Science Supervised by Dr. Irfan Ullah

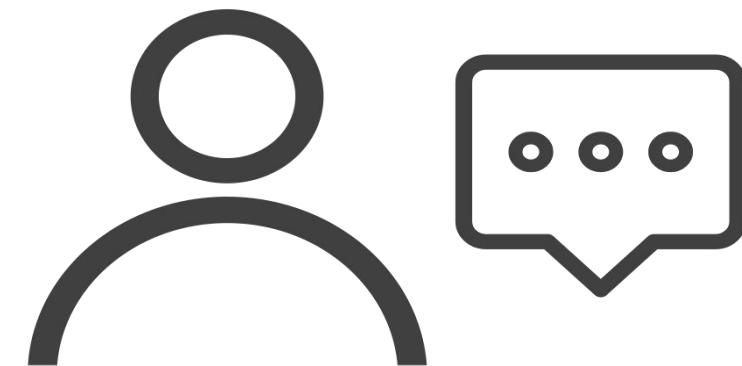
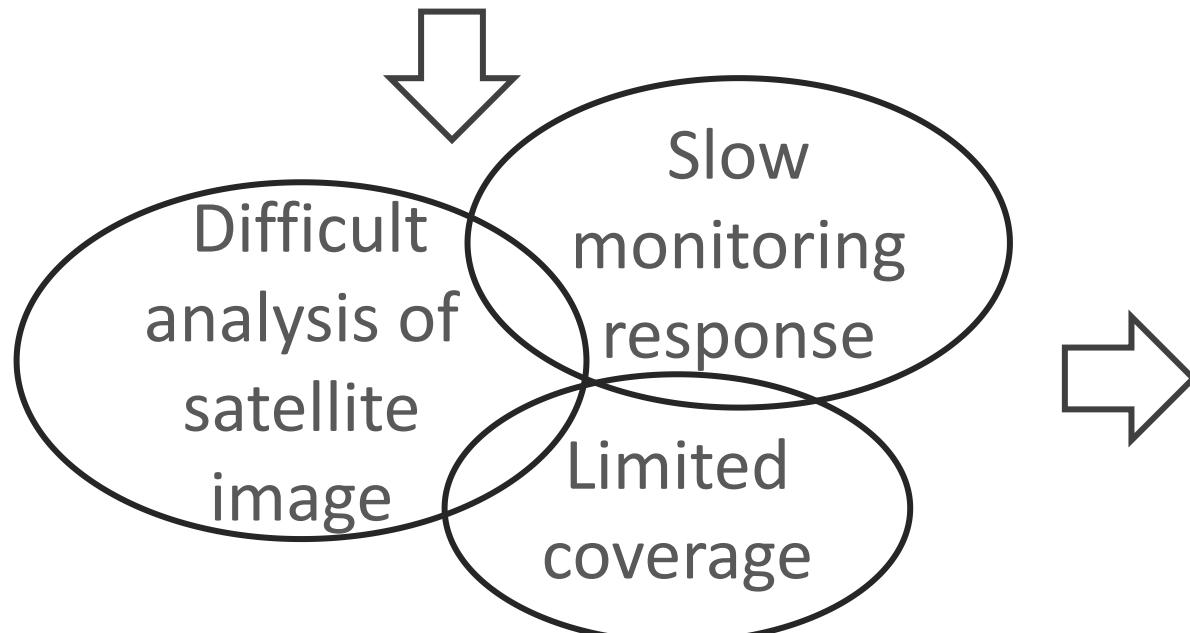
Content

- ① Background Review
- ② Improvement Process
- ③ Experiment Result
- ④ Conclusion

Research Background

The average area burned by each wildfire is up to **20** hectares and the global average annual area burned is more than **25,000** hectares.[1]

Traditional Detection



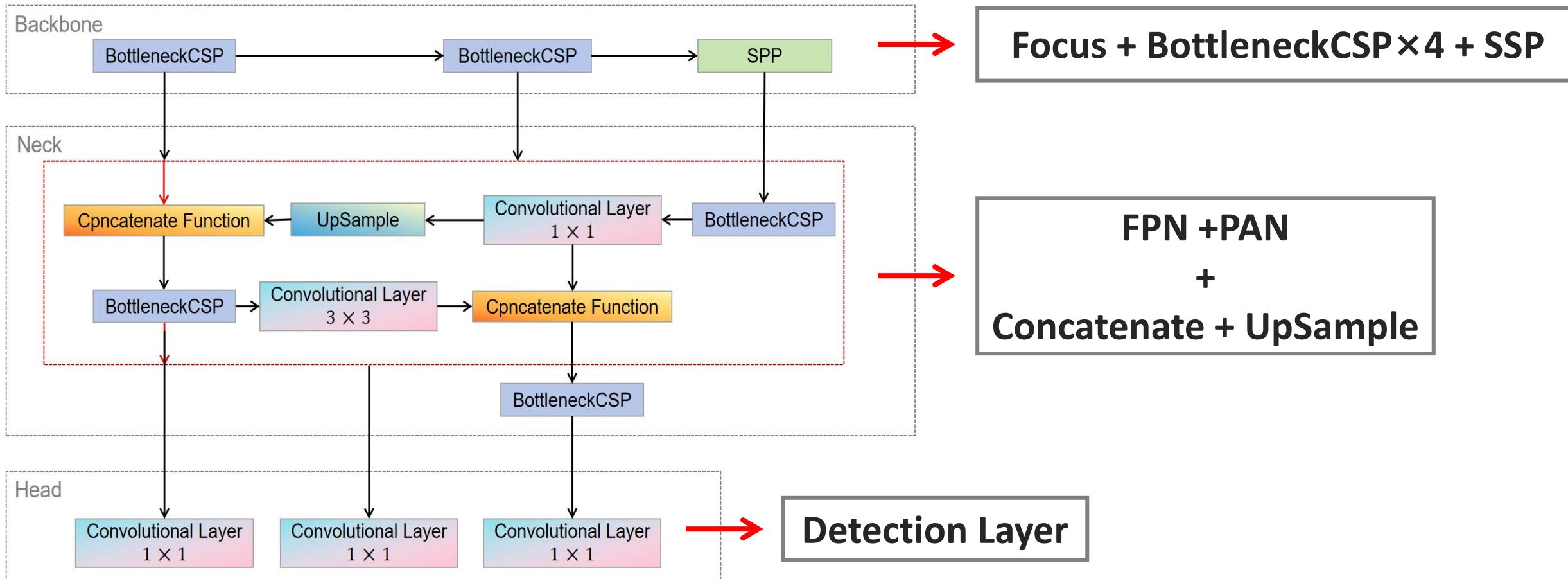
YOLO Algorithm

Target detection -> Real time + Precision

Comparison of Different Research

Research	Model	DataSet	Performance Index
Khan et al.[2]	VGG19	DeepFire	Accuracy = 98.89% Precision = 95.72%
Seydi et al.[3]	YOLOv5 + U-Net (Fire-Net)	Landsat-8	Overall Accuracy = 97.35% Precision = 93.49%
Yuan et al.[4]	YOLOv5 + Transformer	FLAME, self-built fire dataset	Accuracy = 93.25% Precision = 92.85%
Xu et al.[5]	YOLOv5 + EfficientNet	BowFire, FD-dataset, ForestryImages, VisiFire	Accuracy = 99.6% Average Precision = 85.5%
Kang et al.[6]	CNN + RF	Himawari-8 AHI	Overall Accuracy = 98% Precision = 91%
Ding et al.[7]	Mask R-CNN (FSF-Net)	MODIS_Smoke_FPT dataset	Accuracy = 89.12%

YOLOv5 Structure



YOLOv5 (You Only Look Once version 5)

- Single-stage Detection Framework → Real-time Detection
- Efficient Network Architecture Design → Low Computational Cost
- Dynamic Anchor Box → Adaptively Optimize
- End-to-End Training and Inference → Precise Localization

— Why choose YOLOv5?

Conclusion: YOLOv5 Model The model is highly suitable for forest wildfire detection in satellite images

- Multi-scale Feature Fusion
- Highly Modular Architecture
- Strong Initial Feature Extraction Capability

YOLOv5s Model

Lightest version of YOLOv5

Reduce computational complexity

Maintain detection accuracy

1. Dataset Preprocessing

Source of the Dataset

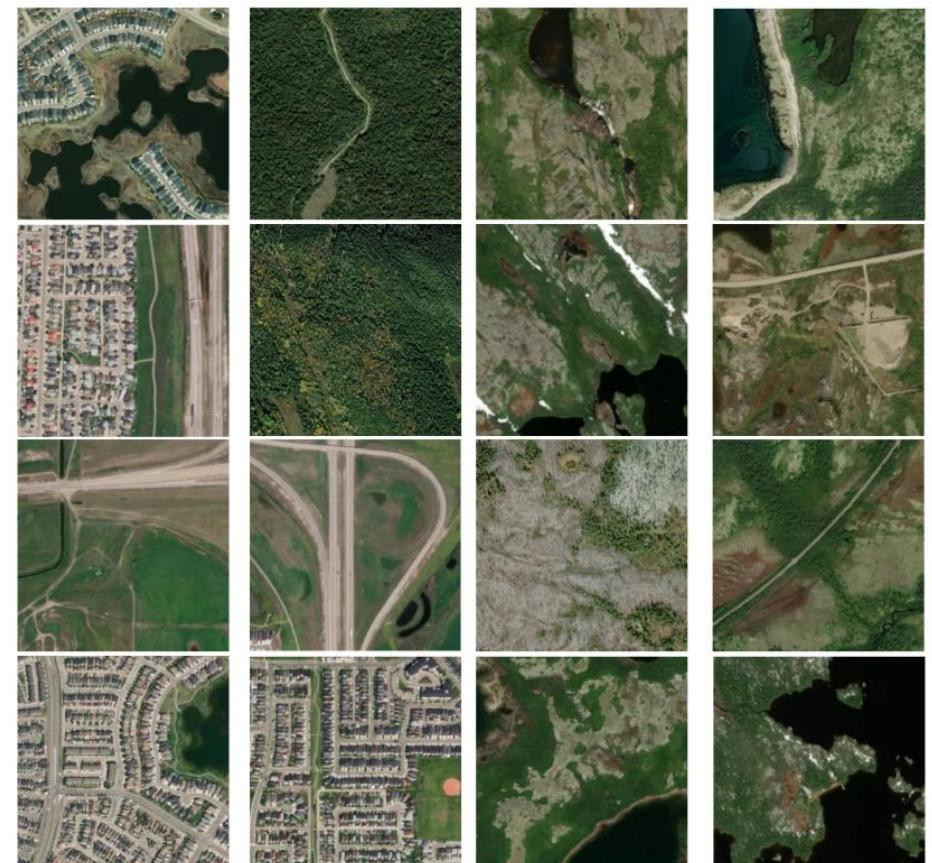
- Wildfire Prediction Dataset (Satellite Images) from Kaggle

Original Dataset Distribution

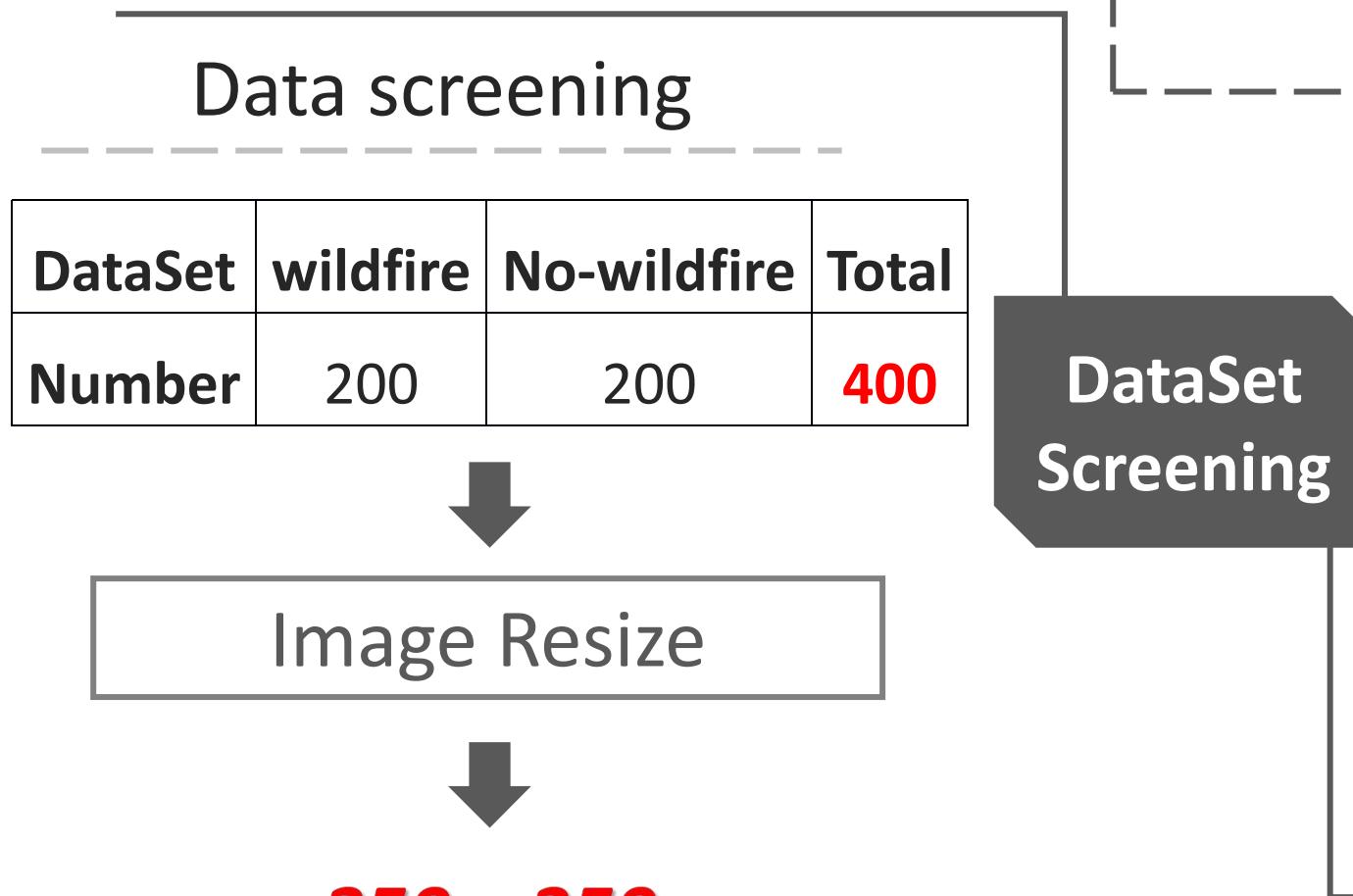
DataSet Selection

DataSet	Training	Testing	Validation	Total
wildfire	15898	3406	3406	22710
No-wildfire	14098	3021	3021	20140
Total	400	6427	6427	42850

Images of wildfire and no-wildfire classes



1. Dataset Preprocessing



Data Screening Criteria

- (1) Image Clarity
- (2) Label Reliability
- (3) Scene Coverage

1. Dataset Preprocessing

Stratified Sampling

- 300 training images and 100 validation images

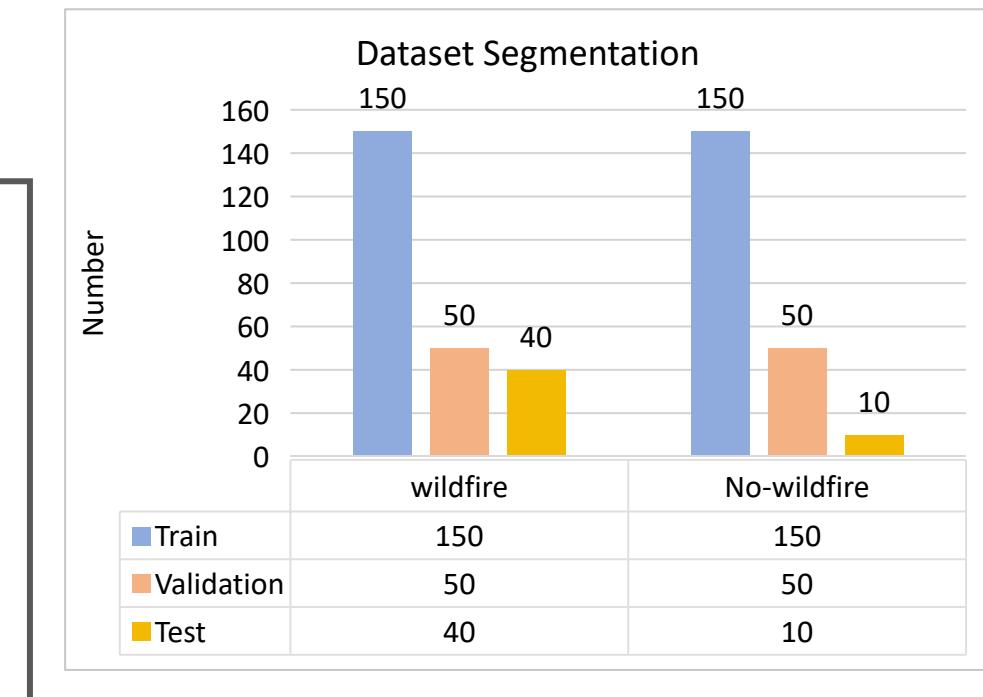
75% : 25%

DataSet Splitting

DataSet	Training	Testing	Total
wildfire	150	50	200
No-wildfire	150	50	200
Total	300	100	400

Dataset Segmentation

A separate test set of **50** images



1. Dataset Preprocessing

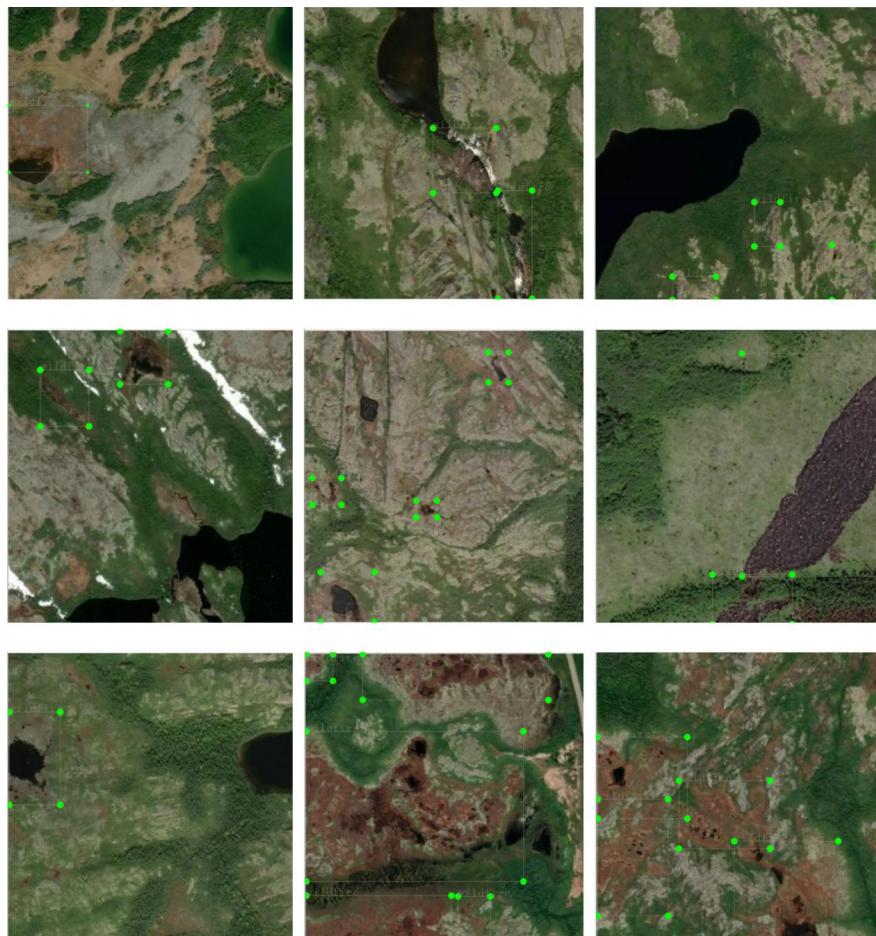


Image
Annotation

LabelImg

Random samples after wildfire image labeling

Wildfire > Positive

No-wildfire > Negative



YOLO Format



1. Object Category
2. Normalized Bounding Box Coordinates

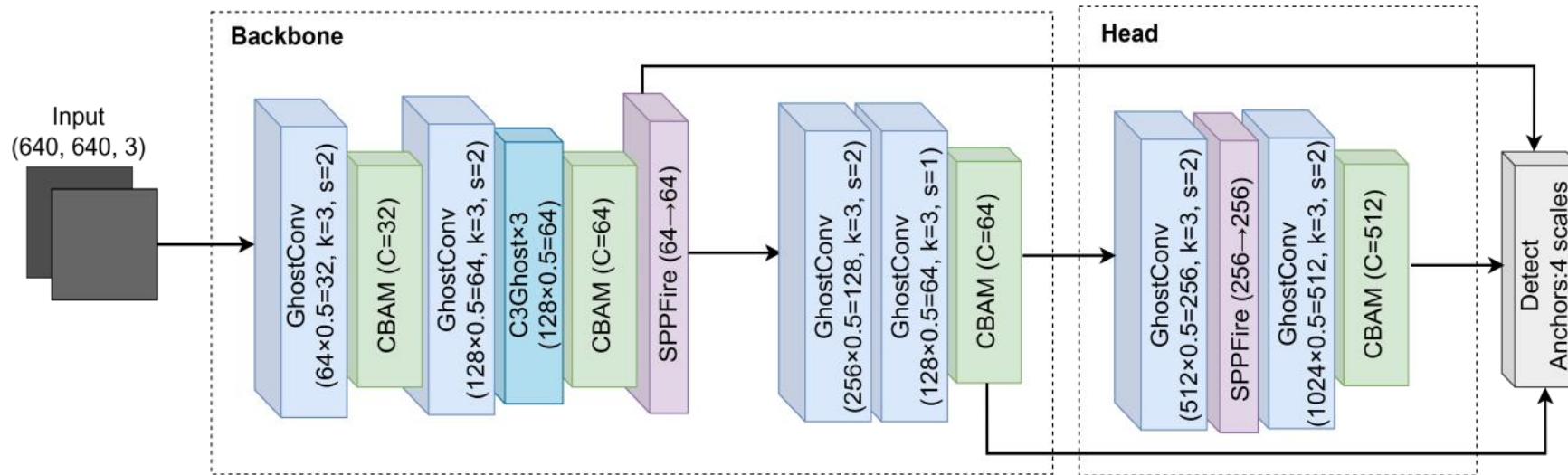
2. Proposed Model -- Based YOLOv5s

- ***GhostConv*** -> Replace the standard convolution with GhostConv.
- ***C3Ghost*** -> Integrate GhostConv in the C3 module.
- ***CBAM Attention*** -> Insert channels and spatial attention modules in the Backbone and Head.
- ***SPPFire*** -> Combine the SPP with the Fire module.



Optimize the hierarchical connection of Backbone
Simplify the output logic of Head

— YOLOv5s-Fire Model Architecture



- Maintain the **efficiency** of YOLOv5s
- Ensure the **precision** of fire detection
- Reducing **inference speed**
- Deployed in **resource-constrained** edge devices.

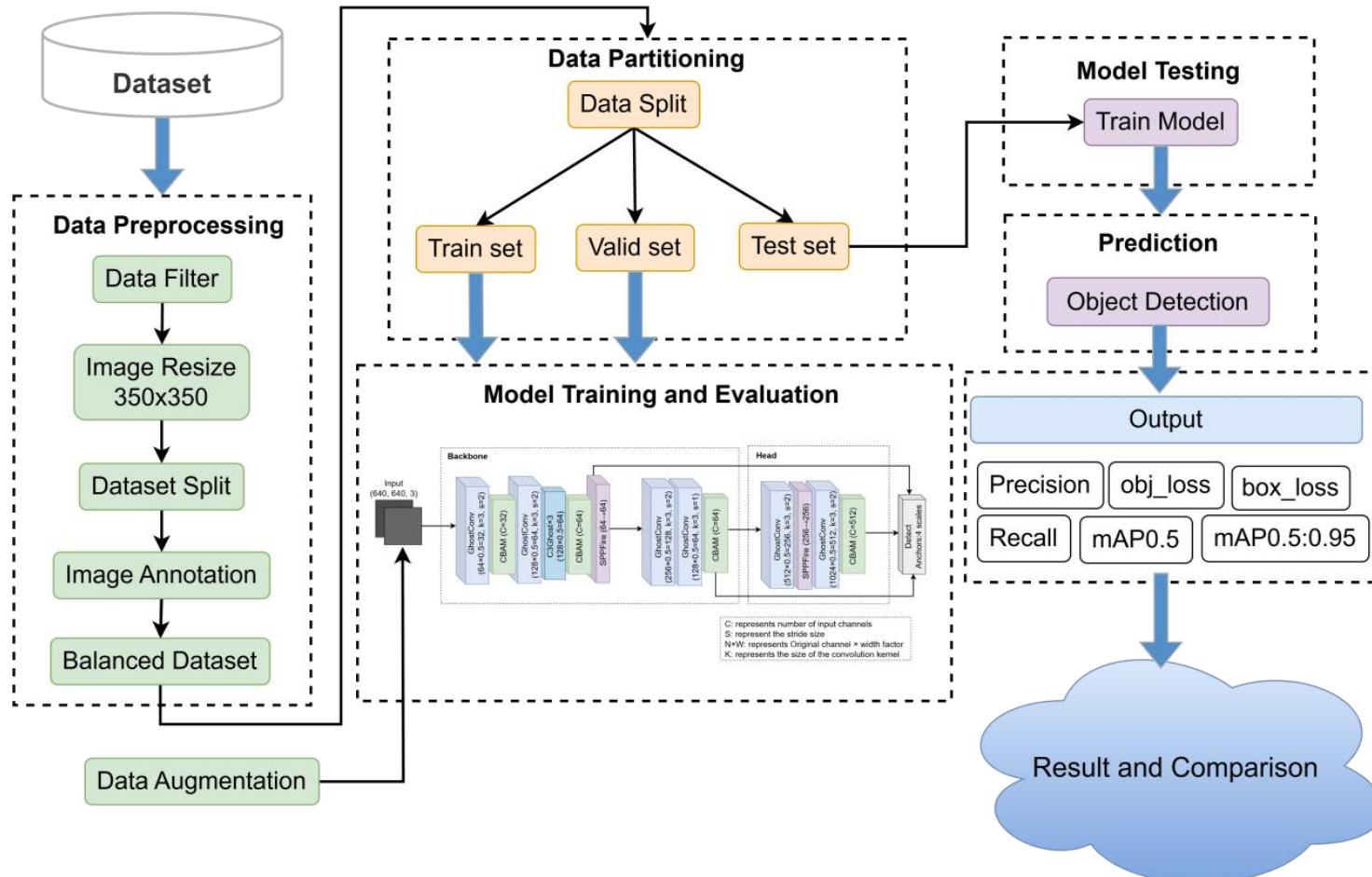
C: represents number of input channels
S: represent the stride size
N×W: represents Original channel × width factor
K: represents the size of the convolution kernel

YOLOv5s
+
CBAM Attention
+
GhostConv
+
C3Ghost
+
SPPFire Module

3. Training Parameter Tuning

Hyper-parameters	
Models	YOLOv5s, YOLOv5n, YOLOv5m, YOLOv5l, YOLOv5s-Fire
Final learning rate	0.2
Warmup epochs	10
Focal Loss	$\gamma = 1.5$
Target existence loss weight	0.7
Anchors	4 → Adapt to target diversity
hsv_s	0.7
Mosaic	0.8
Flipud	0.3

— Overall Architecture Process Structure



1. Dataset Construction

- > Data preprocessing
- > Data Partitioning

2. Model Training & Evaluation

- > End-to-End Training
- > Multi-dimensional Evaluation

3. Comparison of Results

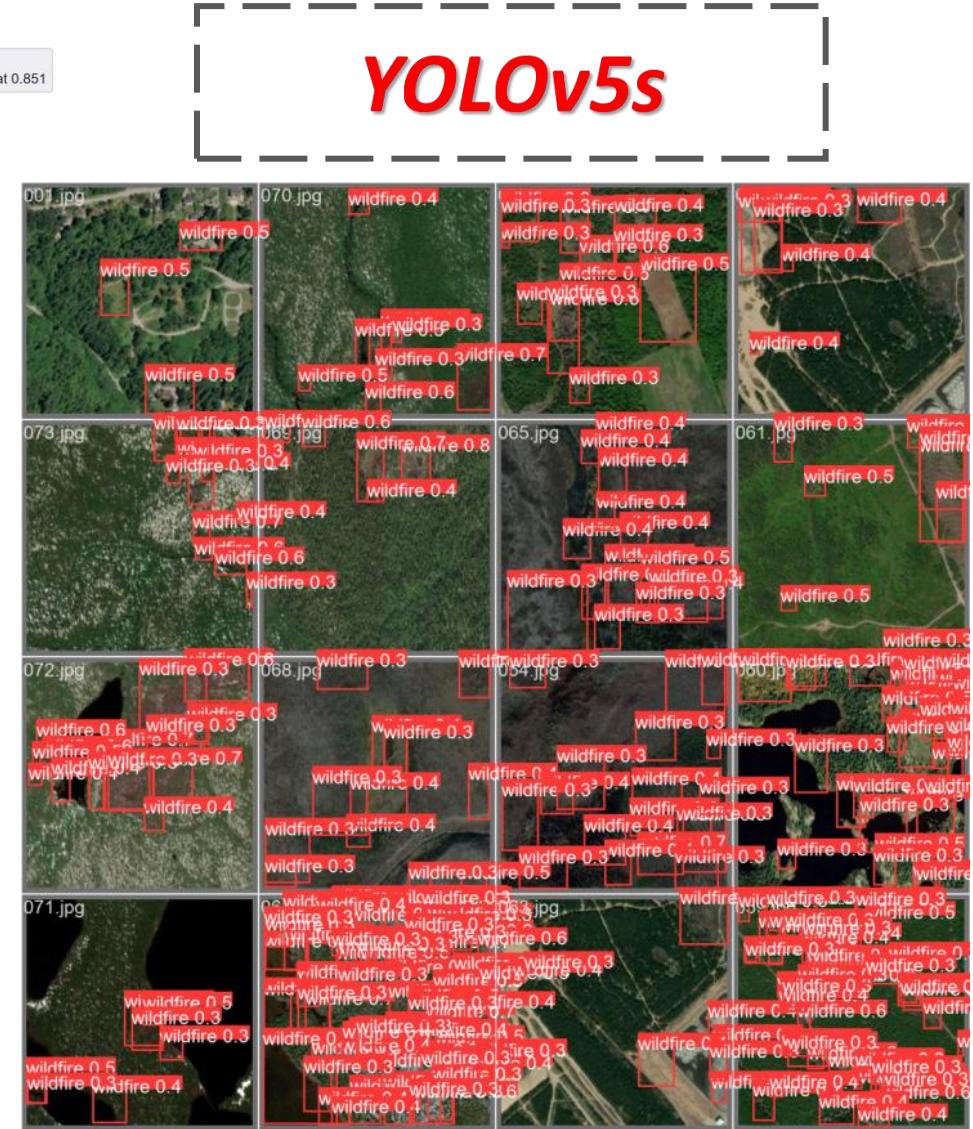
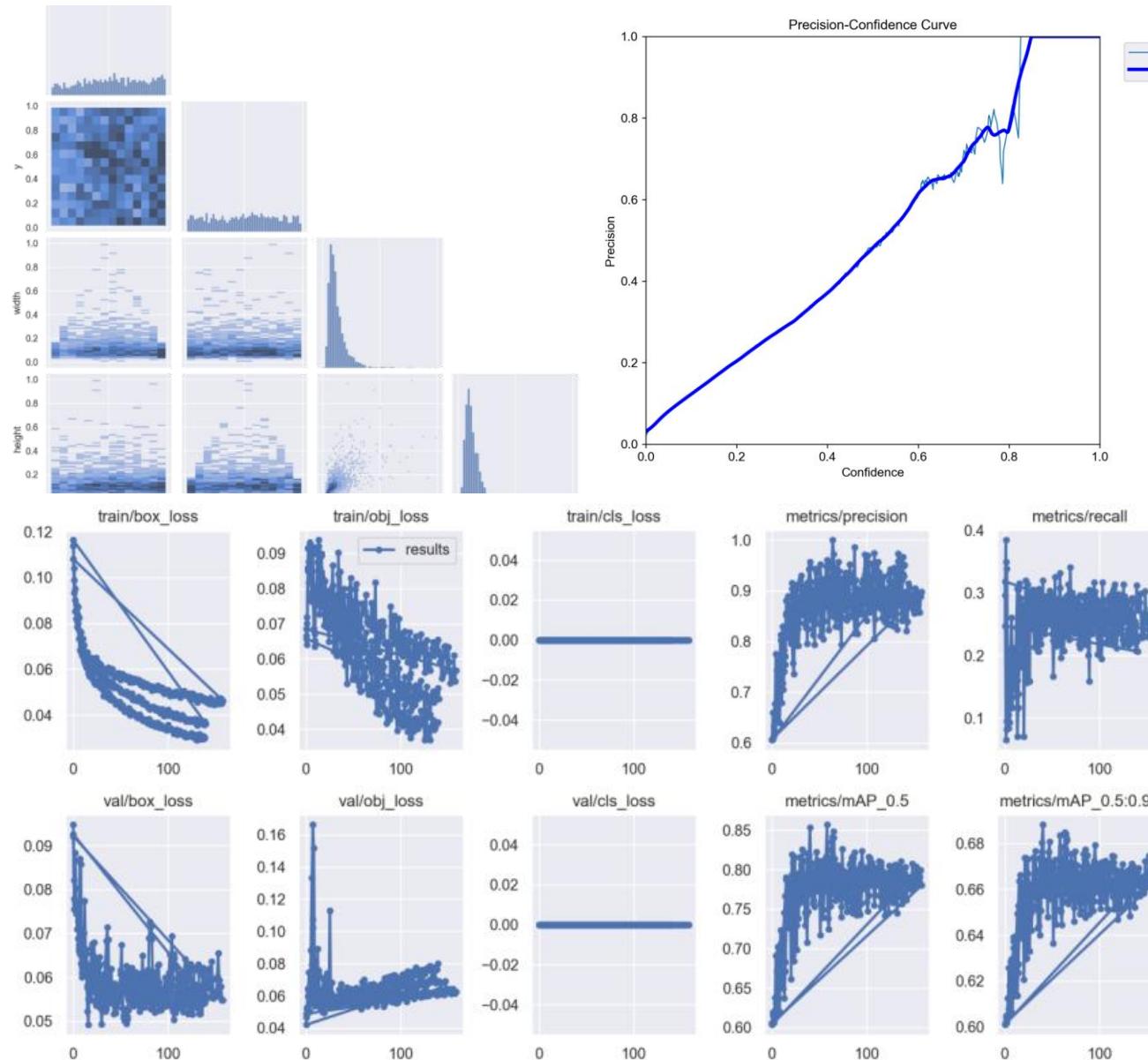
- > Comparison Models
- > Improved Validation

Background Review

Improvement Process

Experiment Result

Conclusion

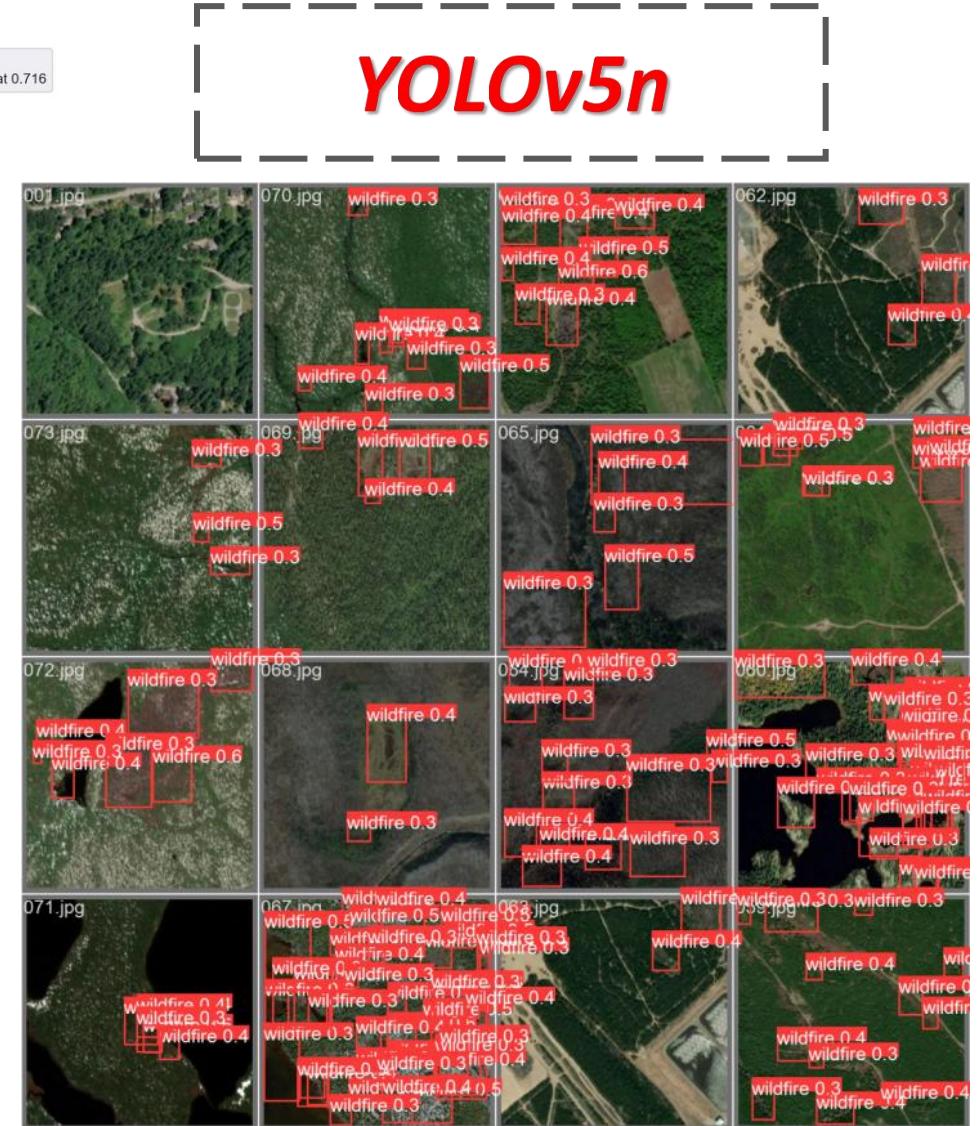
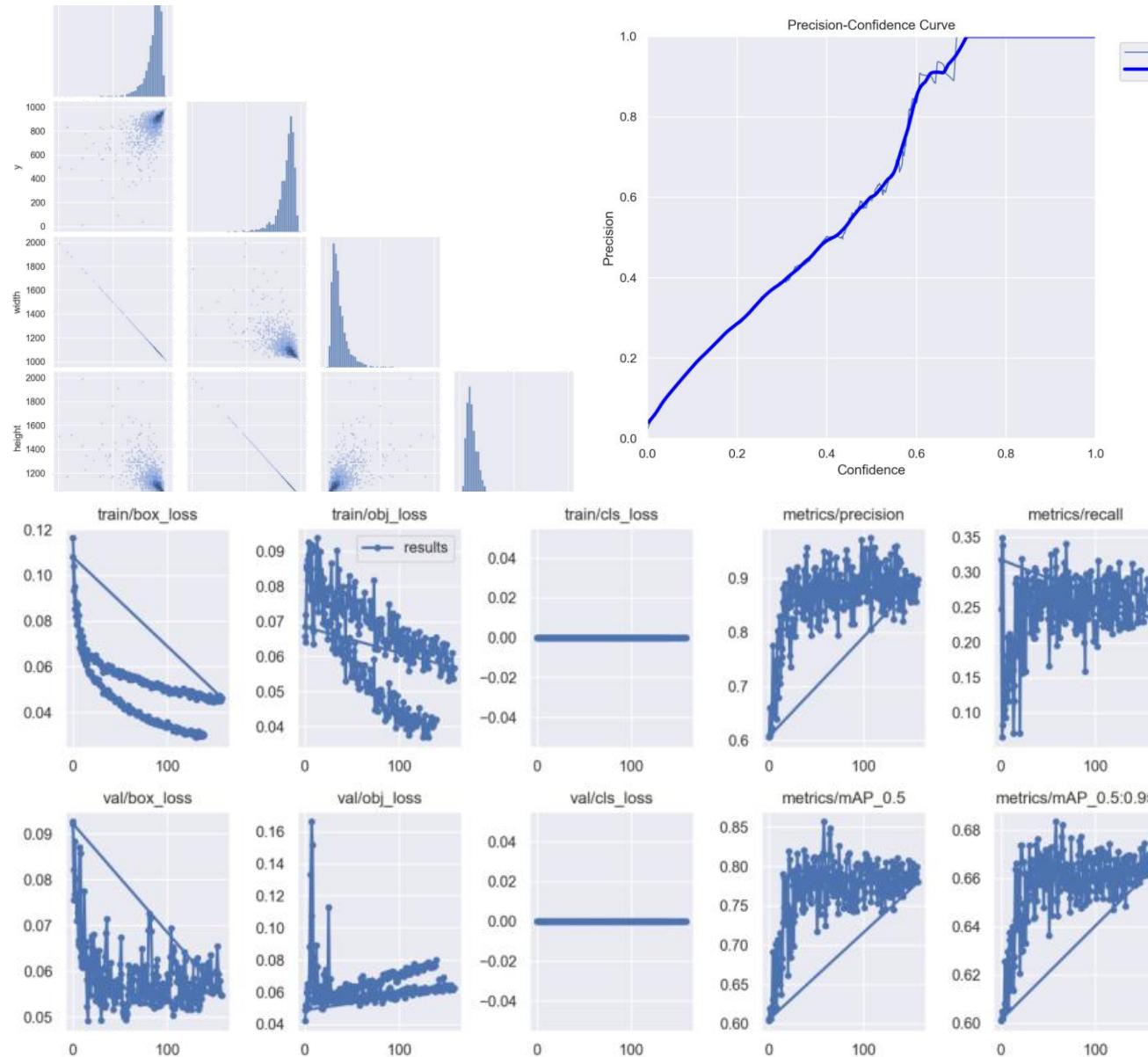


Background Review

Improvement Process

Experiment Result

Conclusion

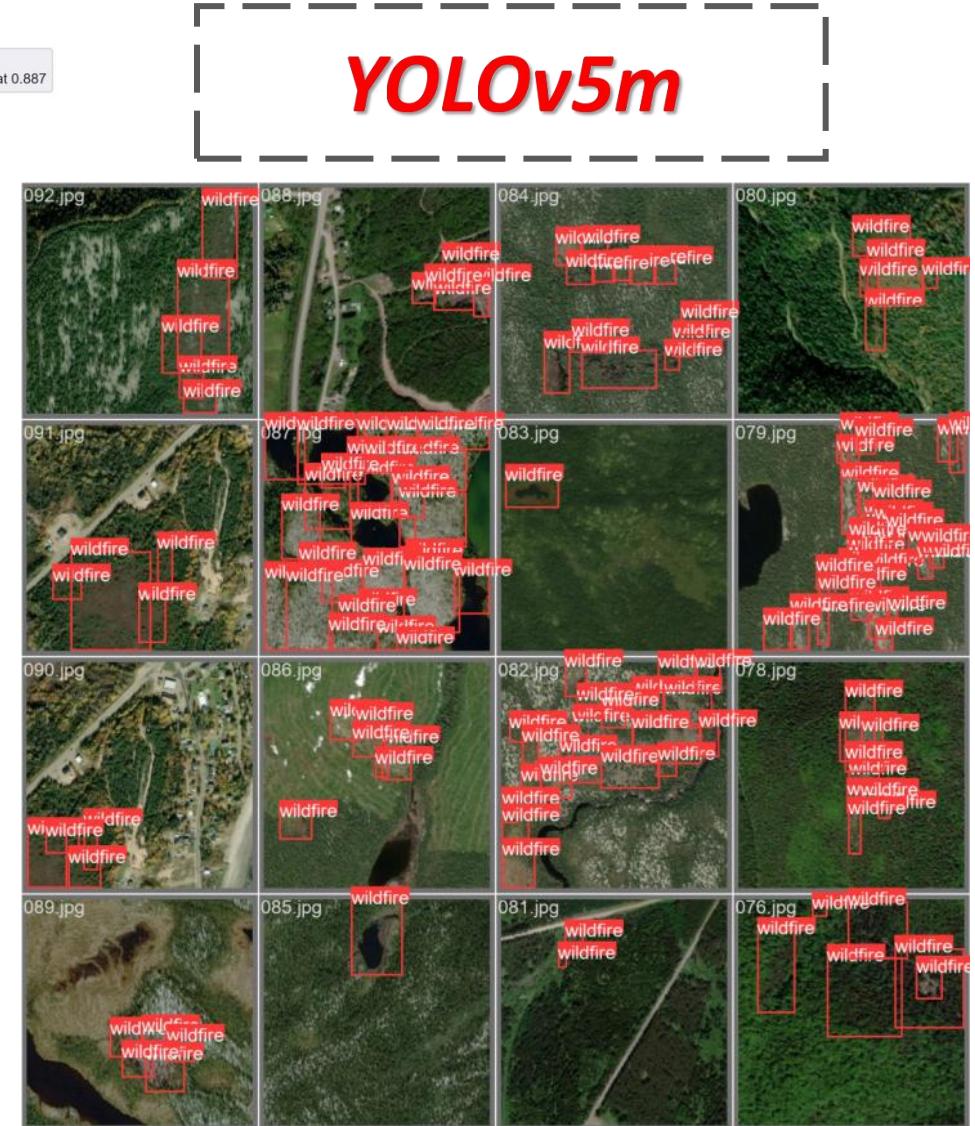
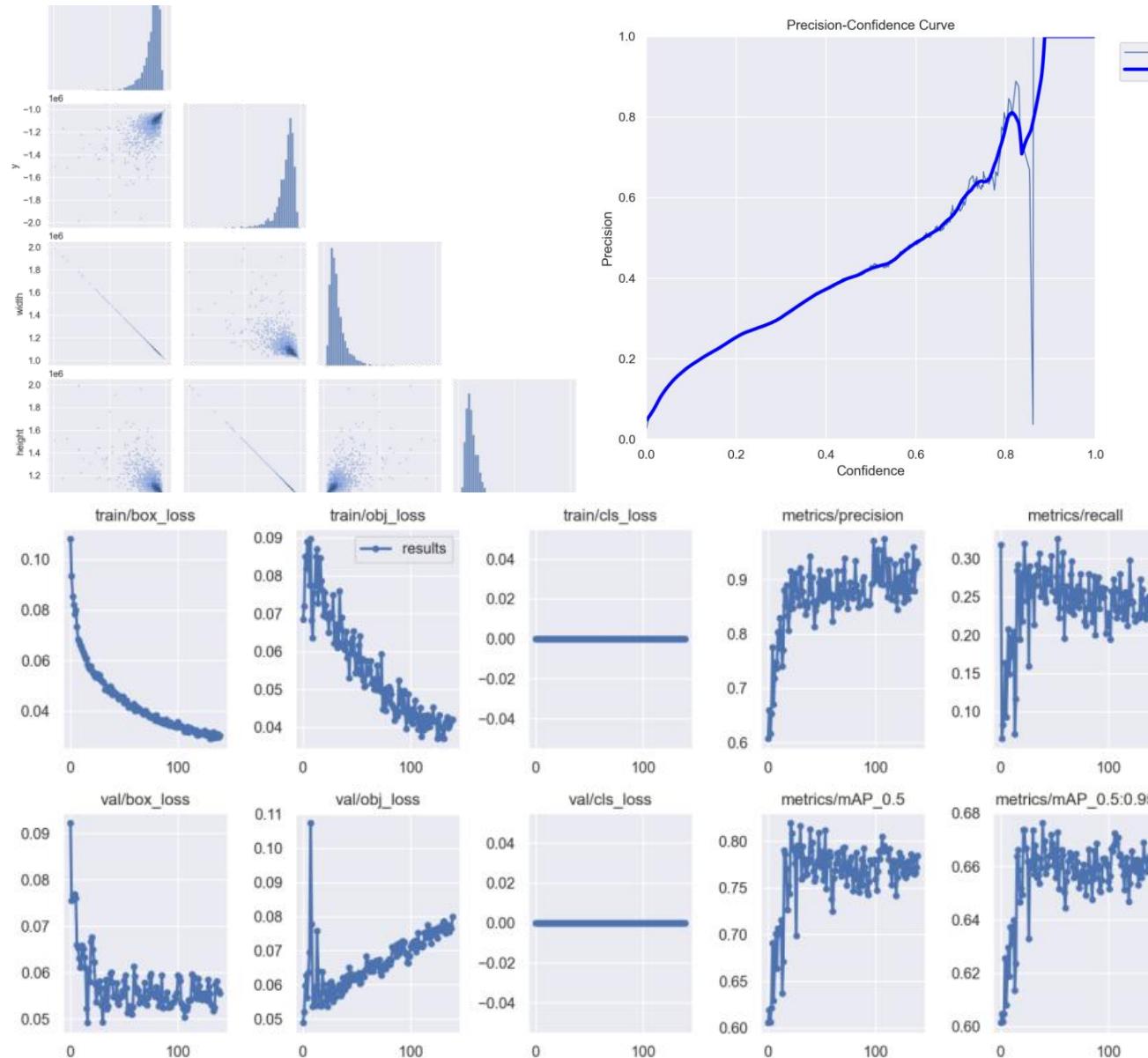


Background Review

Improvement Process

Experiment Result

Conclusion



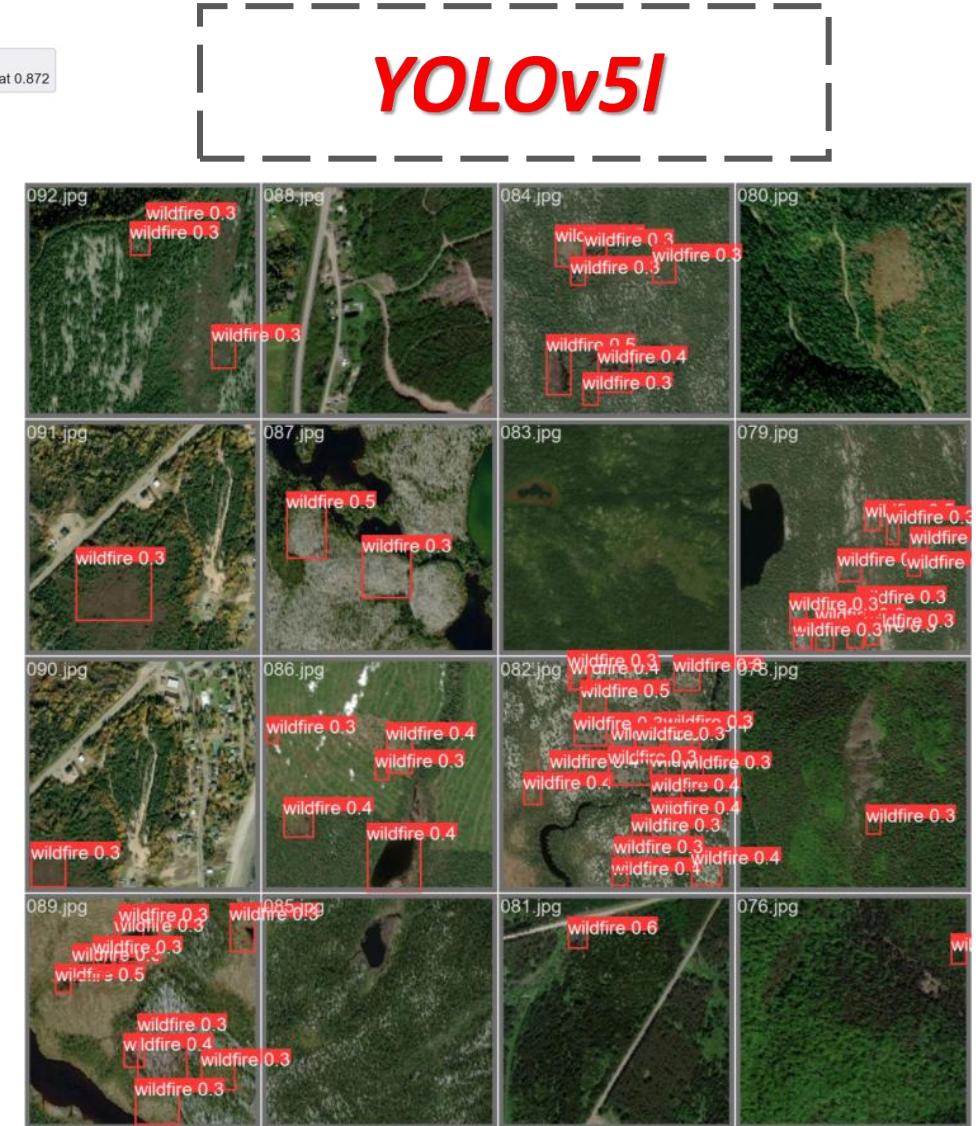
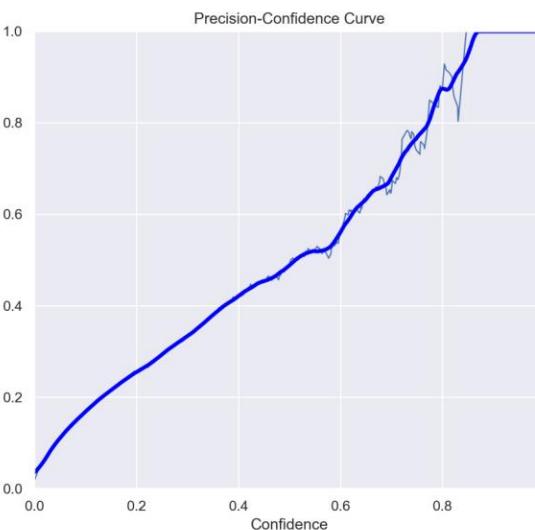
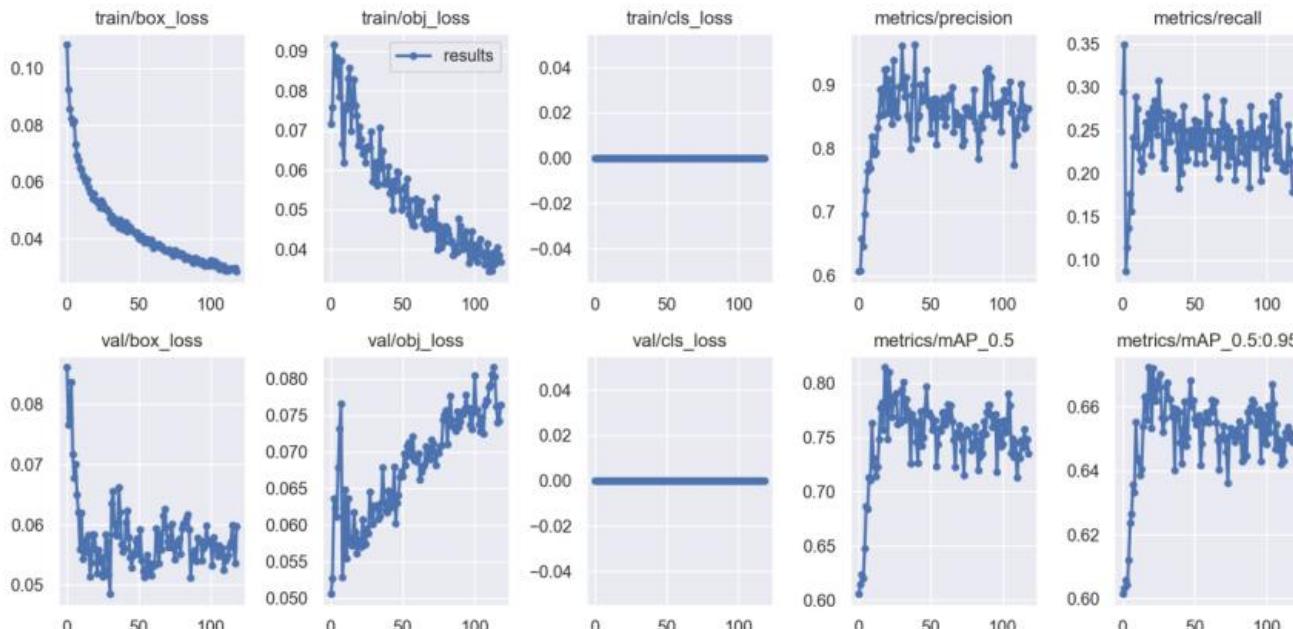
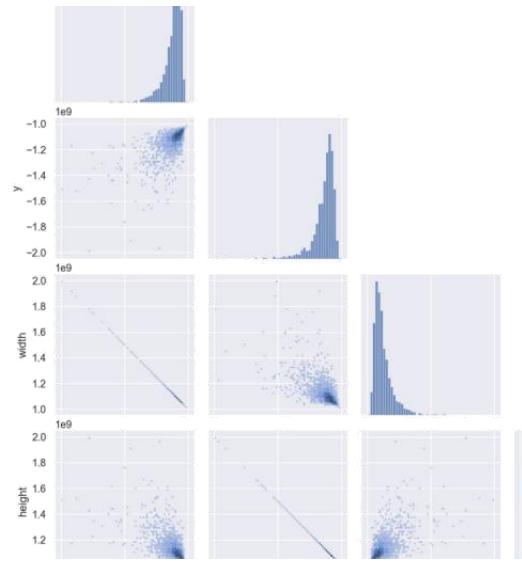
YOLOv5m

Background Review

Improvement Process

Experiment Result

Conclusion

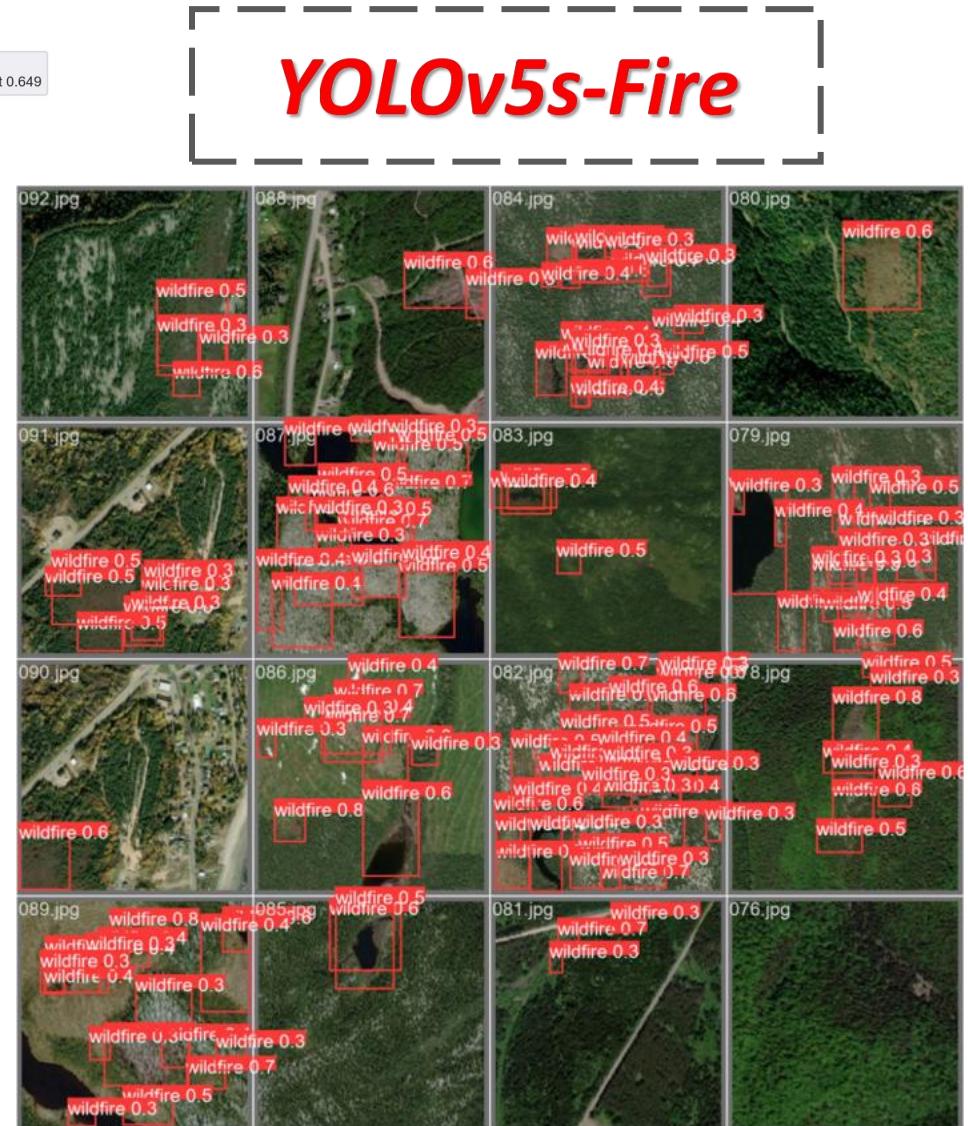
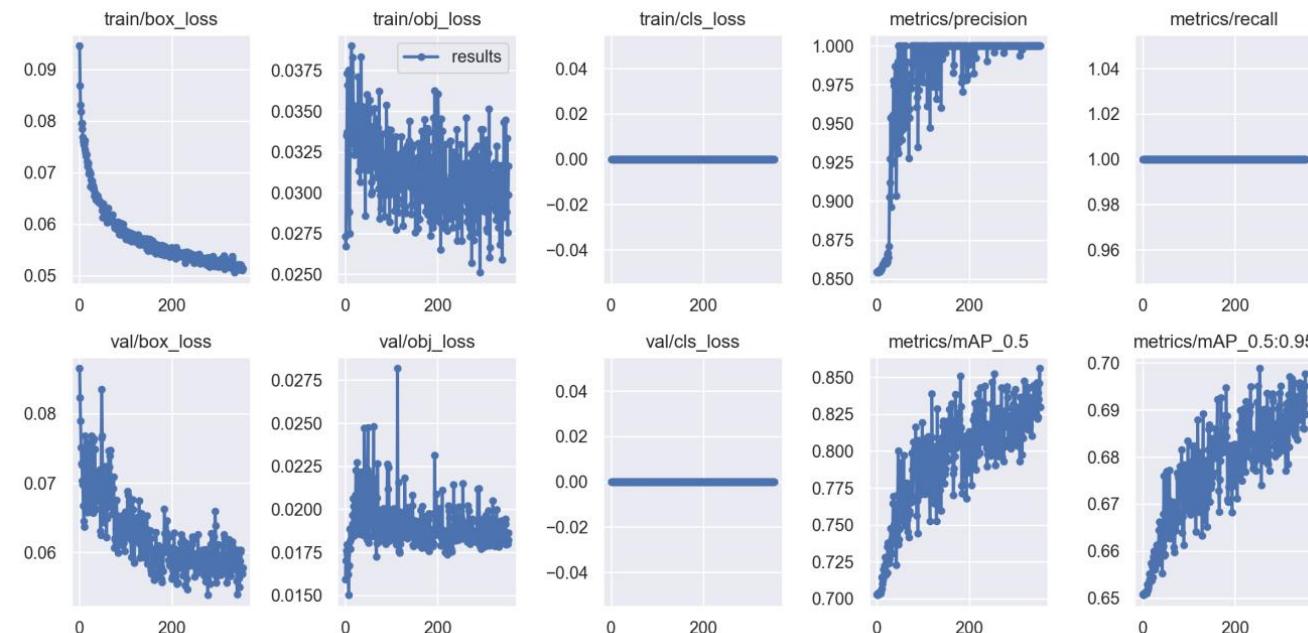
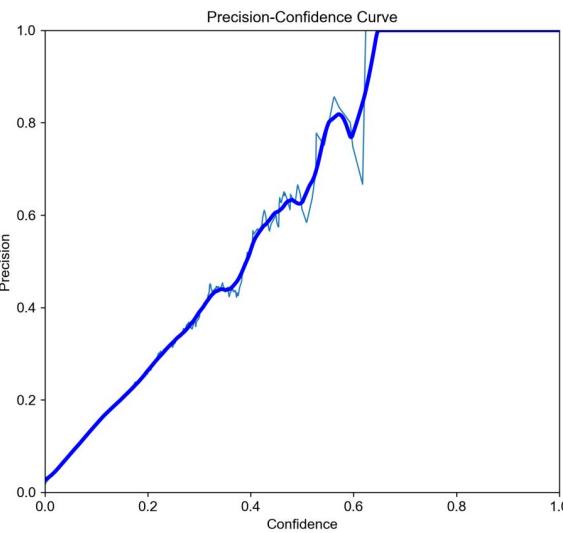
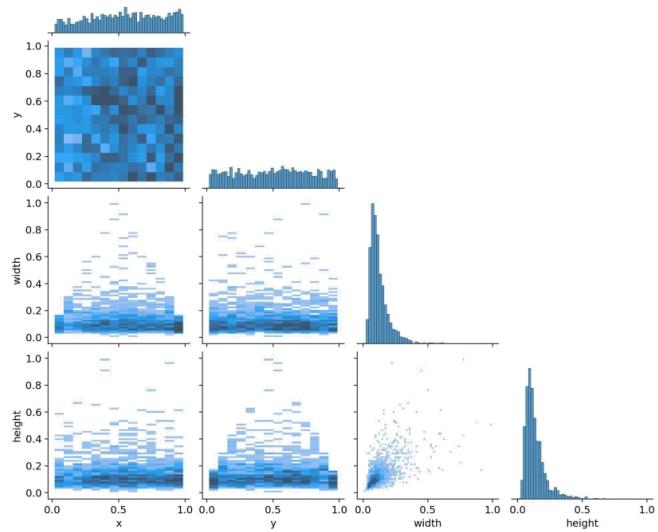


Background Review

Improvement Process

Experiment Result

Conclusion



— Comparison of YOLOv5 Series Models

	Precision	Recall	$mAP_{0.5}$	$mAP_{0.5:0.95}$	box loss	object loss
YOLOv5s	94.8	91.8	85.3	68.86	3.62	4.86
YOLOv5n	94.9	93	85.8	68.41	4.63	5.67
YOLOv5m	94.3	85.6	81.4	67.62	3.03	4.19
YOLOv5l	92.3	86.9	81.3	67.19	2.85	3.68
YOLOv5s-Fire	96.7	94.1	87.5	73.1	2.31	2.45
vs YOLOv5s	↑1.9%	↑2.3%	↑2.2%	↑4.24%	↓36.2%	↓49.6%



The YOLOv5S-Fire improved based on YOLOv5s performs the best!

— Wildfire Detection in Test Image



YOLOv5m



YOLOv5n



YOLOv5l



YOLOv5s



YOLOv5s-Fire

Conclusion:

The paper proposes an enhanced remote sensing image forest fire detection model named YOLOv5s-Fire, which integrates multiple advanced modules. Based on the YOLOv5s framework, the model incorporates the CBAM attention mechanism, BiFPN feature fusion structure, GhostConv modules, and the SPP-Fire module that significantly improve detection accuracy and robustness while effectively controlling model size and computational cost. Through a series of experimental evaluations, the model architecture and hyperparameters were optimized to achieve superior classification performance.

The results demonstrate that YOLOv5s-Fire outperforms all versions of the original YOLOv5 model across multiple evaluation metrics, achieving the 96.7% precision and 94.1% Recall. These results further confirm its efficiency and practicality in real-world remote sensing data processing, providing strong technical support for intelligent forest fire monitoring and emergency response.

Future Work:

1. Architecture Enhancement -> *Transformer Integration*

- Embed Swin Transformer Modules for long-range dependencies.
- Develop Hybrid CNN-Transformer Architecture.

2. Data Augmentation -> *Multi-Source Training*

- Incorporate Sentinel-2 hyperspectral data.
- Fuse humidity and wind meteorological + terrain data (DEM).

3. Deployment optimization

- Support edge device deployment.
- Integrated satellites, Uavs and ground monitoring stations.

Reference List

- [1] E. A. Kadir, H. Irie, and S. L. Rosa, “Modeling of Wireless Sensor Networks for Detection Land and Forest Fire Hotspot,” in 2019 International Conference on Electronics, Information, and Communication (ICEIC), Auckland, New Zealand, Jan. 2019, pp. 1–5. doi: <https://doi.org/10.23919/ELINFOCOM.2019.8706364>.
- [2] A. Khan, B. Hassan, S. Khan, R. Ahmed, and A. Abuassba, “DeepFire: A Novel Dataset and Deep Transfer Learning Benchmark for Forest Fire Detection,” Mobile Information Systems, vol. 2022, pp. 1–14, Apr. 2022, doi: <https://doi.org/10.1155/2022/5358359>.
- [3] S. T. Seydi, V. Saeidi, B. Kalantar, N. Ueda, and A. A. Halin, “Fire-Net: A Deep Learning Framework for Active Forest Fire Detection,” Journal of Sensors, vol. 2022, pp. 1–14, Feb. 2022, doi: <https://doi.org/10.1155/2022/8044390>.
- [4] H. Yuan, Z. Lu, R. Zhang, J. Li, S. Wang, and J. Fan, “An effective graph embedded YOLOv5 model for forest fire detection,” Computational Intelligence, vol. 40, no. 2, Mar. 2024, doi: <https://doi.org/10.1111/coin.12640>.

Reference List

- [5] R. Xzu, H. Lin, K. Lu, L. Cao, and Y. Liu, “A Forest Fire Detection System Based on Ensemble Learning,” *Forests*, vol. 12, no. 2, Feb. 2021, doi: <https://doi.org/10.3390/f12020217>.
- [6] Y. Kang, E. Jang, J. Im, and C. Kwon, “A deep learning model using geostationary satellite data for forest fire detection with reduced detection latency,” *GIScience & Remote Sensing*, vol. 59, no. 1, pp. 2019–2035, Nov. 2022, doi: <https://doi.org/10.1080/15481603.2022.2143872>.
- [7] Y. Ding, M. Wang, Y. Fu, and Q. Wang, “Forest Smoke-Fire Net (FSF Net): A Wildfire Smoke Detection Model That Combines MODIS Remote Sensing Images with Regional Dynamic Brightness Temperature Thresholds,” *Forests*, vol. 15, no. 5, pp. 839–839, May 2024, doi: <https://doi.org/10.3390/f15050839>.

Acknowledgment

This thesis was completed with the help and guidance of my Computer Science and technology research supervisor ***Dr. Md Irfan Ullah***. From the beginning of topic selection until the completion of the entire thesis writing, he spent a great deal of time and effort to provide me with comprehensive and detailed guidance and many targeted suggestions. My mentor's profound professional knowledge, serious scientific attitude, rigorous academic spirit and tireless teaching noble ethics has all exerted a profound influence on me. He has taught me the methodology to carry out the research and to present the research works as clear as possible. It was a great privilege and honour to work and study under his guidance. I am extremely grateful for what he has offered me. I would like to express my deep and sincere gratitude to mentor for giving me the opportunity to do research and providing invaluable guidance throughout this research. I would also like to thank him for his friendship, empathy, and great sense of humour. I am extremely grateful to my parents for their love, prayers, caring and sacrifices to educating and preparing for my future. I dedicate this thesis to them.

Thanks!

Question & Answer