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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

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

- Difficult analysis of satellite image
- Slow monitoring response
- Limited coverage

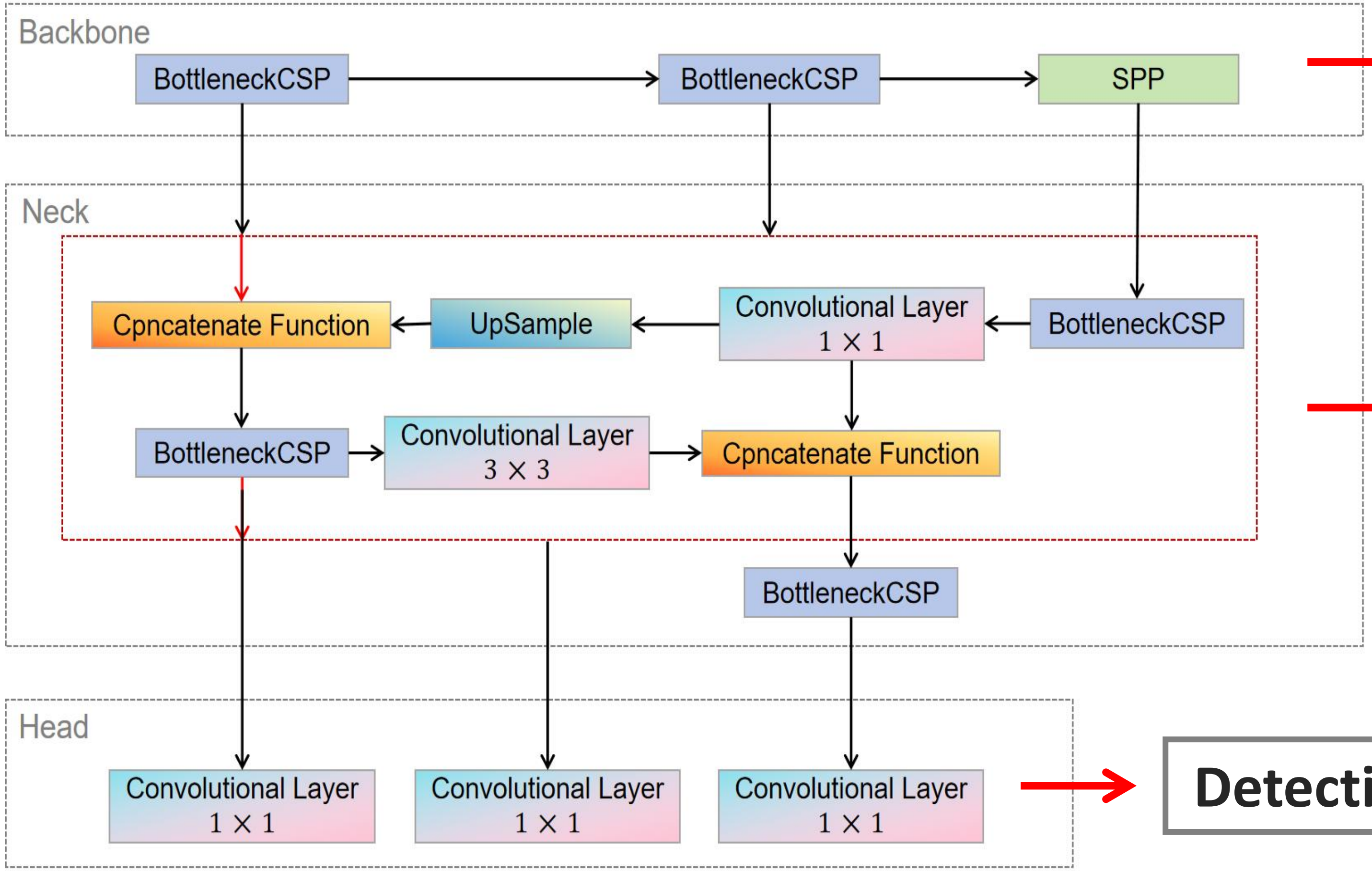
YOLO Algorithm

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



Focus + BottleneckCSP×4 + SSP

FPN +PAN
+
Concatenate + UpSample

Detection Layer

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

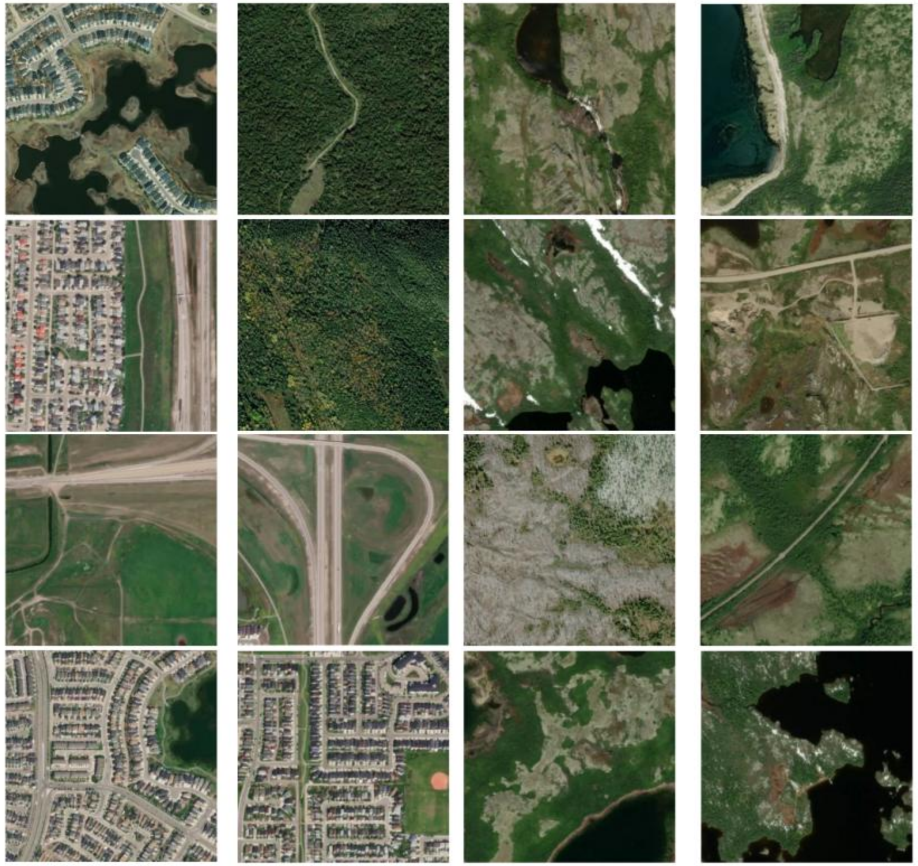
- Wildfire Prediction Dataset (Satellite Images) from Kaggle

Original Dataset Distribution

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

DataSet Selection

Images of wildfire and no-wildfire classes



1. Dataset Preprocessing

Data screening

DataSet	wildfire	No-wildfire	Total
Number	200	200	400

Image Resize

350 × 350

DataSet Screening

Data Screening Criteria

(1) Image Clarity

(2) Label Reliability

(3) Scene Coverage

1. Dataset Preprocessing

Stratified Sampling

- 300 training images and 100 validation images

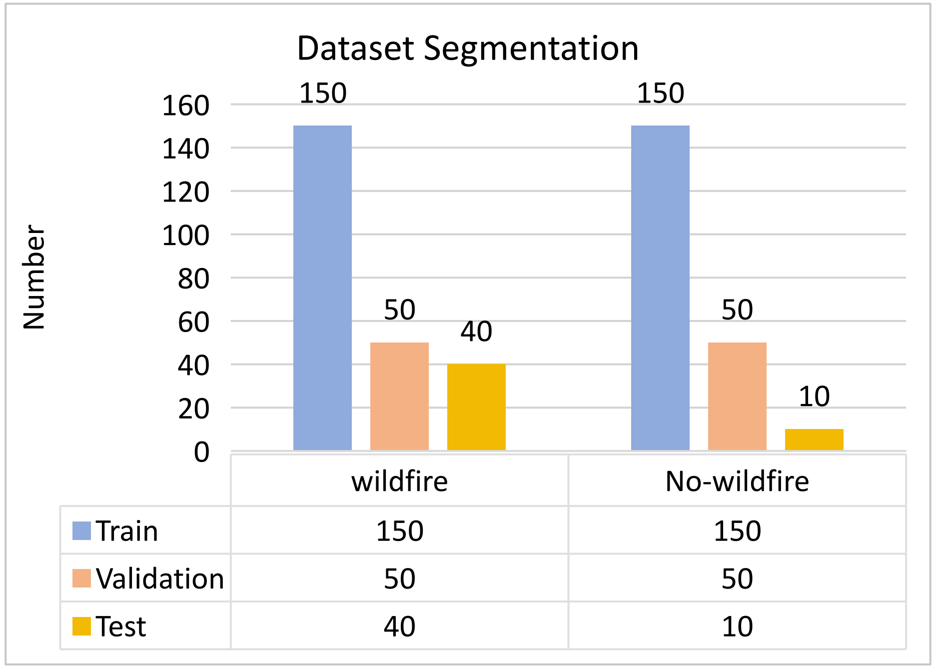
75% : 25%

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

DataSet Splitting

Dataset Segmentation

A separate test set of ***50*** images



1. Dataset Preprocessing

Random samples after wildfire image labeling

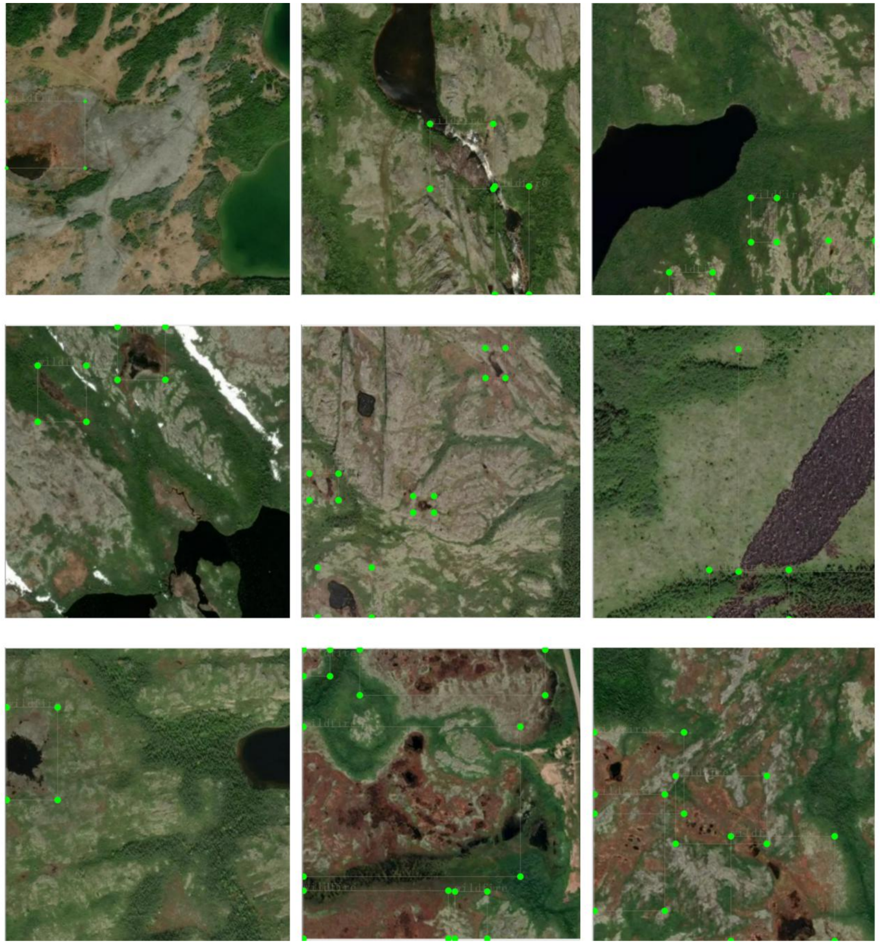


Image Annotation

LabelImg

Wildfire > Positive

No-wildefire > Negtive

***YOLO* Format**

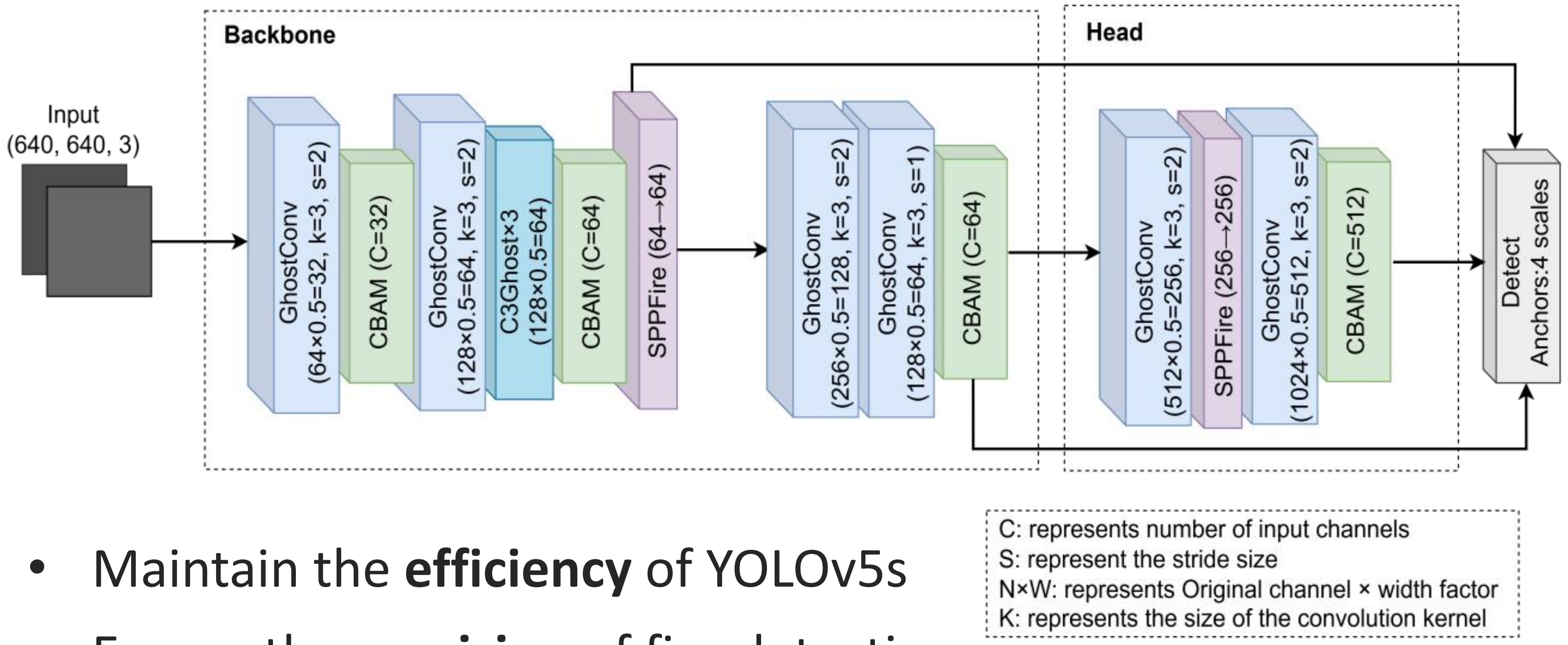
1. Object Category
2. Normalized Bounding Box Coordinates

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



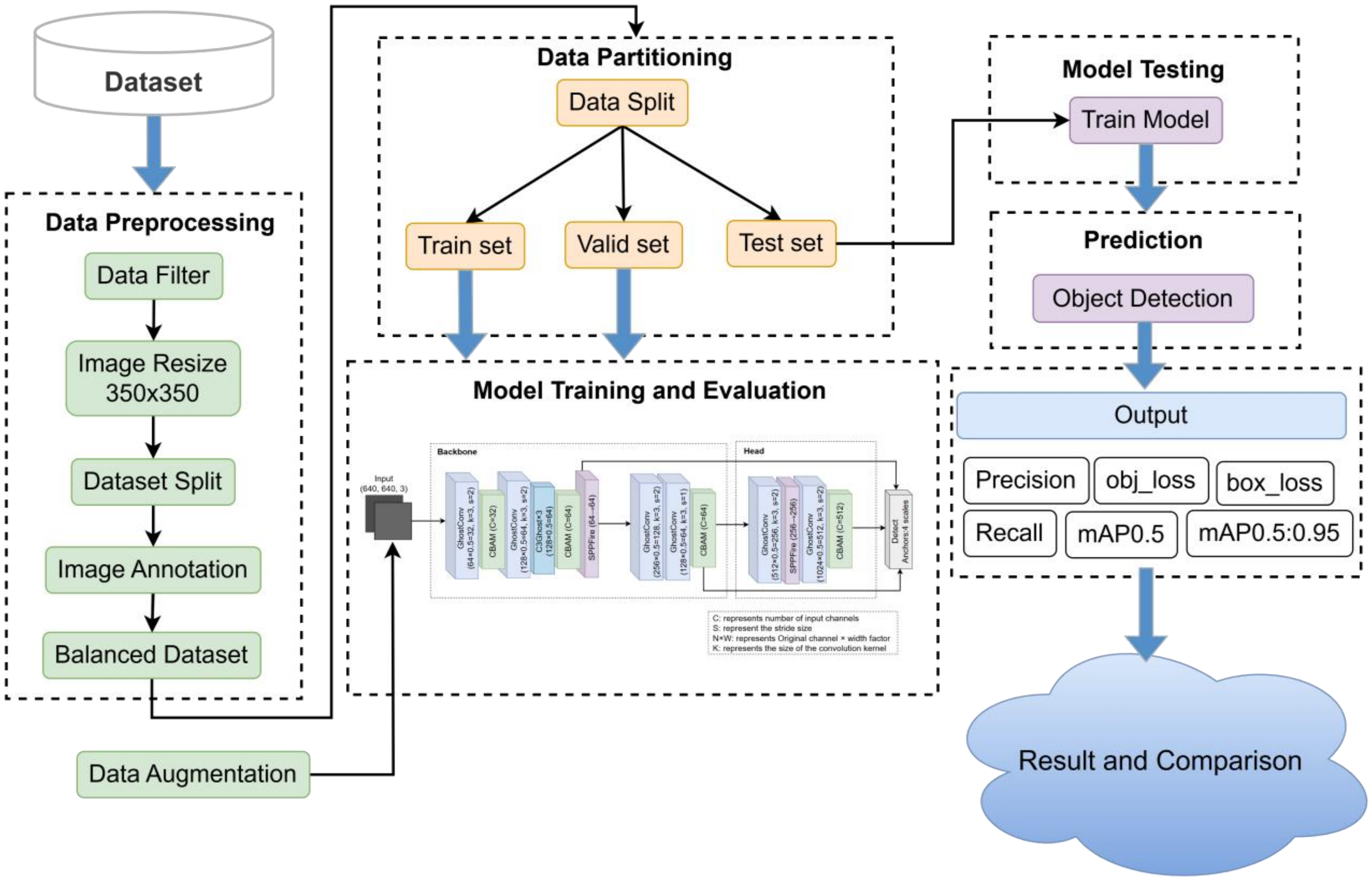
- Maintain the **efficiency** of YOLOv5s
- Ensure the **precision** of fire detection
- Reducing **inference speed**
- Deployed in **resource-constrained** edge devices.

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	Training strategy optimization
Focal Loss	$\gamma = 1.5$	
Target existence loss weight	0.7	
Anchors	4	Adapt to target diversity
hsv_s	0.7	
Mosaic	0.8	Enhance Data Diversity
Flipud	0.3	

—— Overall Architecture Process Structure



1. Dataset Construction

-> Data preprocessing

-> Data Partitioning

2. Model Training & Evaluation

-> End-to-End Training

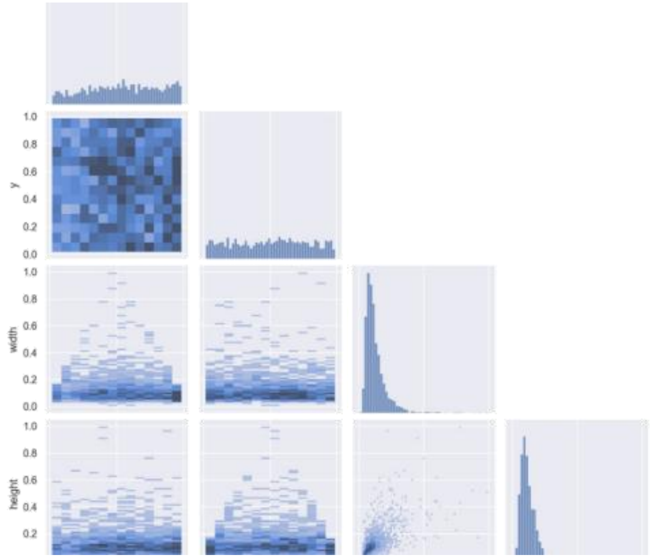
-> Multi-dimensional Evaluation

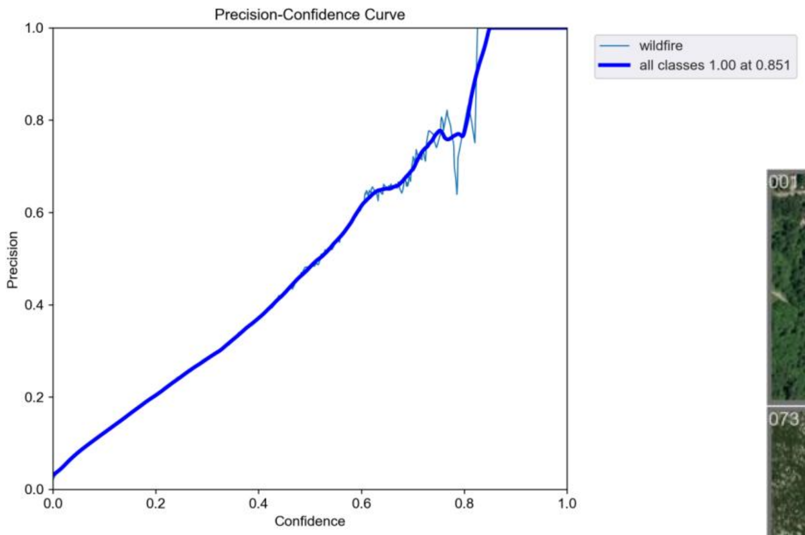
3. Comparison of Results

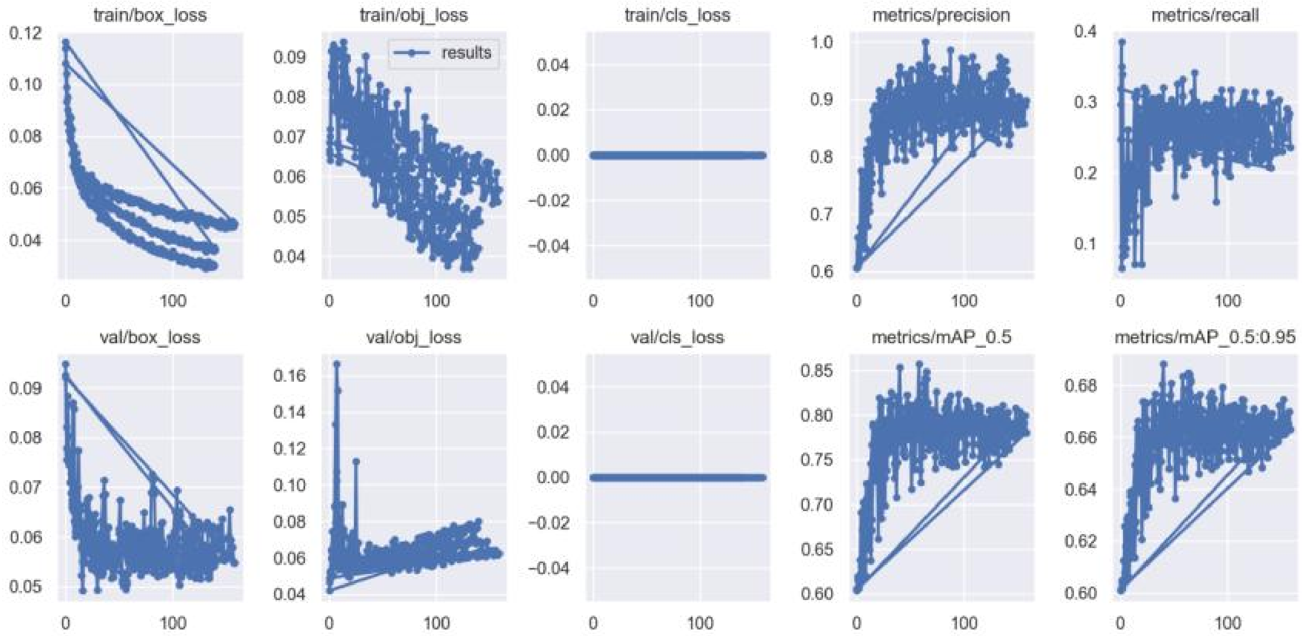
-> Comparison Models

-> Improved Validation

YOLOv5s




Precision-Confidence Curve
wildfire
all classes 1.00 at 0.851
Precision
Confidence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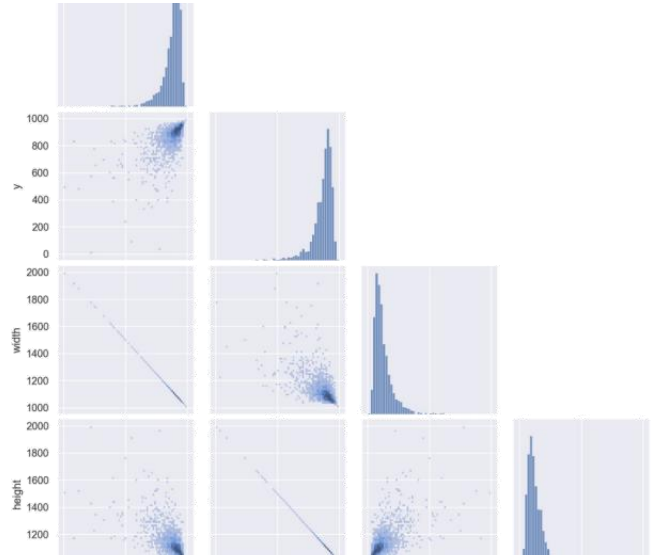
train/obj_loss
results
train/cls_loss
metrics/precision
metrics/recall
val/box_loss
val/obj_loss
val/cls_loss
metrics/mAP_0.5
metrics/mAP_0.5:0.95

YOLOv5n



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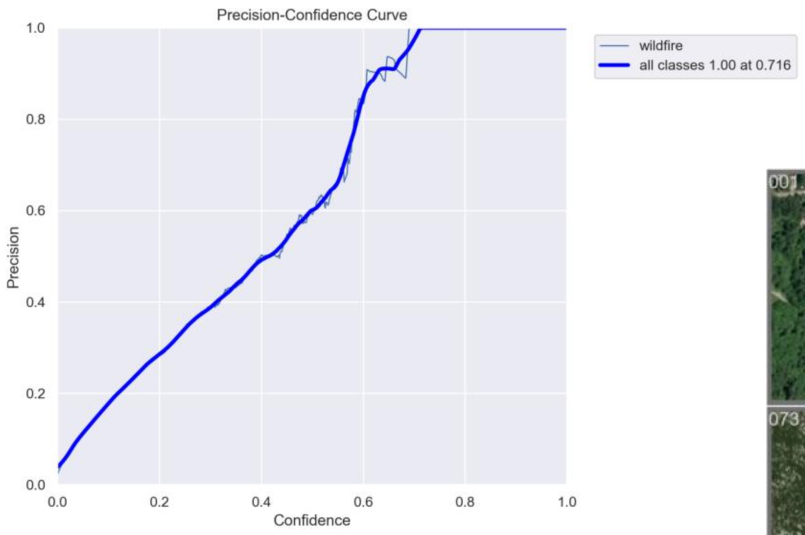
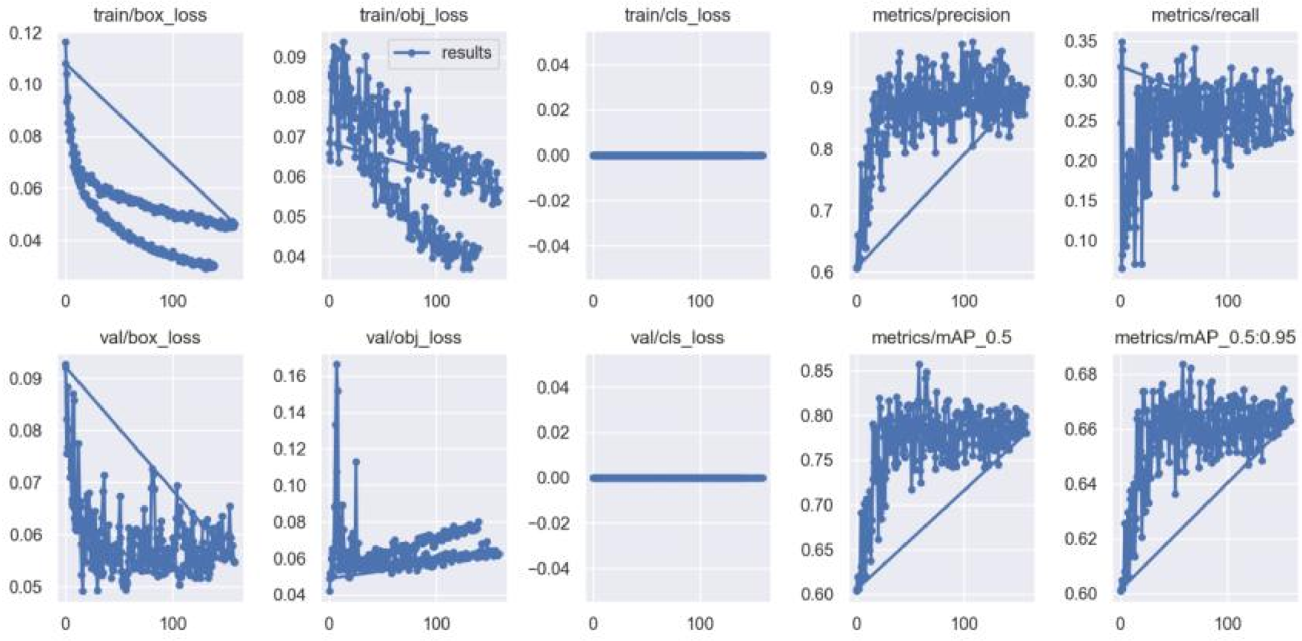


Precision-Confidence Curve
Precision
Confidence
wildfire
all classes 1.00 at 0.716



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results
train/cls_loss
metrics/precision
metrics/recall
val/box_loss
val/obj_loss
val/cls_loss
metrics/mAP_0.5
metrics/mAP_0.5:0.95

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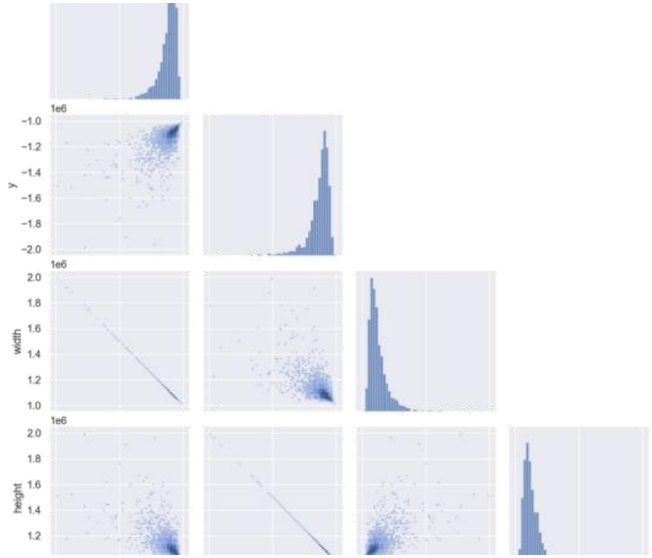
071.jpg
wildfire 0.3
wildfire 0.4
wildfire 0.5
wildfire 0.6

YOLOv5m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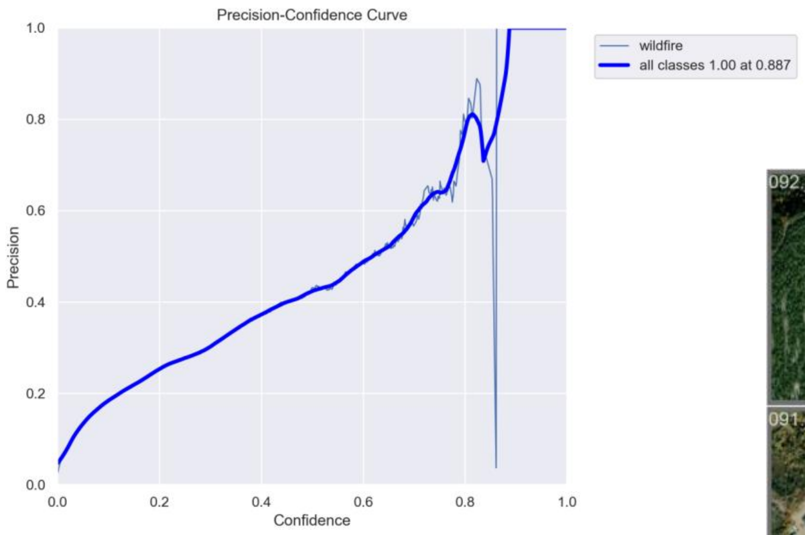
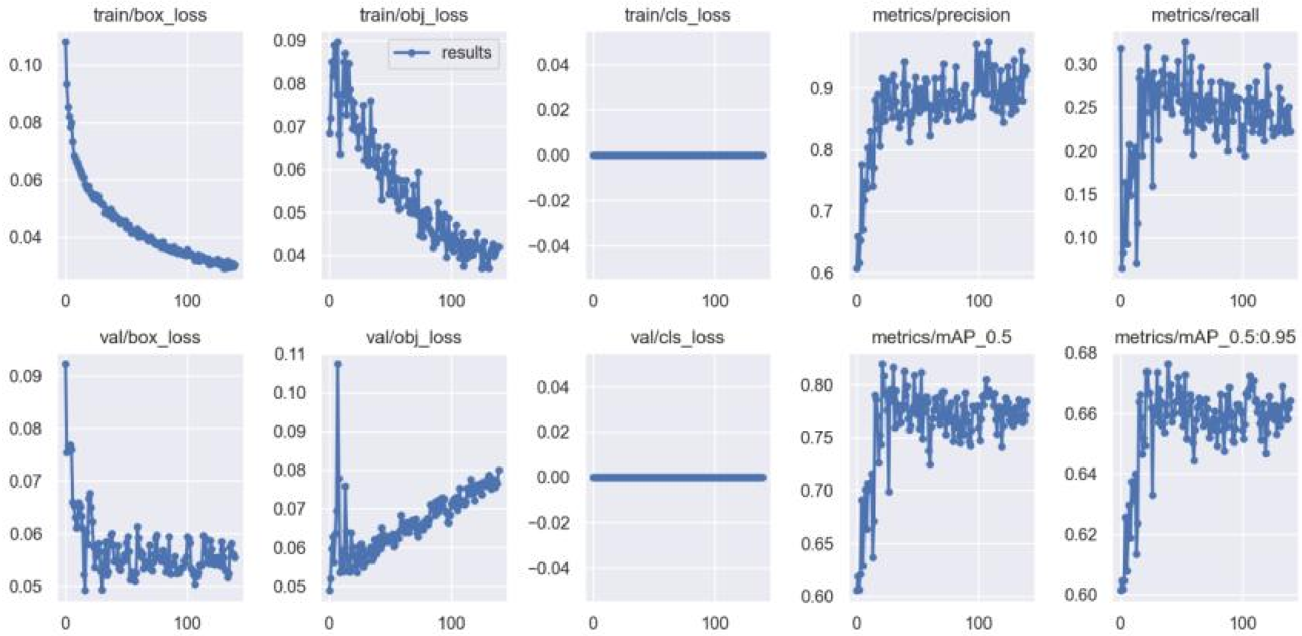

Precision-Confidence Curve
Precision
Confidence
wildfire
all classes 1.00 at 0.887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metrics/recall
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val/cls_loss
metrics/mAP_0.5
metrics/mAP_0.5:0.95


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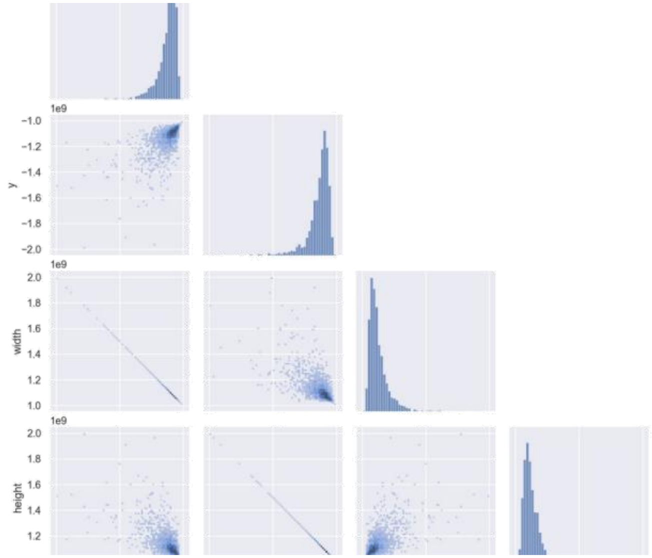
YOLOv5l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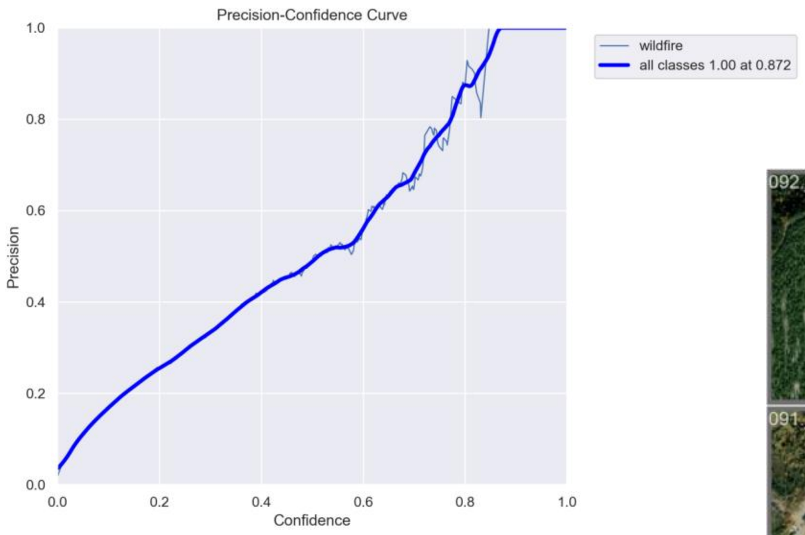
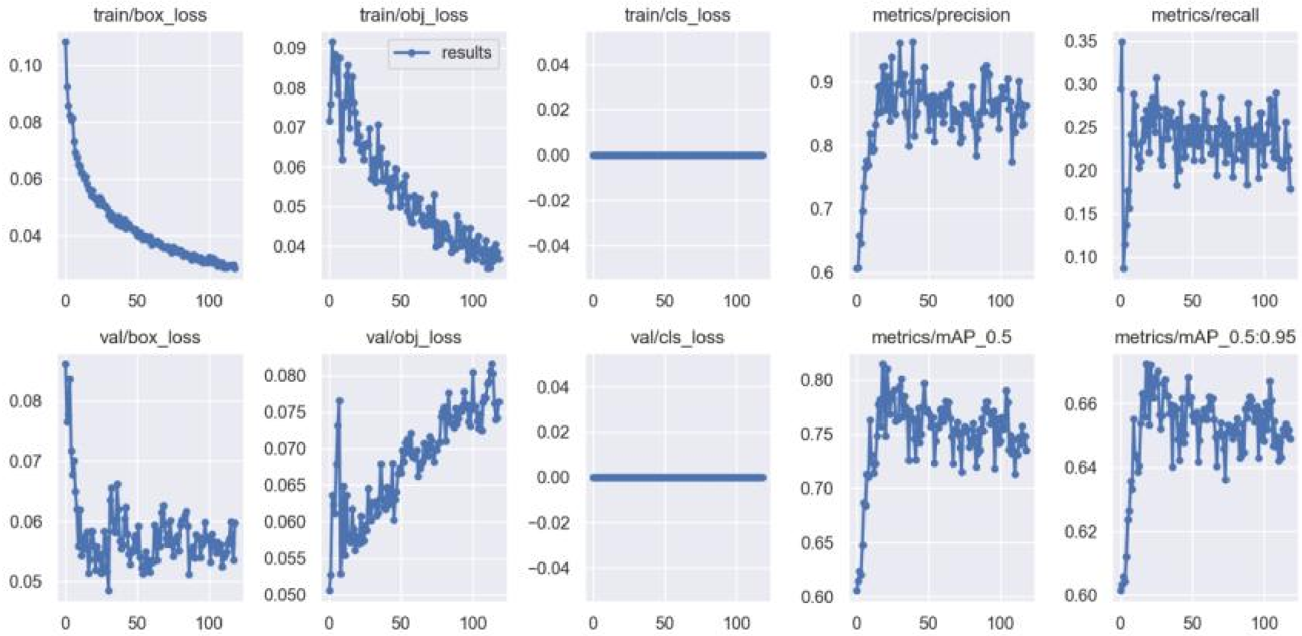

Precision-Confidence Curve
Precision
Confidence
wildfire
all classes 1.00 at 0.872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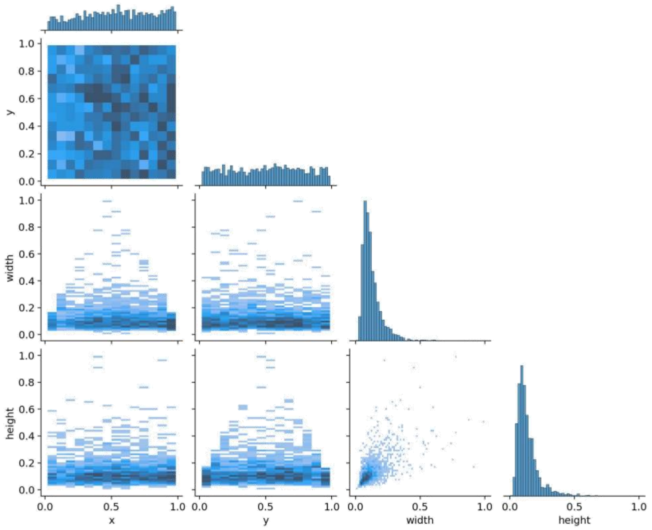
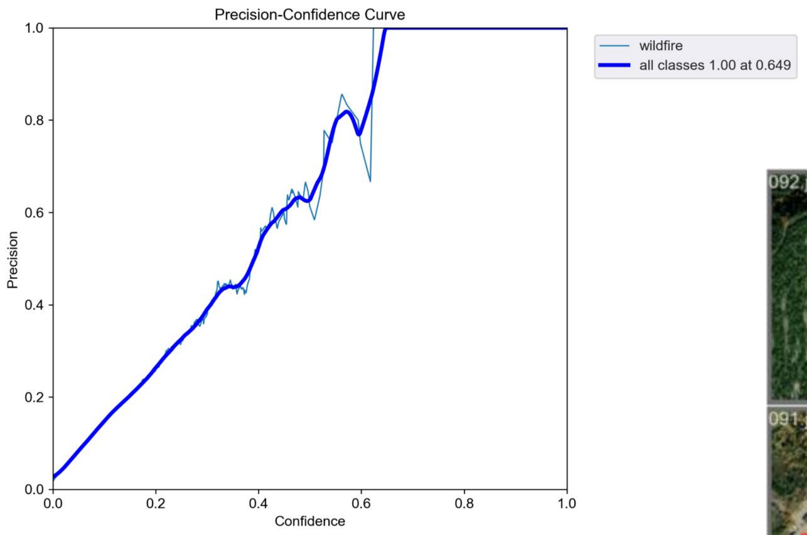
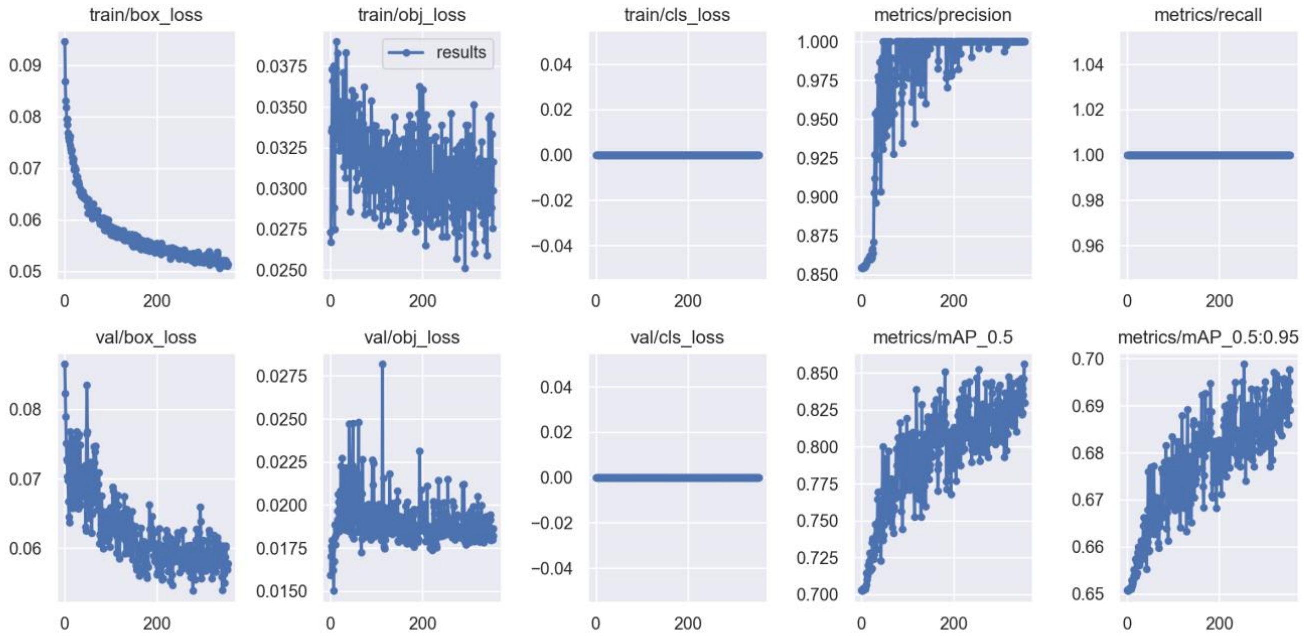




YOLOv5s-Fire



—— Wildfire Detection in Test Image

YOLOv5m

YOLOv5n

YOLOv5l

YOLOv5s

YOLOv5s-Fire

—— 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!

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.

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CDUT Sino-British Collaborative Education
OXFORD BROOKES UNIVERSITY

Thanks!

Question & Answer