Semantic Segmentation on Unbalanced Remote Sensing Classes for Active Fire

ICML Workshop Tracking Climate Change with Machine Learning

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Introduction and Objective

- Active fire detection plays an important role in wildfire early warning systems.
- **Unmanned Aerial Vehicles (UAVs)** and **drones,** are well suited for fire detection as they are **manoeuvrable**, **deployable**, and **flexible** to **frequently revisit** regions of interest, performing long-duration observation over priority areas.
- Future wildfire detection sensors would equip an **on-orbit processing** module that filters the useless raw images before data transmission.

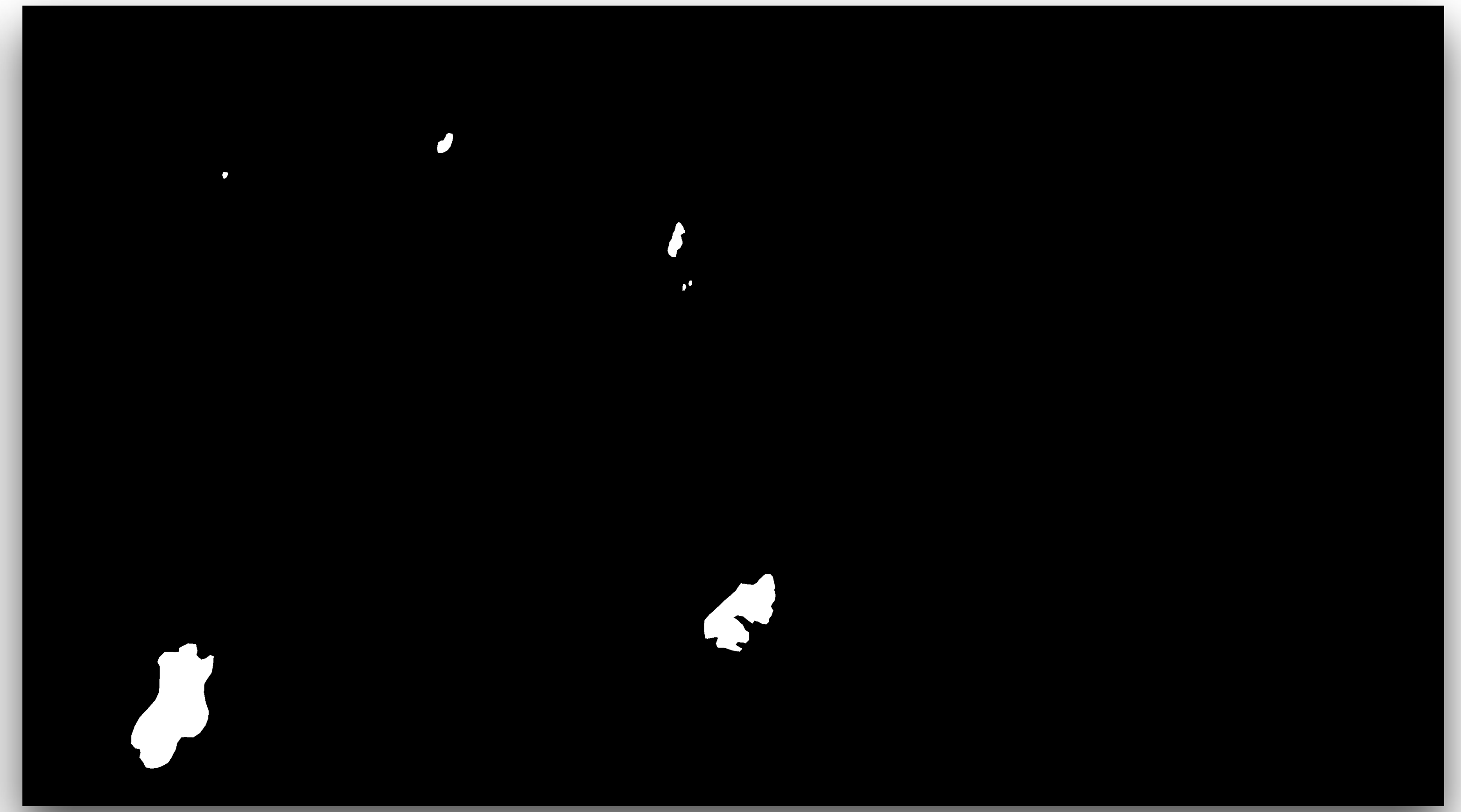
Dataset

FLAME (Fire Luminosity Airborne-based Machine learning Evaluation)

DJI Phantom

5.6%

Frame	Phantom	Normal(.JPEG)	2003 frames	3480 × 2160	–	5.3 GB	Segmentation	Train/Val/Test	Y(Fire)
Mask	–	Binary(.PNG)	2003 frames	3480 × 2160	–	23.4 MB	Segmentation	Train/Val/Test	Y(Fire)



Shamsoshoara, A., Afghah, F., Razi, A., Zheng, L., Fulé, P. Z., & Blasch, E. (2021). Aerial imagery pile burn detection using deep learning: The FLAME dataset. *Computer Networks*, *193*, 108001. https://ieee-dataport.org/open-access/flame-dataset-aerial-imagery-pile-burn-detection-using-drones-uavs

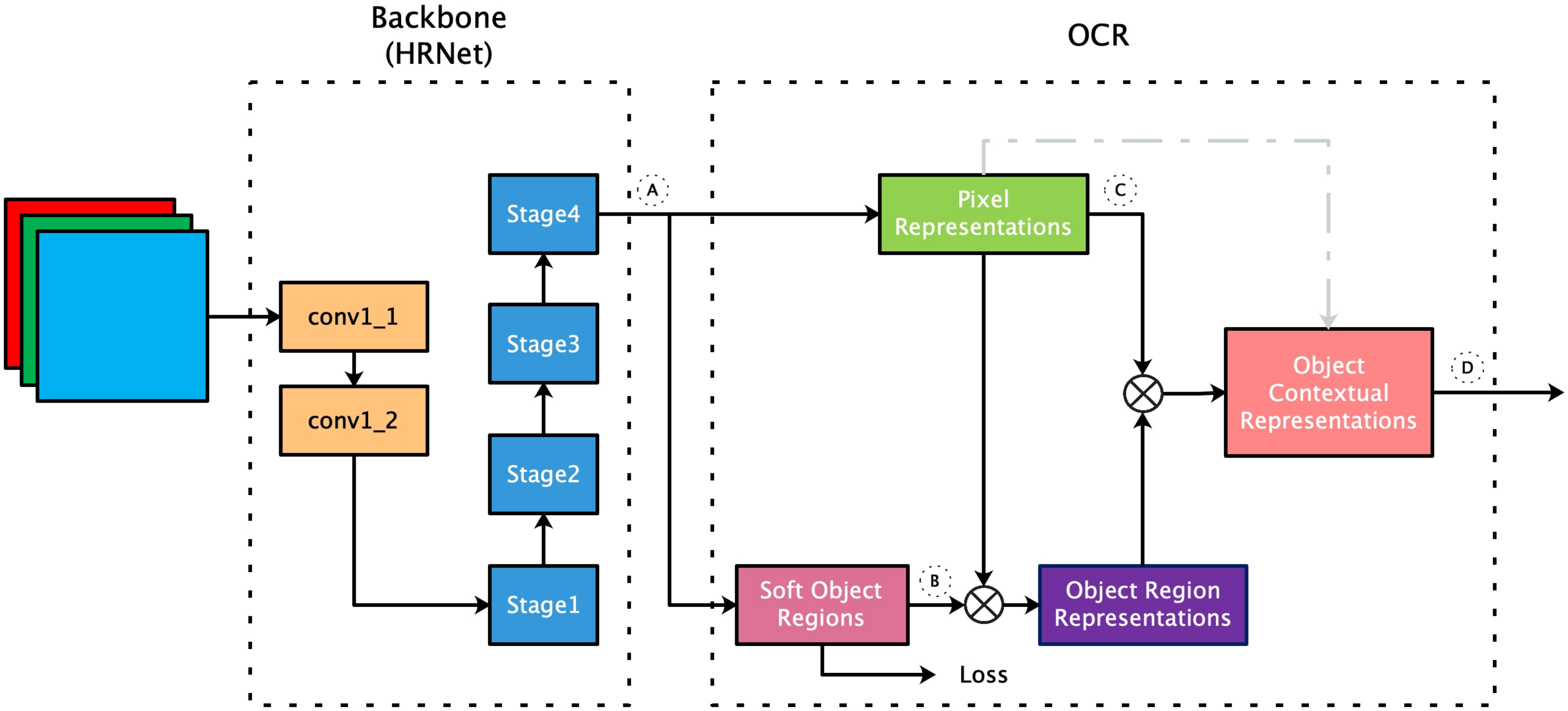
Challenge and Solutions

•Challenge is the unbalanced data between fire-related objects (active fire pixels) and background information.

- 1. Constraint the cropping centre within a specific distance range containing labeled targets and then clip these raw training images into 512x512 patches. (5.6% —> 7.9%)
- 2. Refine the **object-contextual representation (OCR)** module to strengthen the active fire pixel representation using a self-attention unit.
- 3. Use the **mixed loss of weighted cross-entropy loss and Lovasz hinge loss** to improve the segmentation accuracy further by optimising the IoU of the foreground class.

Proposed Approach

AF-Net, a refined OCRNet architecture with HRNet backbone



Feature Maps

The feature visualisation for HRNet and OCR module, and segmentation results

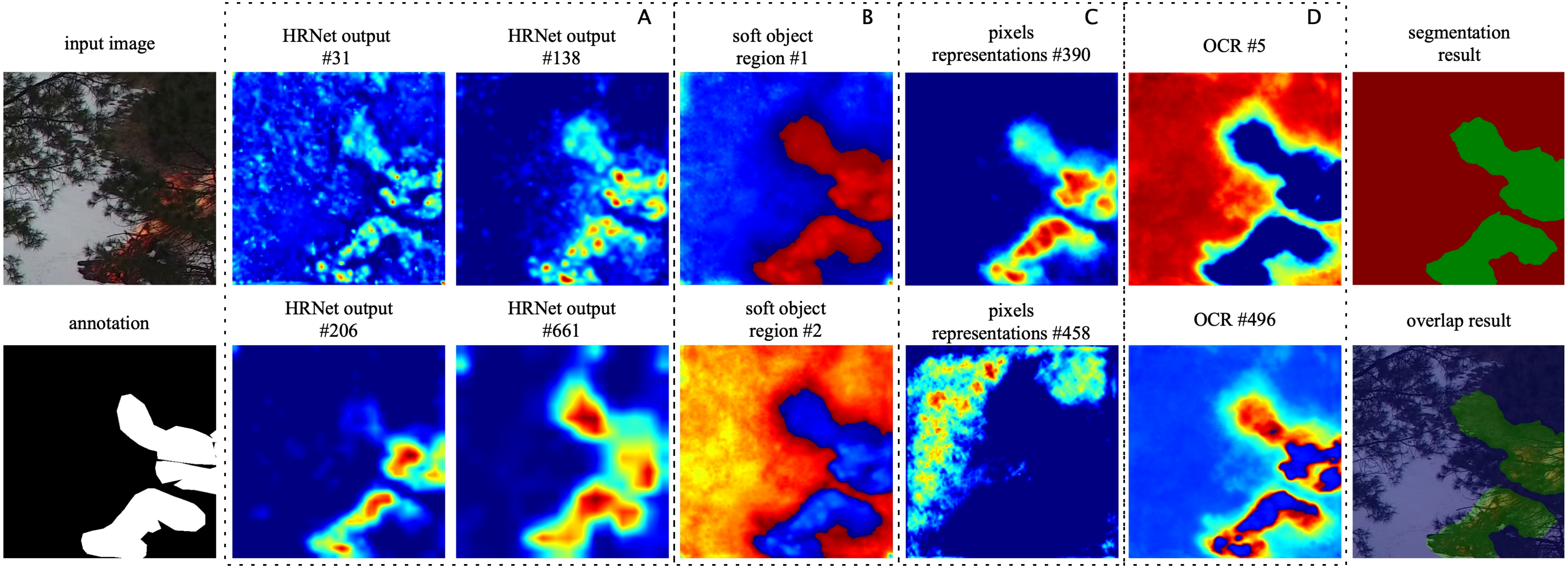


TABLE I: Performance evaluation of the different models for the fire segmentation.

Group	Model	Backbone	BS	Loss	Dataset	Class IoU (%)	mIoU (%)
0	U-Net		8	BCE			78.17
1	U-Net		8	BCE	A	[99.8, 66.4]	83.10
2	U-Net		8	BCE	B	[99.82, 76.59]	88.21
3	U-Net		8	WBCE	B	[99.84, 78.67]	89.26
4	FCN	HRNet-W48	8	WBCE+Lovasz	B	[99.85, 78.61]	89.23
5	OCRNet	HRNet-W48	8	WBCE	B	[99.86, 79.16]	89.51
6	OCRNet	HRNet-W48	4	WBCE+Lovasz	B	[99.87, 80.21]	90.04
7	OCRNet	HRNet-W18	8	WBCE+Lovasz	B	[99.79, 68.01]	83.90
8	OCRNet	HRNet-W48	8	WBCE+Lovasz	B	[99.88, 81.75]	90.81
9	AF-Net	HRNet-W48	8	WBCE+Lovasz	B	[**99.9**, **82.38**]	**91.14**

Group	Model	Backbone	BS	Loss	Dataset
0	U-Net		8	BCE	
1	U-Net		8	BCE	A
2	U-Net		8	BCE	B
3	U-Net		8	WBCE	B
4	FCN	HRNet-W48	8	WBCE+Lovasz	B
5	OCRNet	HRNet-W48	8	WBCE	B
6	OCRNet	HRNet-W48	4	WBCE+Lovasz	B
7	OCRNet	HRNet-W18	8	WBCE+Lovasz	B
8	OCRNet	HRNet-W48	8	WBCE+Lovasz	B
9	AF-Net	HRNet-W48	8	WBCE+Lovasz	B

Conclusion and Discussion

- We present an object-contextual representation approach for **active fire segmentation** from **VHR** remote sensing images.
- We mainly address the **unbalanced classes problem**, where the training process can get stuck in a local minimum.
- *1) preprocess data samples to maintain the class balance in cropped patches.*
- *2) advanced OCNet architecture with HRNet backbone to enhance the representation of an object class.*
- *3) weighted binary cross-entropy loss and Lovasz hinge loss further optimise the foreground segmentation.*