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Semi Supervised Domain Adaptation for Wildfire Detection

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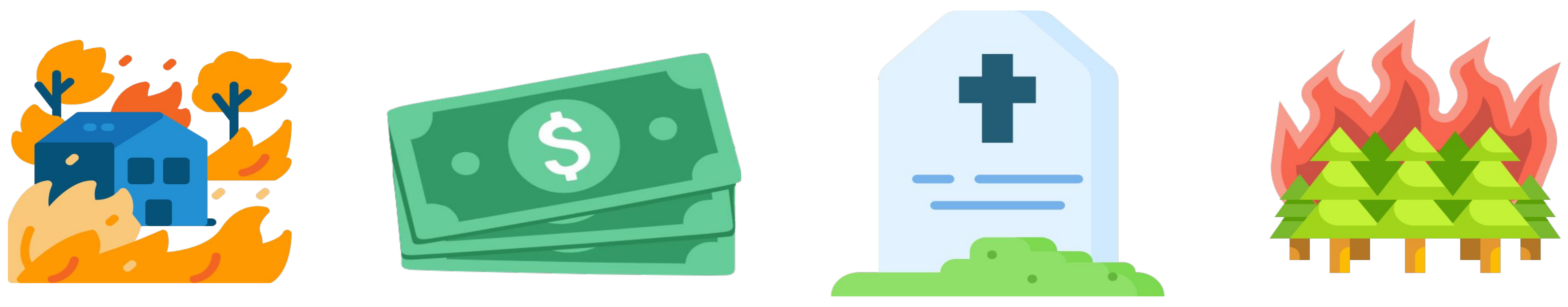
Introduction

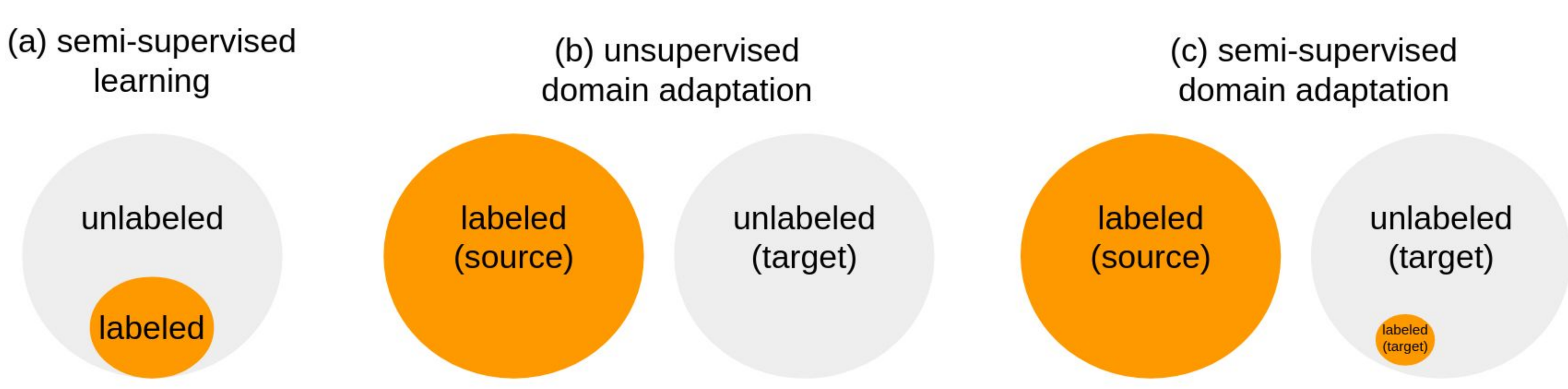
- **Effects of Climate change**
  - **Numbers of climate catastrophic wildfires annually increasing worldwide**
  - **Global warming exacerbates such wildfires**
  - **Saving forests from wildfires could delay global warming which store carbons**



2K homes | $ 4 ~ 6 billion | 115 death | 2.7K acres

Damage caused by wildfires in Lahaina, Hawaii, Aug. 8, 2023

- **Why we need Semi-Supervised Domain Adaptation?**
- Domain shift occurs for Training & Testing environment
- Limted Number of target domain images allowed in real world
- Enhance the performance in target domain using state-of-the-art semi-supervised learning & unsupervsied domain adaptation
- **Semi-supervised Domain Adaptation (SSDA):** Applies source labeled data and a few target labeled data with large unlabeled target data



Our Method : Semi-supervised Domain Adaptation for Object Detection

- **Concept**: Define wildfire detection as an object detection problem requiring only small amount of target domain labeled data
- **Advantage**: Enhances the accuracy of wildfire detection with downsizing the label cost, allowing fast-adapt wildfire detection service to remote sensing applications, saving time and money

Our Contributions

- **Propose semi-supervised domain adaptation benchmark for wildfire detection**
- Opensource wildfire dataset gathered by HPWREN

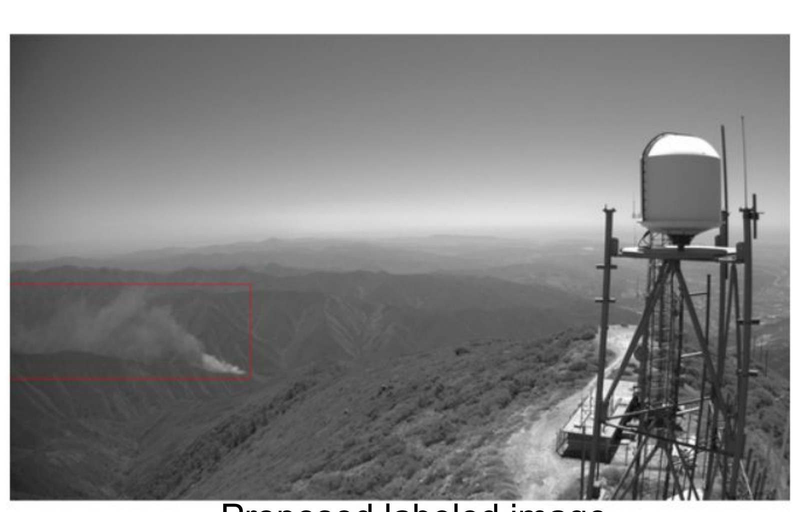
	Previous labels	Proposed labels	Total HPWREN
# of directories	9	283	342
# of images	609	2,575	27,174

- Propose additional labels & SSDA protocols for object detection

	source	target 0.5%	target 1.0%	target 3.0%	target validation
foreground images	309	44	94	257	451
background images	300	58	111	359	630
total images	609	102	205	616	1,081

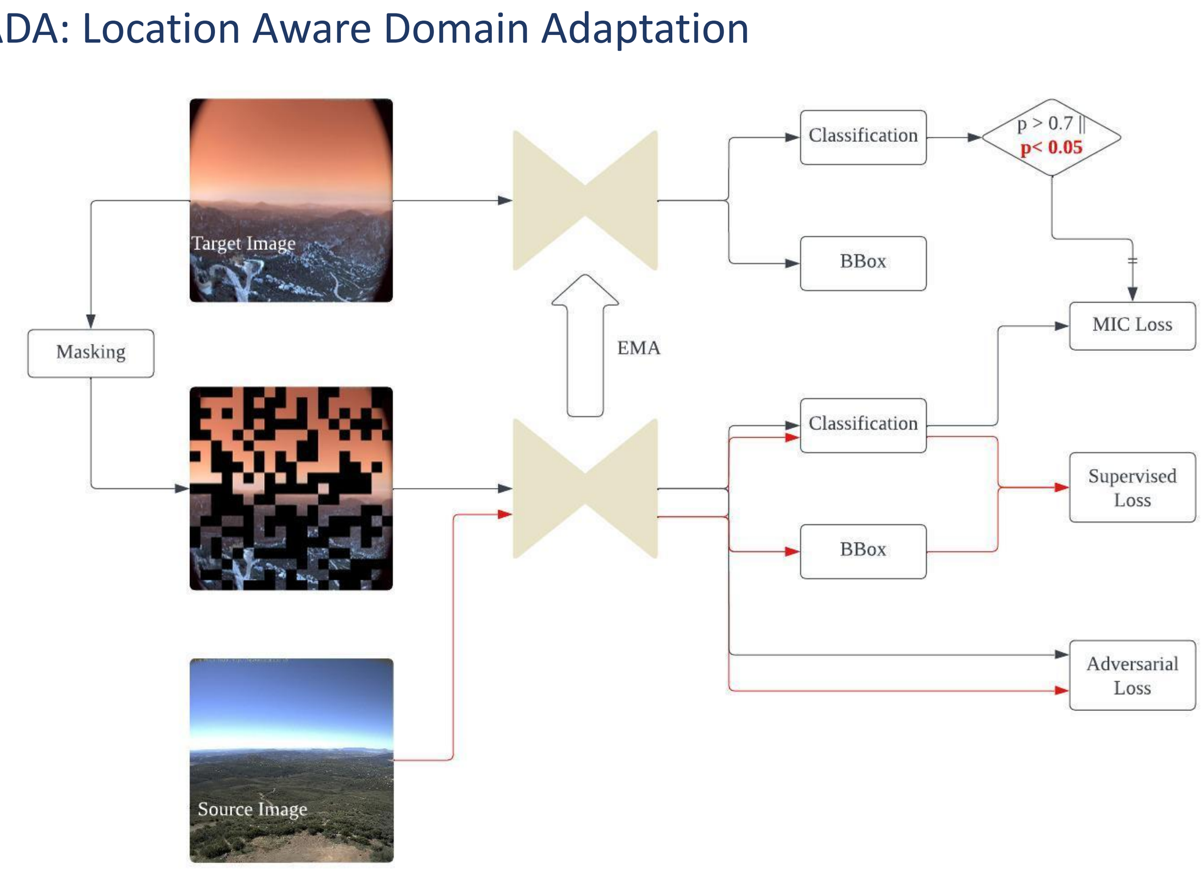
- Suggest New labeling policy

Original HPWREN labeled image



Proposed labeled image

- **Propose strong baseline framework for wildfire detection**
- LADA: Location Aware Domain Adaptation



Our Contributions (cont.)

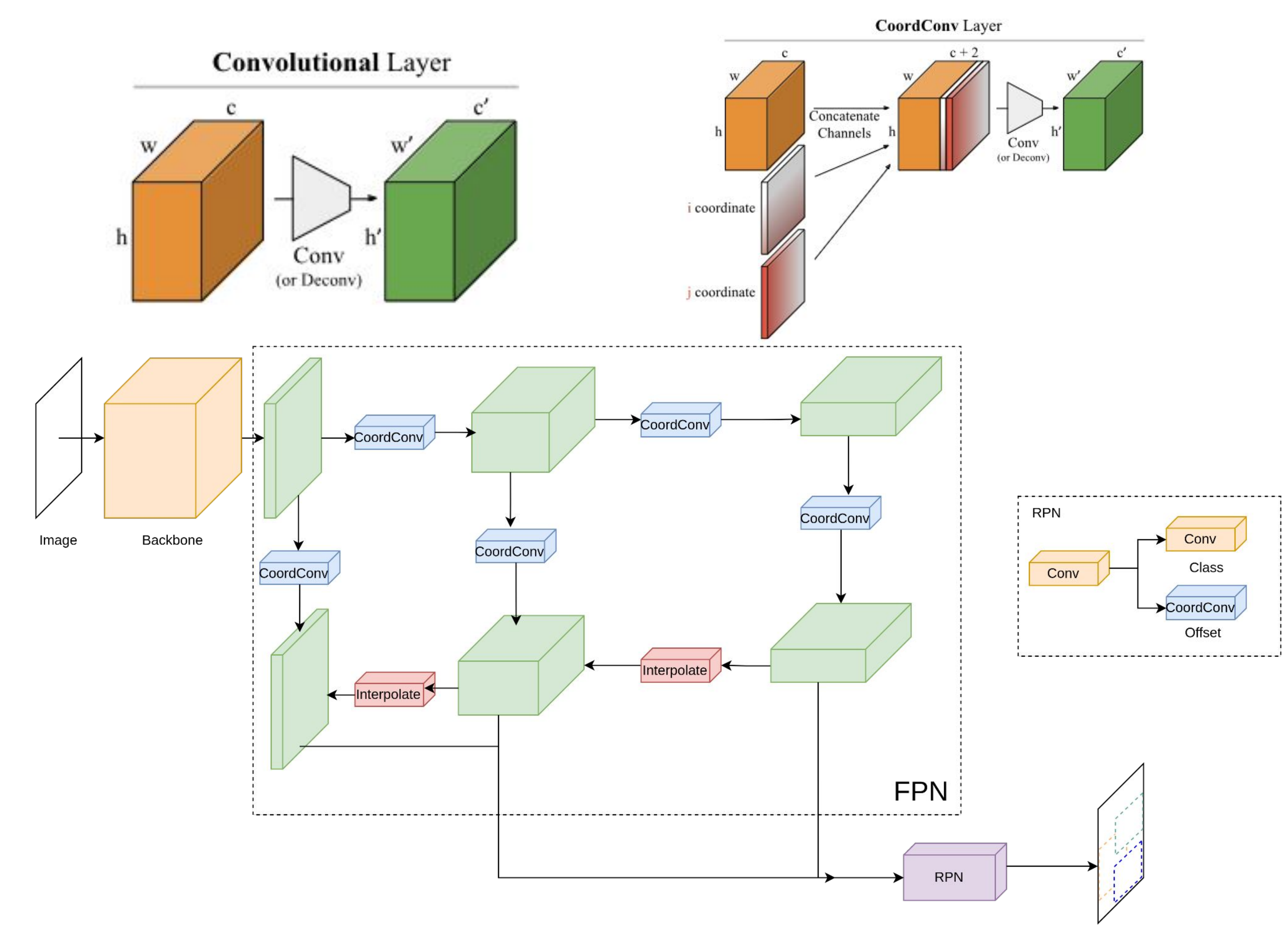
- **Propose strong baseline framework for wildfire detection**
- **Pseudo labeling** : Use teacher-student framework to get pseudo labels from teacher network updated by exponential moving average (EMA). We use pseudo labels for confidence background images as well as foreground images unlike previous researches.

$$\theta_s - \frac{\partial L}{\partial \theta_s} \rightarrow \theta_s$$

$$\lambda_e \theta_t + (1-\lambda_e)\theta_s \rightarrow \theta_t$$

$$\begin{cases} \hat{p_i} > \tau_u \\ \hat{p_i} < \tau_l \end{cases}$$

- **Translational Variance features :** Motivated by coordconv, we replaced naive convolution layers in FPN (feature pyramid network) and RPN (region proposal network) to coordinate convolution layer, allowing additional layers to learn patterns dependant in locations objects occurred.



- **Losses :** Use same losses from our baseline model

$$min_{\theta_s} \frac{1}{N_s}\sum_{k=1}^{N_s} L_k^S + \frac{1}{N_t}\sum_{k=1}^{N_t}(\lambda^M L_k^M) + \frac{1}{N_t+N_s}\sum_{k=1}^{N_t+N_s}(\lambda^A L_k^A + \lambda^C L_k^C)$$

  - supervised loss : Use labeled source data for object detection
  - masked consistency loss : align masked & unmasked image output
  - adversarial loss : align source & target domain predictions
  - consistency loss : align domain predictions for instance & image level

- **Experimental Result**
- **mean Average Precision (mAP / mAP@0.5)**

Type	Methods	Label target images		
		0.5%	1.0%	3.0%
Source only	SADA	6.9/21.9	9.7/28.7	17.8/48.0
	LADA	**7.9/24.0**	**10.2/31.5**	**18.8/48.4**
SSDA	SADA	9.7/27.3	12.3/34.9	20.4/53.0
	LADA	**10.0/29.1**	**14.0/38.0**	**20.9/52.3**

- **ablation study**
  - **labeling policy**

	0.5%	1.0%	3.0%
original	1.5/7.0	2.8/12.9	7.9/29.6
propsed	7.9/24.0	10.2/31.5	18.8/48.4

Conclusion

- **Proposed semi-supervised domain adaptation benchmark** for wildfire object detection (SSDA-OD) which diversifies thirtyfold greater than existing wildfire benchmarks, and present a new labeling policy tailored for wildfire detection
- **Suggest robust baseline for SSDA-OD** which uses confidenct background images as well for pseudo labeling, and uses translational variance features to extract wildfire patterns dependent in position