



Image-based Early Detection System for Wildfires

OMKAR RANADIVE, JISU KIM, SERIN LEE,
YOUNGSEO CHA, HEECHAN PARK, MINKOOK CHO,
YOUNG K. HWANG

2021 Wildfire Statistics for USA

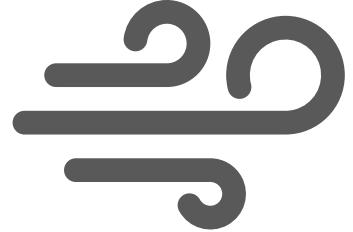


58,733 fires



7.13 million acres burned

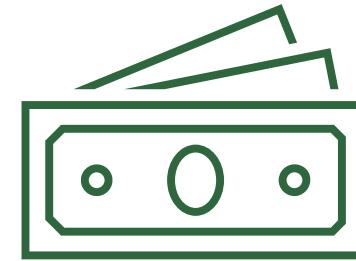
Damage caused by wildfires



Air Pollution



Structural damage



Billions in losses



Death

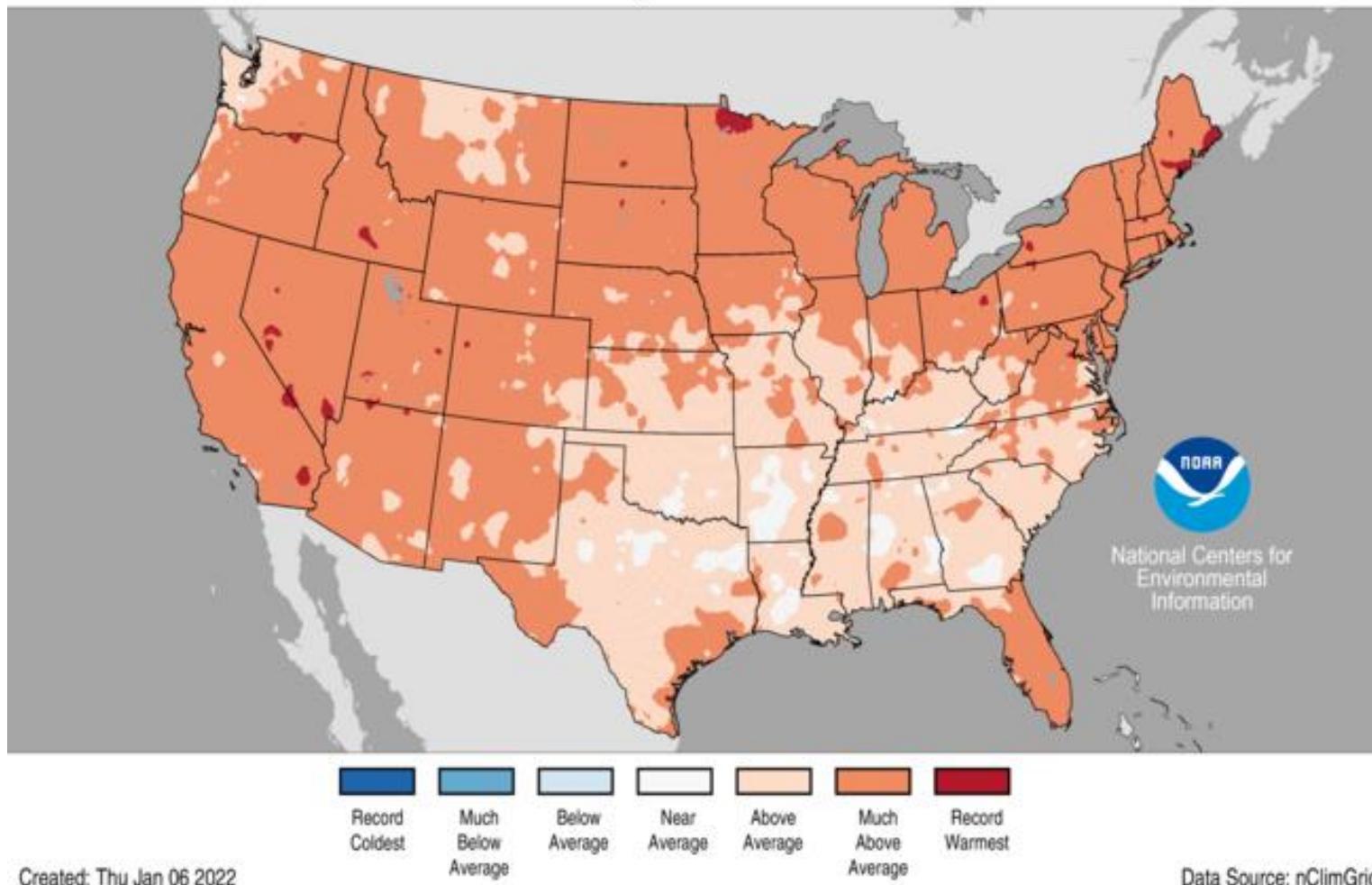
Effects of climate change

- Global warming is causing warmer and drier conditions
- Drier soils and vegetation are more susceptible to burning
- A global increase in large and severe wildfires is expected in the coming years

Mean Temperature Percentiles

January–December 2021

Ranking Period: 1895–2021



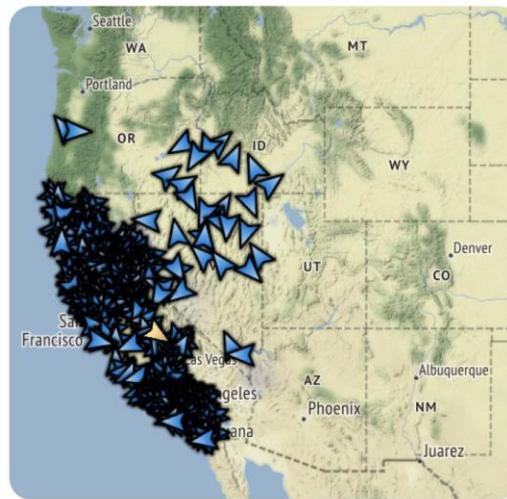
Alert Wildfire Cameras

- Began as a collaboration between Nevada Seismological Lab and Forest Guard Team
- Currently, it is a big network with **700+** PTZ cameras

Network Partners



Coverage Area



Cameras



AXIS Q6055-E PTZ Network Camera

The Dataset

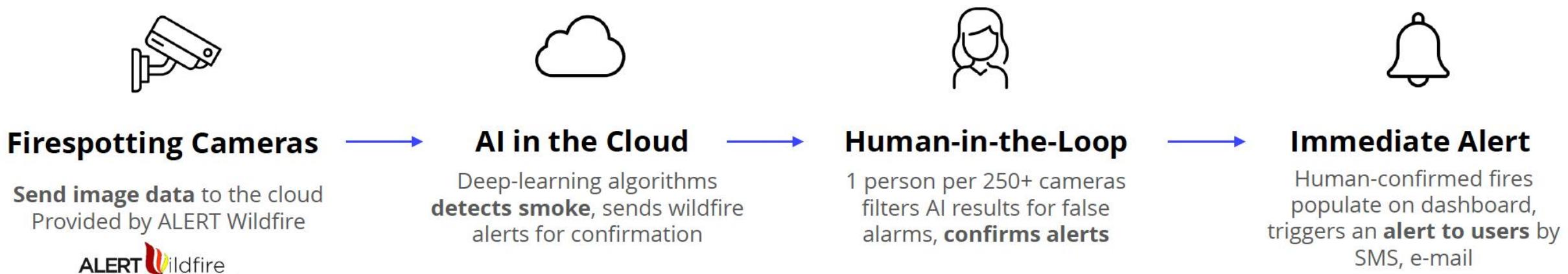


The Dataset

- We gathered data from over 400 different Alert Wildfire cameras
- We labeled the images with bounding boxes and categorized them as wildfire vs non-wildfire
- The final dataset consists of 90,000 images

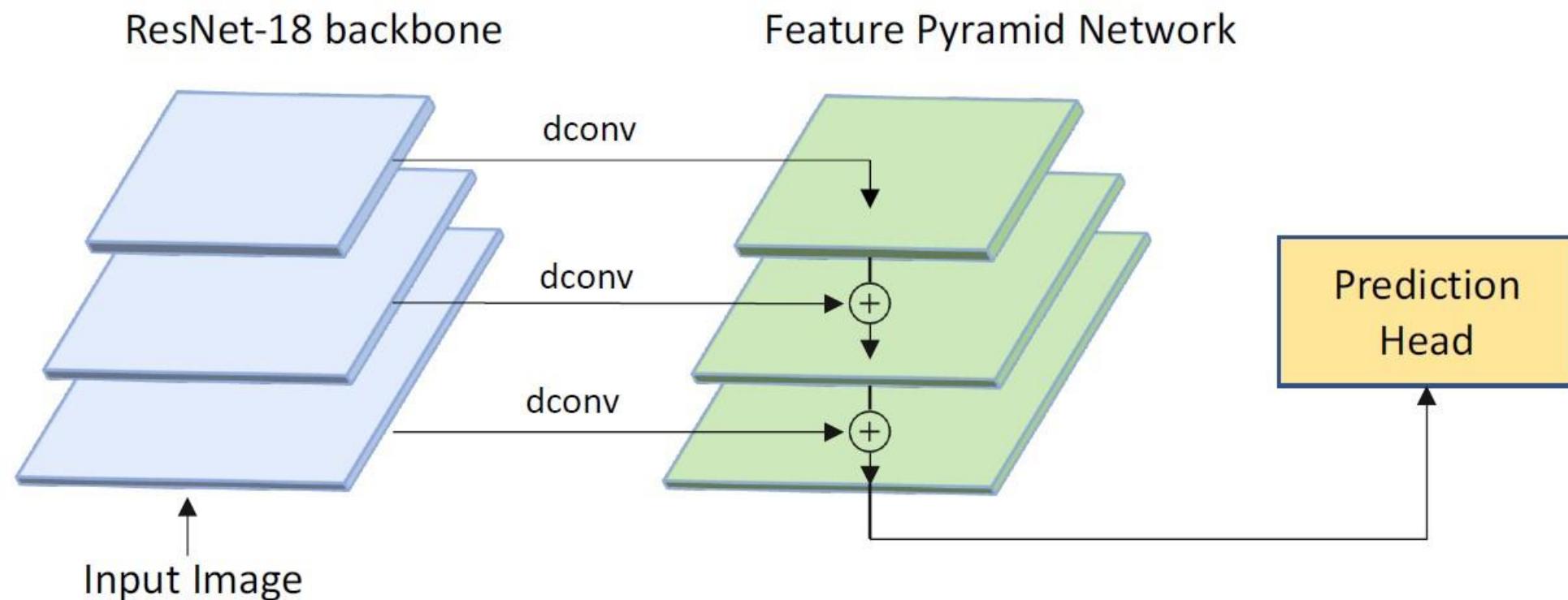
Key idea: Perform **early** detection of wildfires; i.e., ideally, detect the smoke

Wildfire Alert System Overview

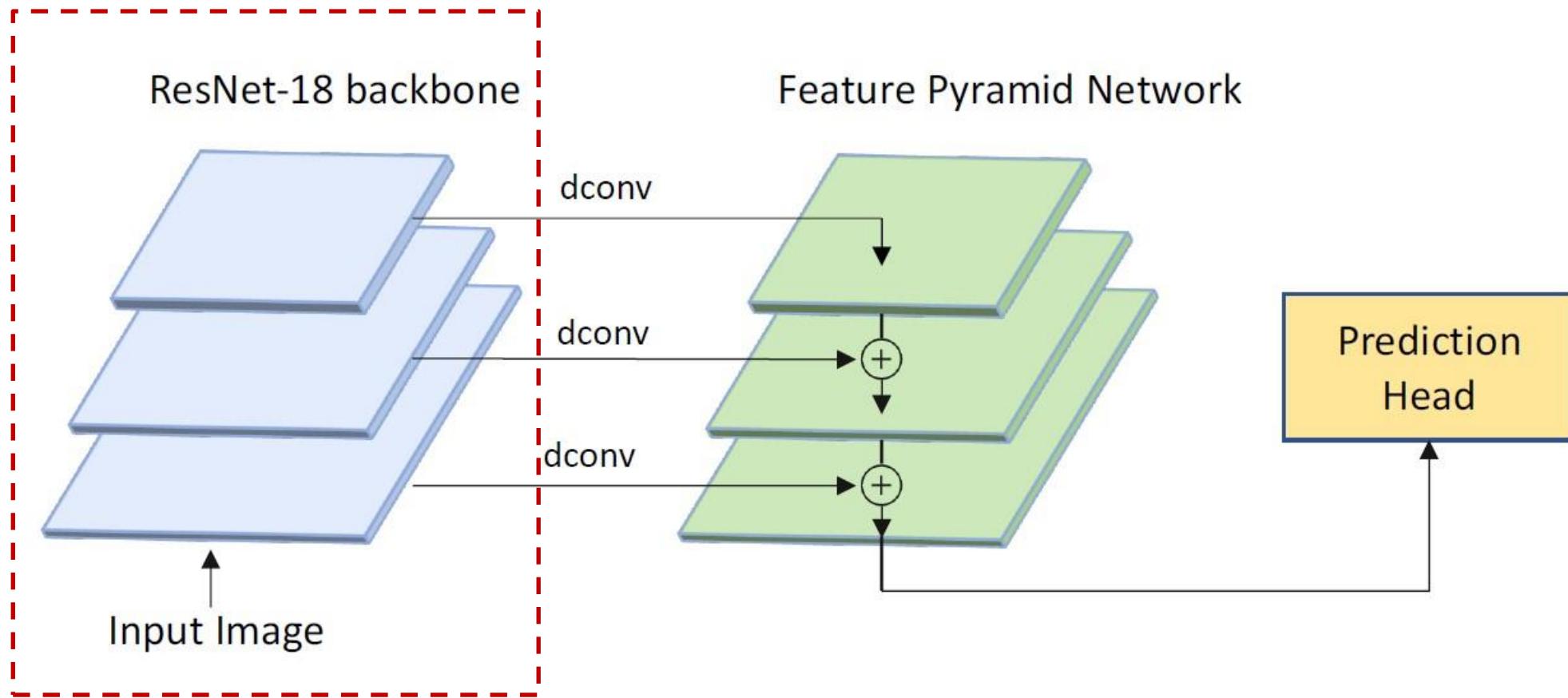


Smoke is difficult to detect - it can be of varying scales

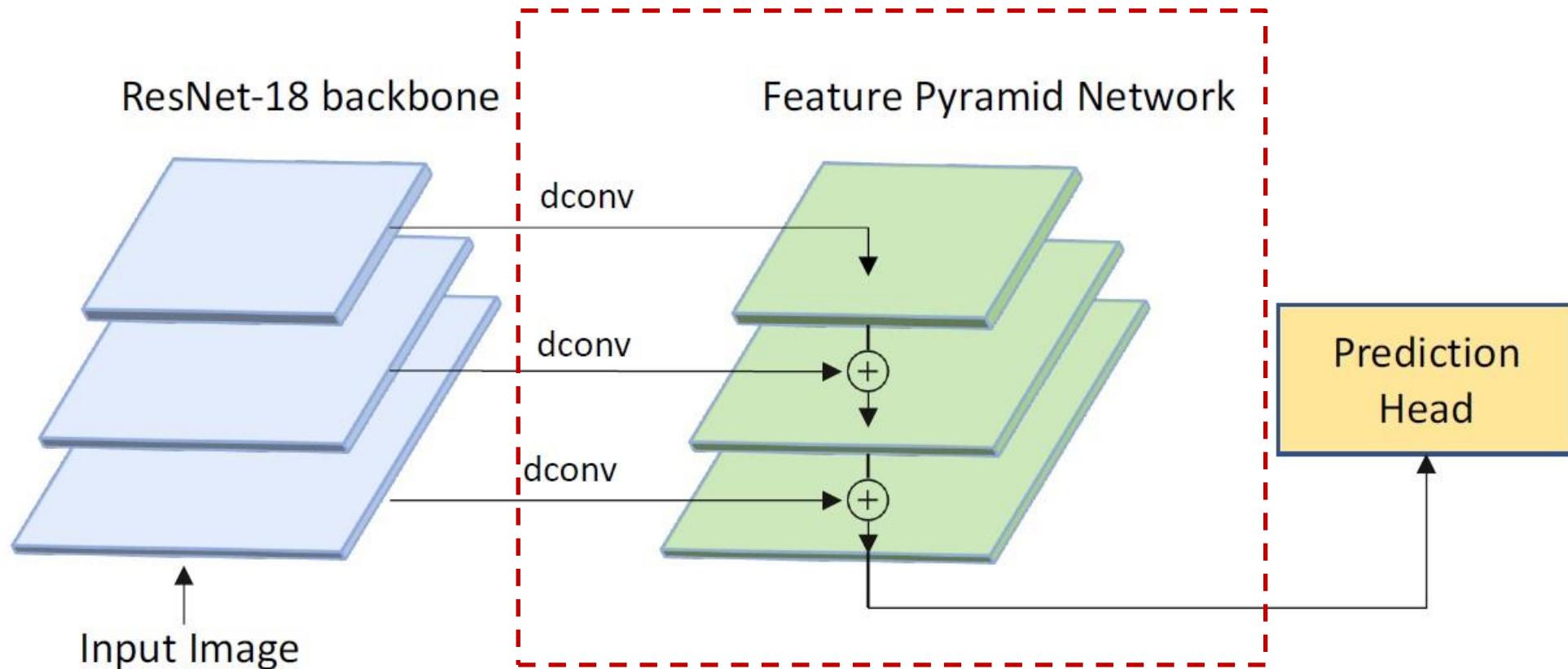
Model Architecture



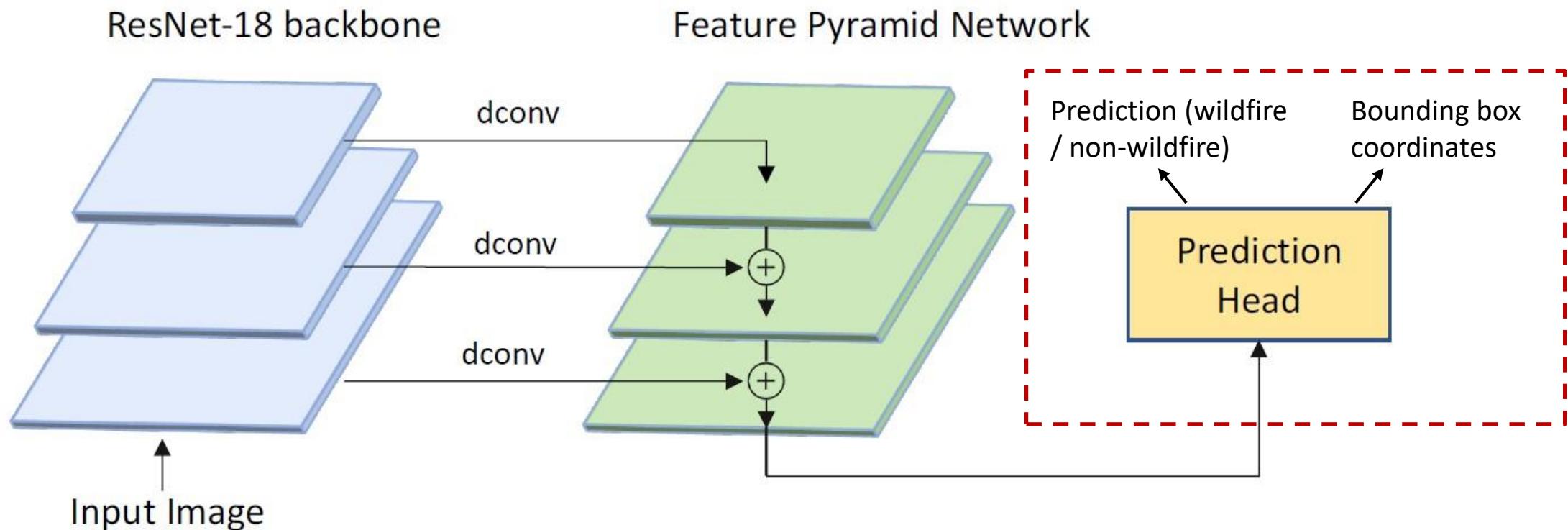
Model Architecture



Model Architecture



Model Architecture

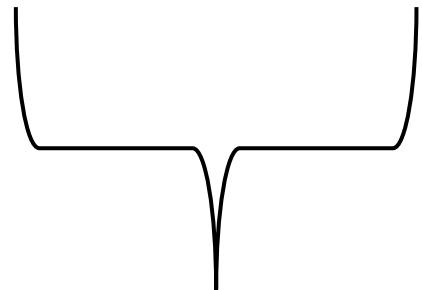


Loss Function

$$loss = \frac{1}{N_{pos}} \left(\sum_{x,y} L_{cls}(p_{x,y}, c_{x,y}) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{reg}(t_{x,y}, t_{x,y}^*) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{cen}(t_{x,y}^*) \right)$$

Loss Function

$$loss = \frac{1}{N_{pos}} \left(\sum_{x,y} L_{cls}(p_{x,y}, c_{x,y}) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{reg}(t_{x,y}, t_{x,y}^*) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{cen}(t_{x,y}^*) \right)$$



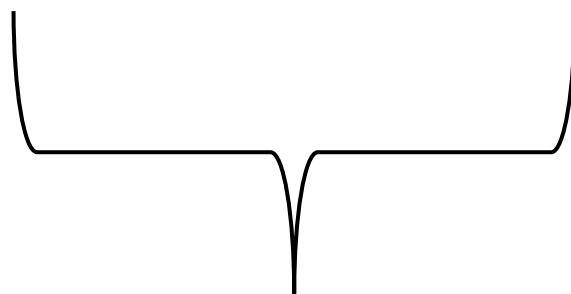
Focal Loss

$p_{x,y}$: Predicted score

$c_{x,y}$: Ground truth label

Loss Function

$$loss = \frac{1}{N_{pos}} \left(\sum_{x,y} L_{cls}(p_{x,y}, c_{x,y}) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{reg}(t_{x,y}, t_{x,y}^*) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{cen}(t_{x,y}^*) \right)$$



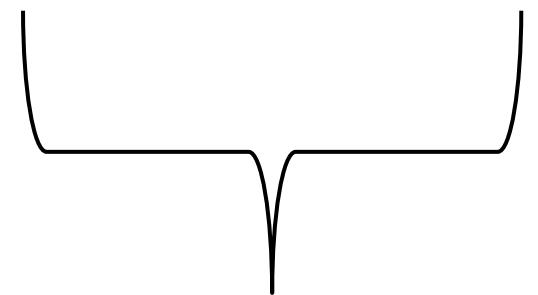
IOU Loss

$t_{x,y}$: Ground truth coordinates

$t_{x,y}^*$: Predicted coordinates

Loss Function

$$loss = \frac{1}{N_{pos}} \left(\sum_{x,y} L_{cls}(p_{x,y}, c_{x,y}) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{reg}(t_{x,y}, t_{x,y}^*) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{cen}(t_{x,y}^*) \right)$$



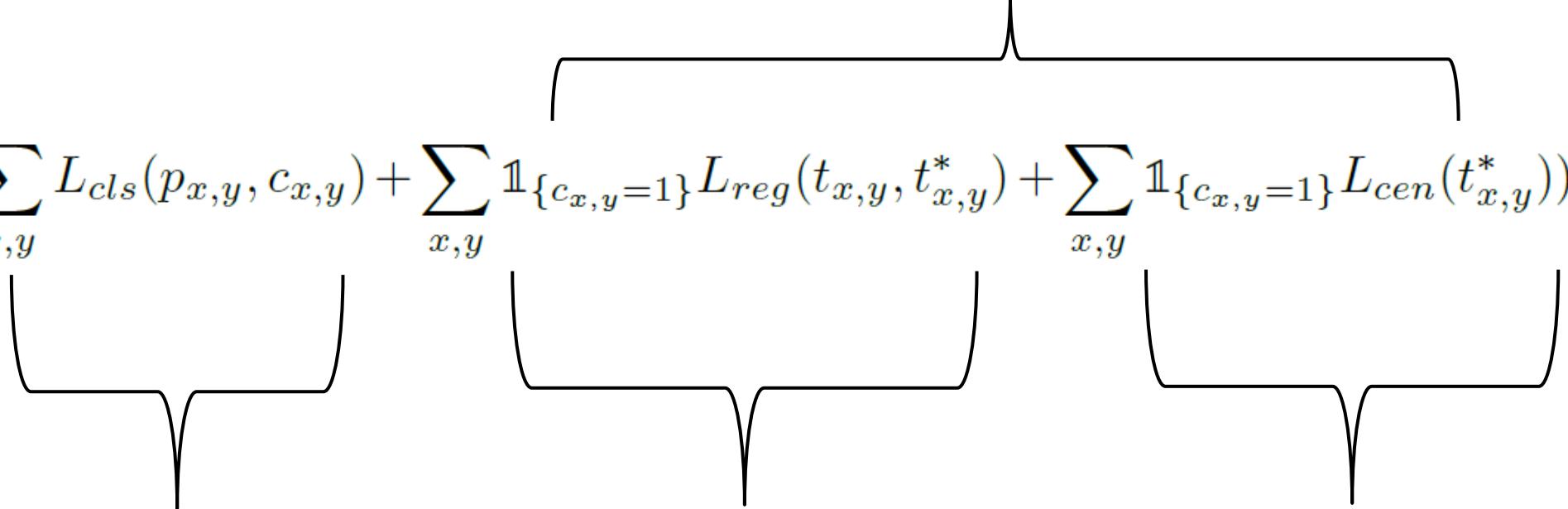
Centerness Loss

$t_{x,y}^*$: Predicted coordinates

Loss Function

$$loss = \frac{1}{N_{pos}} \left(\sum_{x,y} L_{cls}(p_{x,y}, c_{x,y}) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{reg}(t_{x,y}, t_{x,y}^*) + \sum_{x,y} \mathbb{1}_{\{c_{x,y}=1\}} L_{cen}(t_{x,y}^*) \right)$$

Only calculated for positive samples



Focal Loss

$p_{x,y}$: Predicted score

$c_{x,y}$: Ground truth label

IOU Loss

$t_{x,y}$: Ground truth coordinates

$t_{x,y}^*$: Predicted coordinates

Centerness Loss

$t_{x,y}^*$: Predicted coordinates

Adaptive Training Sample Selection (ATSS)

- Model performance is dependent on how pos/neg samples are selected
- ATSS selects samples based on statistical characteristics
- We use a modified version of ATSS

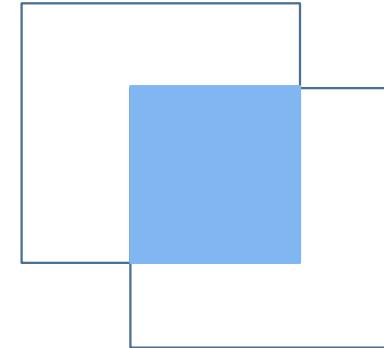
Modified Adaptive Training Sample Selection

Begin by considering all points
inside the ground truth bounding
box as candidate points



Modified Adaptive Training Sample Selection

Calculate IOU between ground truth
bounding box and the bounding box \rightarrow IOU
predicted by each candidate point



Modified Adaptive Training Sample Selection

Calculate final score for each candidate point as follows:

$$Score_{x,y} = (IOU)_{x,y} * p_{x,y}$$

Then, calculate the threshold as follows:

$$T = \mu_{scores} + \sigma_{scores}$$

Samples with score > T are considered as positive samples

Modified Adaptive Training Sample Selection



Original ATSS



Modified ATSS

Results



Results

- Highly accurate (91.6%)
- High true positive rate (81.6%) and low false positive rate (7.5%)
- Evaluation Study (Jun'22 – Jul'22): Total of 869 wildfire smoke events

Time taken to detect wildfire smoke	% of smoke events detected (cumulative)
Within 60 seconds from start of the smoke	60.5%
Within 3 minutes from start of the smoke	76.8%
Within 5 minutes from start of the smoke	86.9%
Over 5 minutes from start of the smoke	100%

Conclusion

- The system is currently being used in the USA to monitor and detect wildfire smoke from hundreds of cameras daily
- First responders can respond faster and protect people and property better
- Our system is also being used by utility companies to protect transmission lines and other infrastructure assets
- ML based monitoring systems are crucial in the fight against climate change