

# SmokeyNet for Wildfire Smoke Detection

**Mai H. Nguyen**

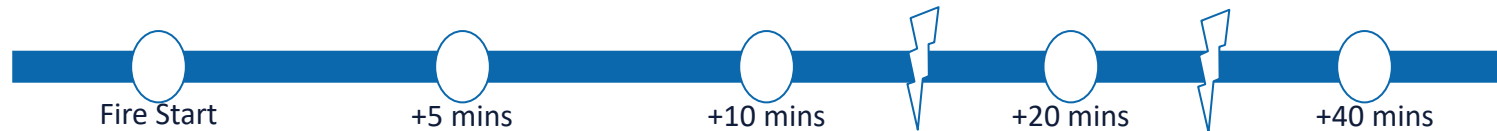
**San Diego Supercomputer Center**

**UC San Diego**

# Motivation

- Size and frequency of wildfires in U.S. have increased in recent years
- Since 1980, 20 major wildfires in U.S. exceeded \$1 billion in damages
  - 16 of these events have occurred since 2000
- Wildfires can spread quickly; thus, early detection is essential to minimize damage

Fires can spread quickly:



# Challenges

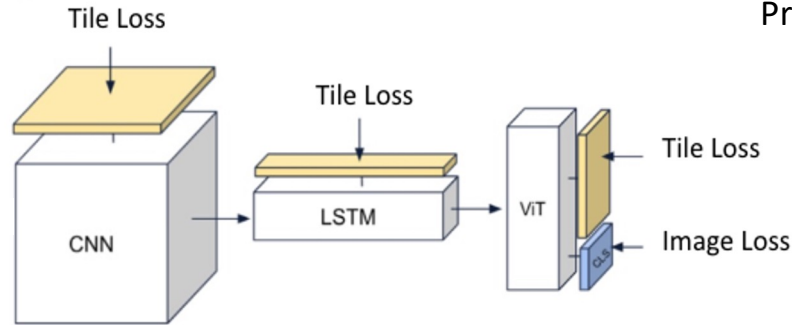
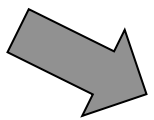
- Smoke is transparent and amorphous
- Smoke plumes can be small, faint, dissipating
- Many false positives from clouds, fog, haze



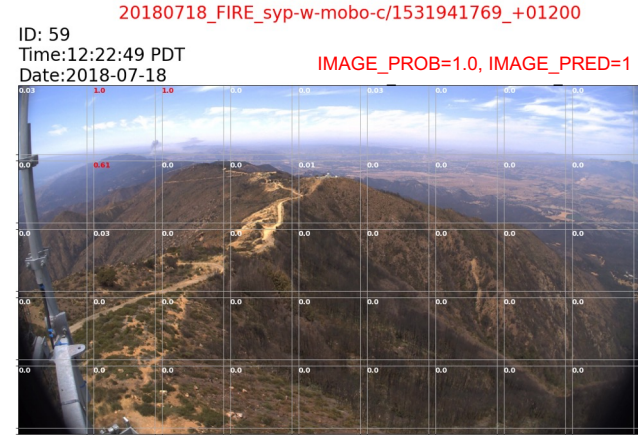
# SmokeyNet



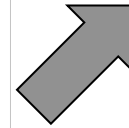
Tiled Image Sequence



CNN: convolutional neural network  
LSTM: long short-term memory  
ViT: vision transformer



Predicted Tile & Image Probabilities



# FlgLib Dataset

## Fire Ignition images Library (FlgLib)

- 315 sequences of wildland fire images from optical cameras
- ~25,000 images
- 101 cameras across 30 weather stations
- San Diego, Riverside, Imperial counties
- 3 July 2016 to 12 July 2021
- Each sequence consists of
  - Images at 1-minute intervals
  - Typically 40 minutes before and 40 minutes after ignition
- Part of HPWREN
  - High Performance Wireless Research and Education Network
  - <https://hpwren.ucsd.edu/HPWREN-FlgLib/>

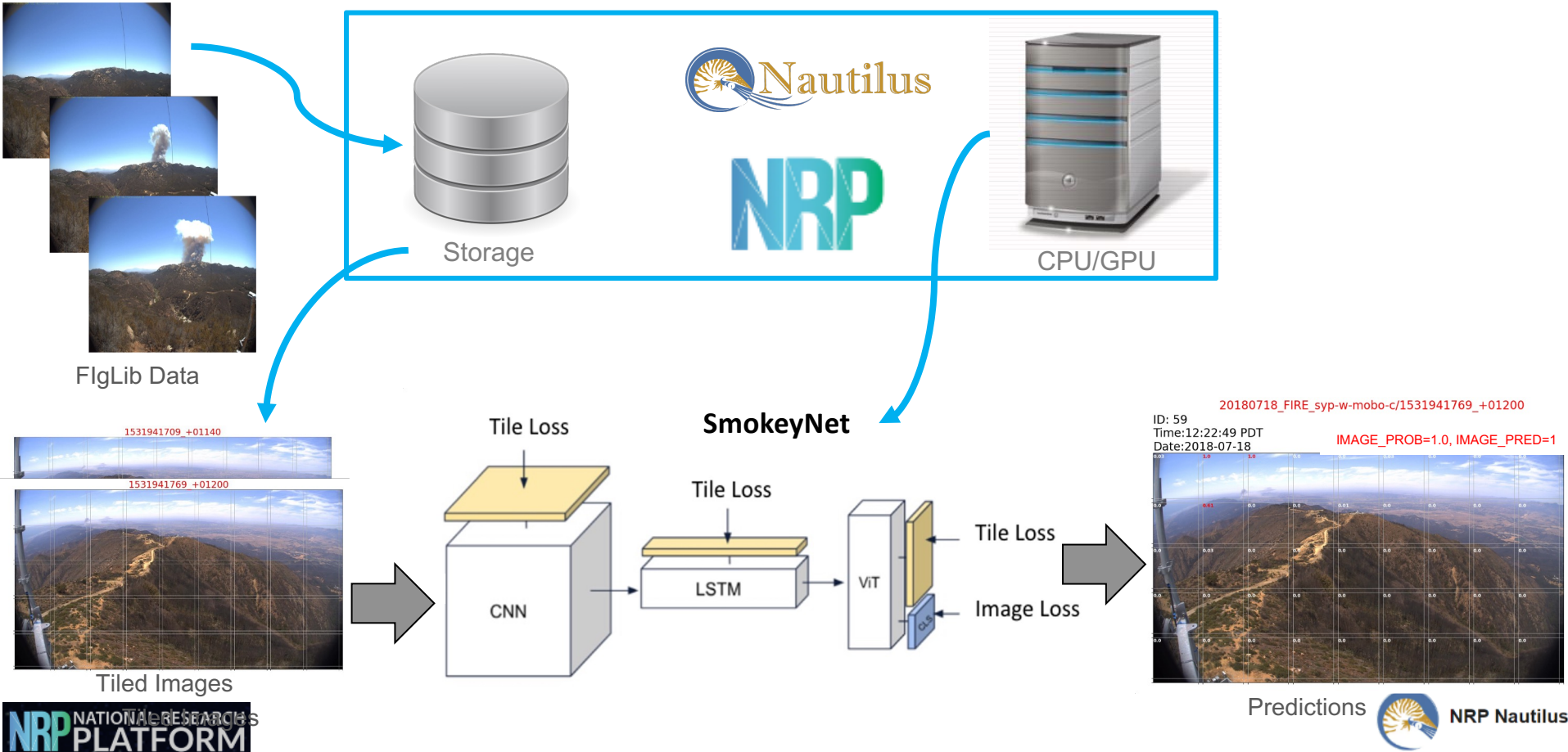


[https://hpwren.ucsd.edu/HPWREN-FlgLib/HPWREN-FlgLib-Data/20210711\\_FIRE\\_wc-e-mobo-c/1626027054\\_+00900.jpg](https://hpwren.ucsd.edu/HPWREN-FlgLib/HPWREN-FlgLib-Data/20210711_FIRE_wc-e-mobo-c/1626027054_+00900.jpg)

Image sequence: [https://hpwren.ucsd.edu/HPWREN-FlgLib/HPWREN-FlgLib-Data/20210711\\_FIRE\\_wc-e-mobo-c/20210711\\_FIRE\\_wc-e-mobo-c.mp4](https://hpwren.ucsd.edu/HPWREN-FlgLib/HPWREN-FlgLib-Data/20210711_FIRE_wc-e-mobo-c/20210711_FIRE_wc-e-mobo-c.mp4)



# SmokeyNet Workflow Using NRP



# Baseline SmokeyNet Results

Model	Params (M)	Time (ms/img)	A	F1	P	R	TTD (mins)
<b>SmokeyNet: ResNet34 + LSTM + ViT (2 frames)</b>	56.9	51.6	<b>83.49</b>	<b>82.59</b>	<b>89.84</b>	76.45	3.12
ResNet50 (1 frame)	26.1	50.4	68.51	74.30	63.35	<b>89.89</b>	<b>1.01</b>
FasterRCNN (1 frame)	41.3	55.6	71.56	66.92	81.34	56.88	5.01
MaskRCNN (1 frame)	43.9	56.9	73.24	69.94	81.08	61.51	4.18
ResNet34 + LSTM (2 frames)	38.9	53.3	79.35	79.21	82.00	76.74	2.64

Accuracy (A), F1, precision (P), recall (R), and time-to-detection (TTD) on test set, averaged over five runs. Number of params (Params) in millions and inference time (Time) in msec per image are also shown.

# Multiple Data Sources

Can incorporating other types of data help performance?

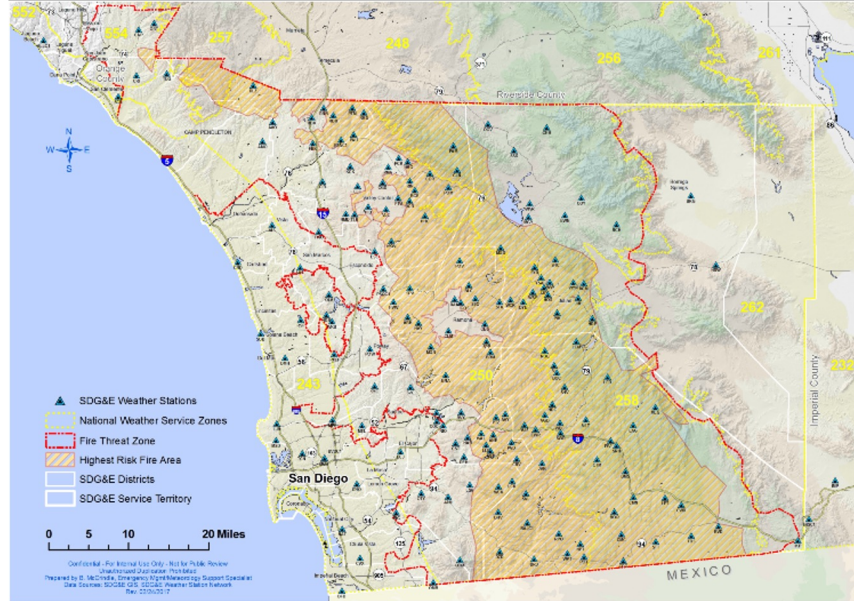
Use multiple input data sources:

FlgLib images + **Weather Data** + **Satellite-Based Detections**



# Weather Data

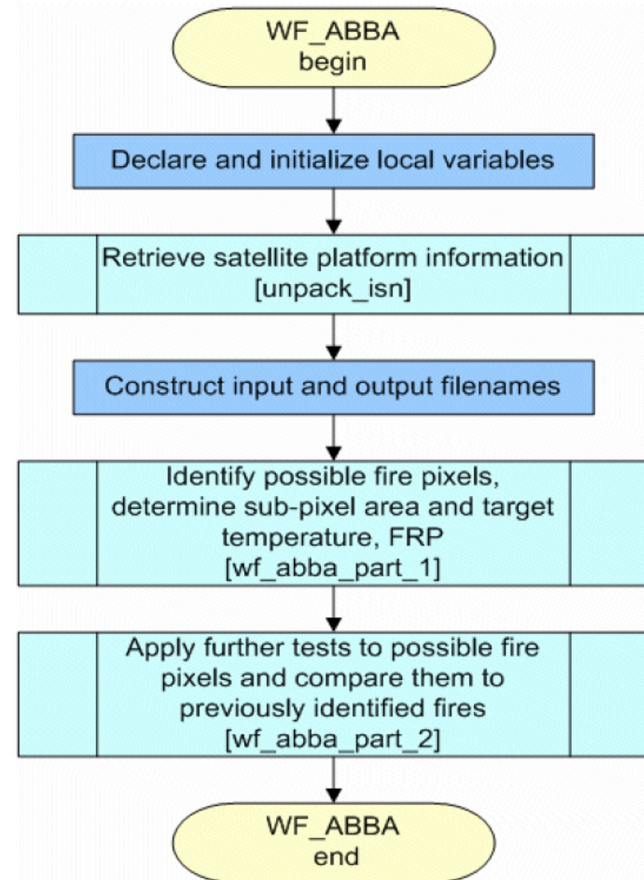
- Weather data is captured for each FlgLib image
- Weather data from HPWREN, SDG&E, SC-Edison weather stations
- Weather features
  - Air Temperature
  - Relative Humidity
  - Wind Speed
  - Wind Gust
  - Wind Direction
  - Dew Point Temperature



San Diego Gas and Electric (SDG&E) weather stations

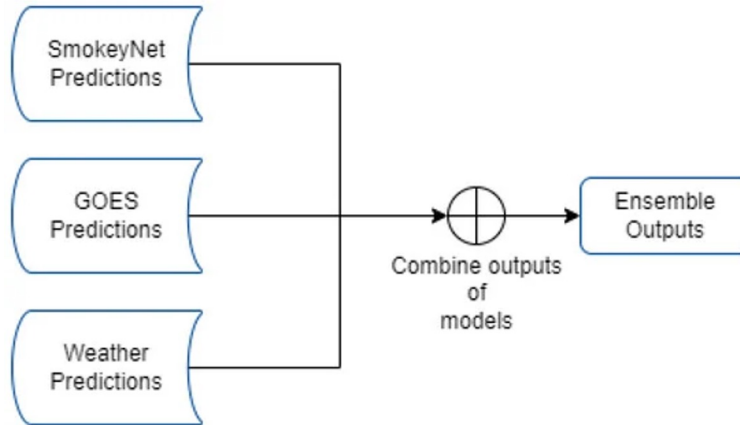
# Satellite-Based Fire Detections

- WFABBA: Wildfire Automated Biomass Burning Algorithm
- Rule-based system used to detect fires from the satellite images
- Uses heuristics to determine thermal anomalies that can be associated with wildfires
- Input: Satellite image data from the GOES-R series Advanced Baseline Imager (ABI)
- We use WFABBA detections from GOES-16 and GOES-17



# SmokeyNet Ensemble

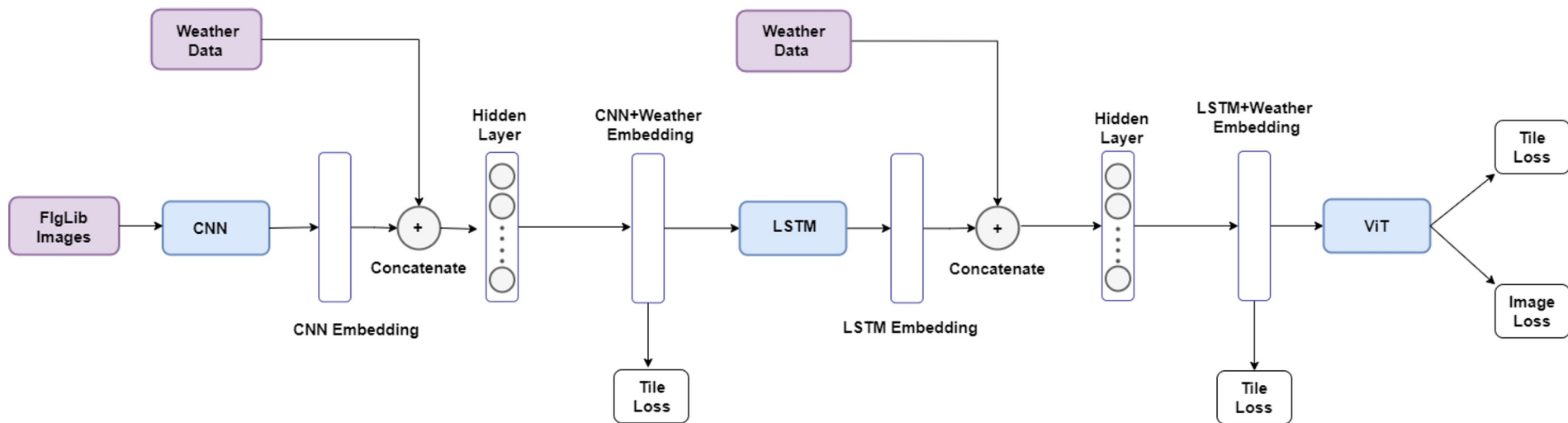
- FlgLib images + weather data + satellite-based fire detections
  - weather data: sensor measurements from weather stations
  - satellite data: fire detections from WFABBA based on GOES-16 & GOES-17



- Findings
  - Performance of the ensemble model is not much better than baseline SmokeyNet
  - GOES and Weather models are weak signals, and hence the ensemble models learn to give the largest weight to input signals coming from baseline SmokeyNet

# Multimodal SmokeyNet

Incorporate weather data directly into SmokeyNet



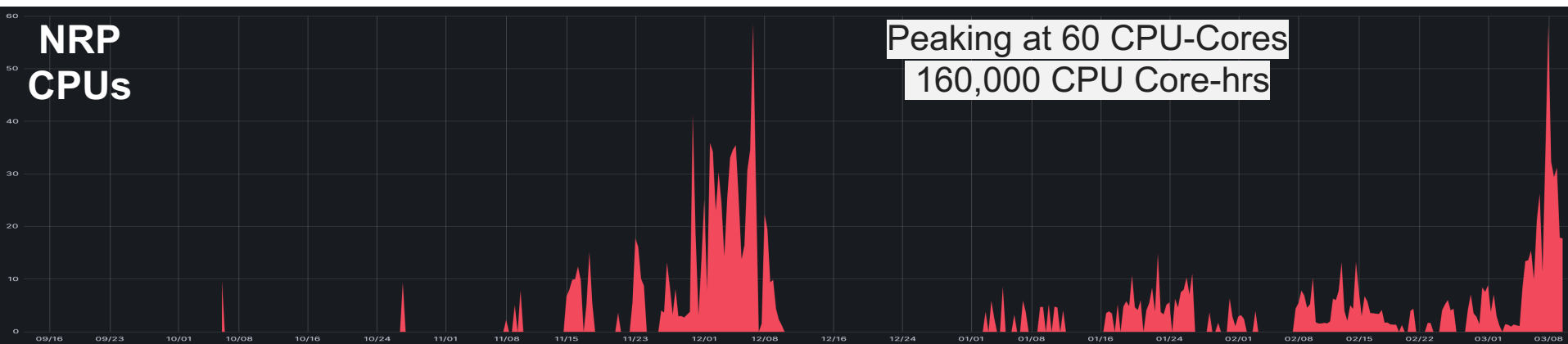
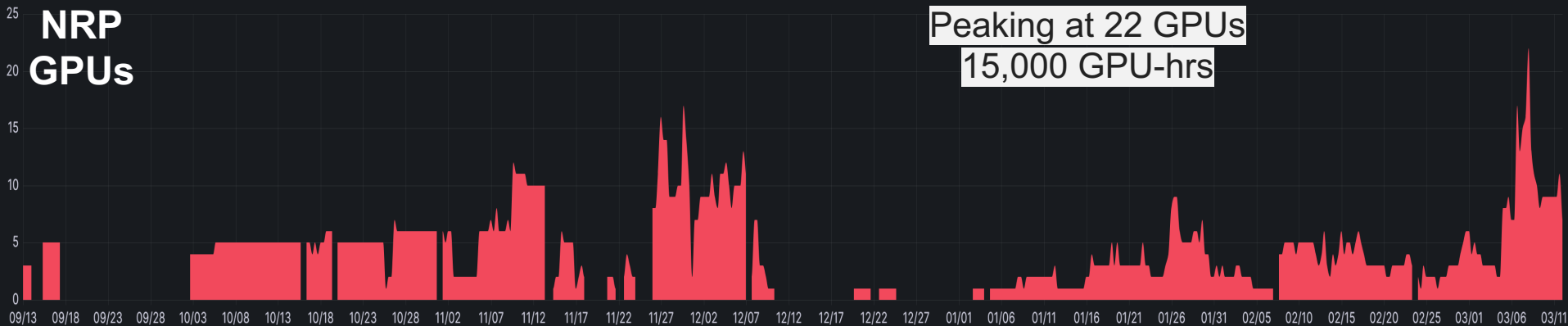
# Multimodal SmokeyNet Results

Model	Accuracy	F1	Precision	Recall	TTD (mins)
SmokeyNet	80.12	77.52	<b>90.43</b>	68.00	4.70
SmokeyNet with Random Weather	79.50	76.96	88.22	67.92	4.77
Multimodal SmokeyNet	<b>80.48</b>	<b>78.62</b>	88.19	<b>71.20</b>	<b>4.06</b>

Accuracy, F1, Precision, Recall, and Time-to-Detection (TTD) on test set, averaged over eight runs

# Mai H. Nguyen, UC San Diego

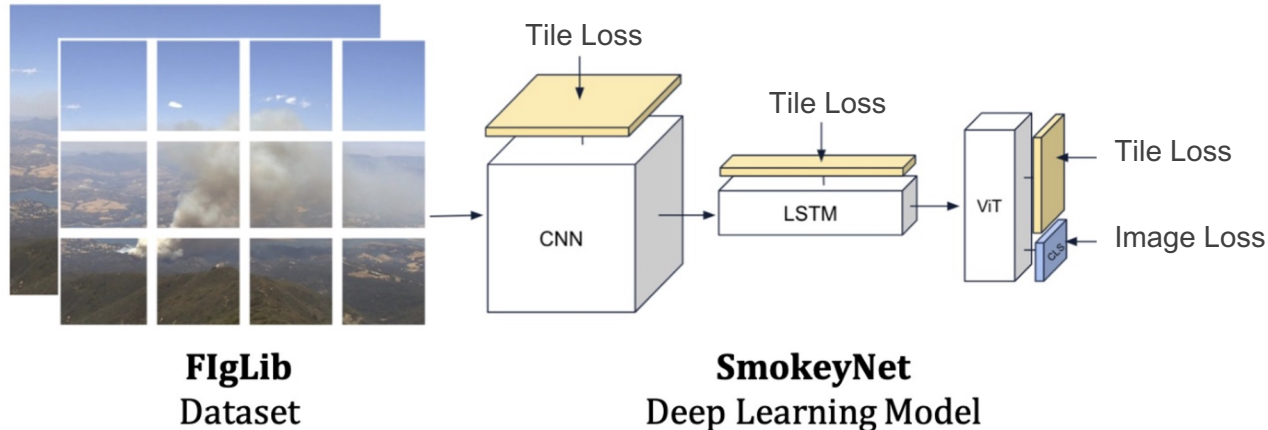
## GPU/CPU Usage Per Day, Last 6 Months





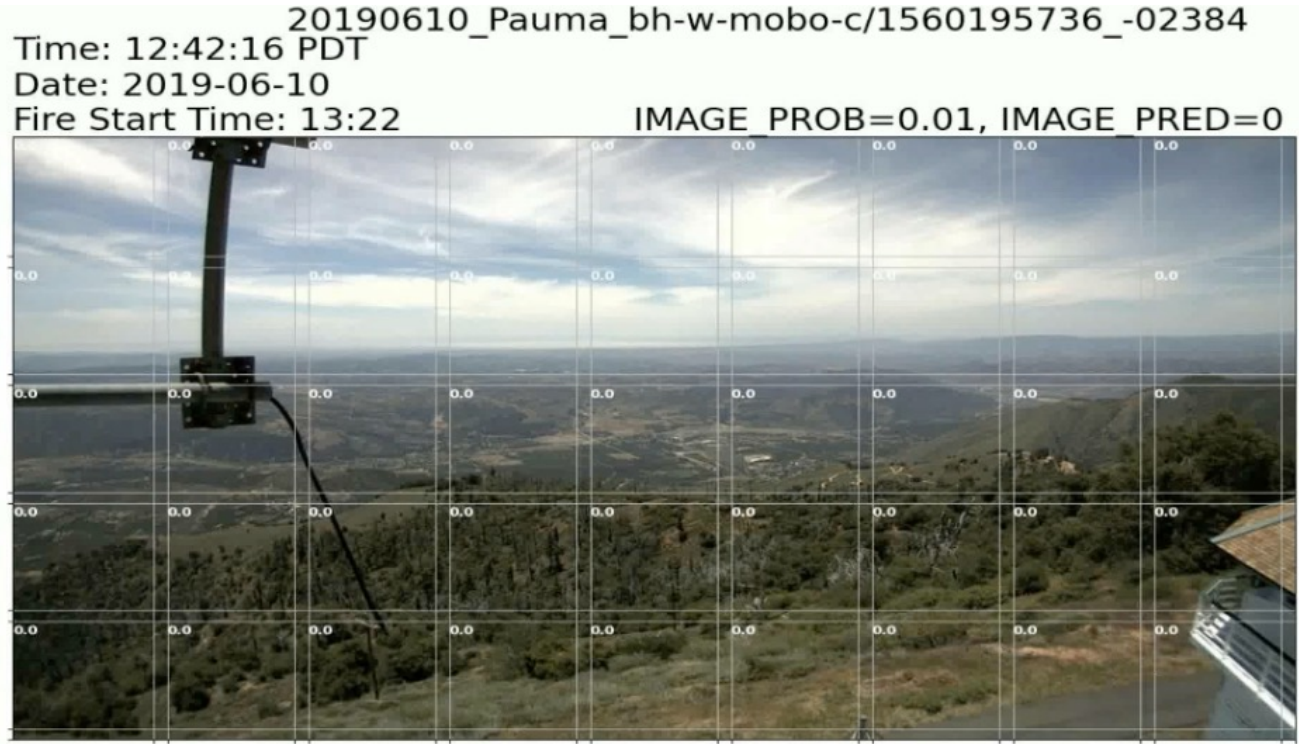
# Summary

- SmokeyNet: Deep learning approach for detecting smoke plumes from wildfires
  - Can incorporate different data sources for multimodal wildfire smoke detection
  - Can be used for early notification of wildfires
- FlgLib: Dataset of labeled wildland fire images



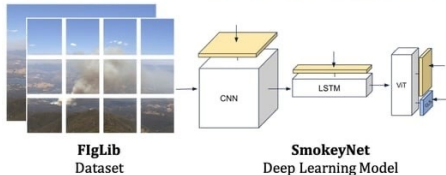
# Future Work

- Investigate use of unlabeled data to further improve detection
- Research ways to decrease false positives
- Test generality of approach to other geographical areas and camera types
- Deploy SmokeyNet as an early notification system for effective real-time wildfire smoke detection



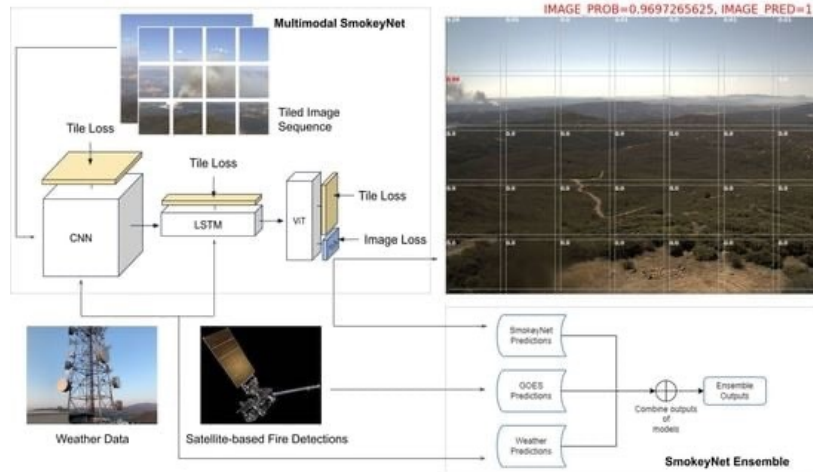
# SmokeyNet References

**FigLib & SmokeyNet:  
Real-Time Wildfire Smoke Detection**



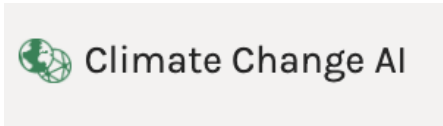
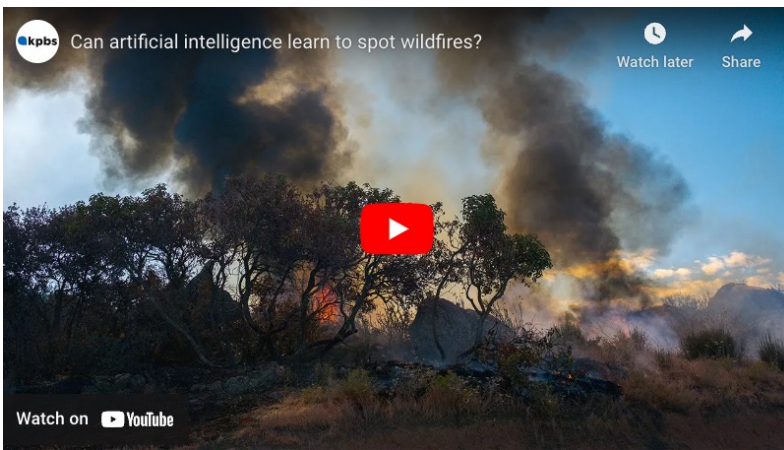
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kpbs

<https://www.kpbs.org/news/science-technology/2023/09/06/can-artificial-intelligence-learn-to-spot-wildfires>



NeurIPS Workshop on Tackling  
Climate Change with Machine  
Learning  
<https://www.kpbs.org/news/science-technology/2023/09/06/can-artificial-intelligence-learn-to-spot-wildfires>

# WIFIRE



The **BurnPro<sup>3D</sup>** platform gives our public sector partners **next-generation fire science** using **data** and **AI** to optimize prescribed burns at an unprecedented scale.



# Collaborators & Acknowledgments



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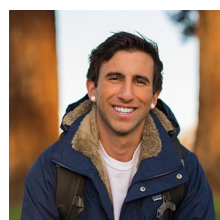
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