UC San Diego

# Multimodal Wildland Fire Smoke Detection

Tackling Climate Change with Machine Learning
NeurIPS Workshop 2022

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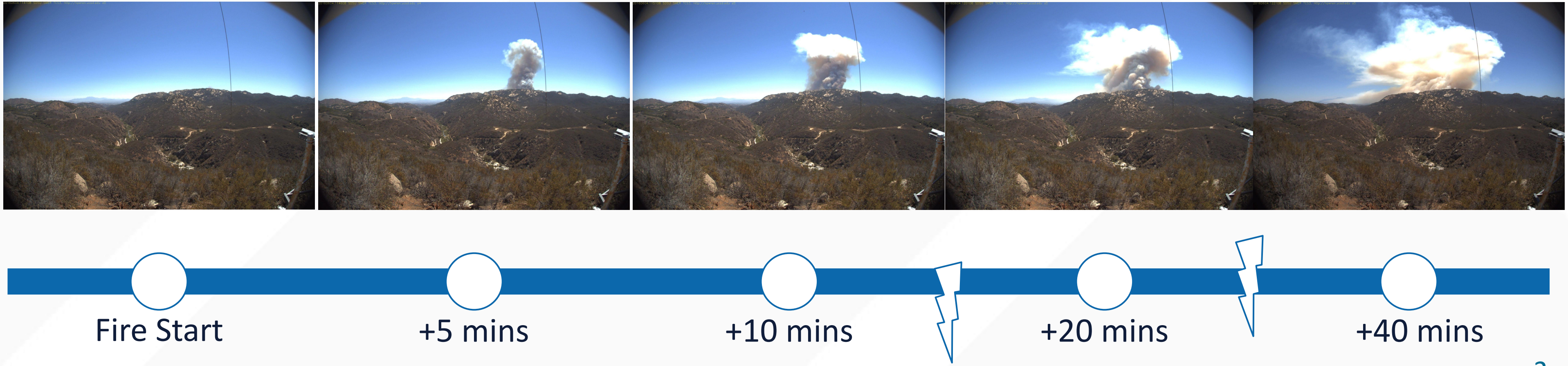
# Motivation

- Since 1980, 20 major wildfire events have occurred in the US, costing $1 billion in damages
- 16 of these events have occurred since 2000
- To minimize destruction, early detection is essential since fires can spread quickly

## Fires can spread quickly:



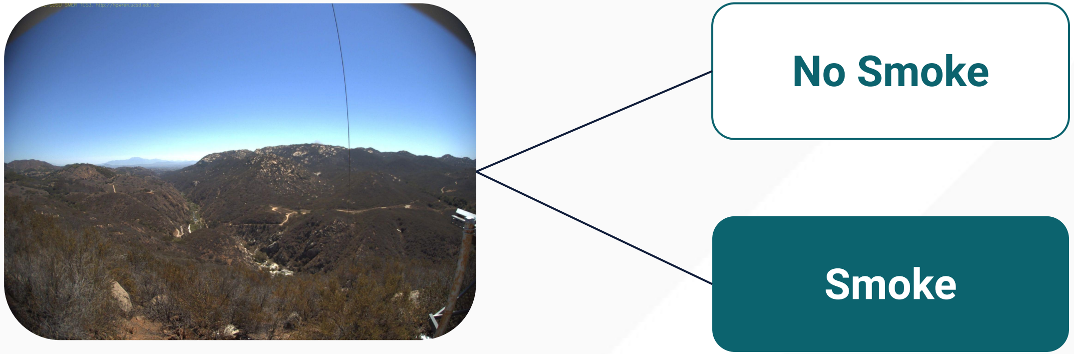
# Goals

**Goal:** Early and accurate detection of wildfires

**Approach:** Deep learning-based system for automated wildfire smoke detection to provide early notification of wildfires

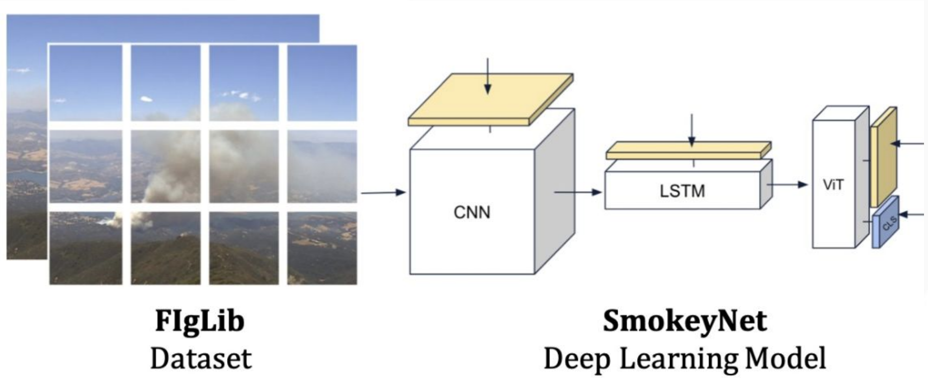
**Performance Objectives:**

Quick Time-to-Detection
High F1
Real-time Performance



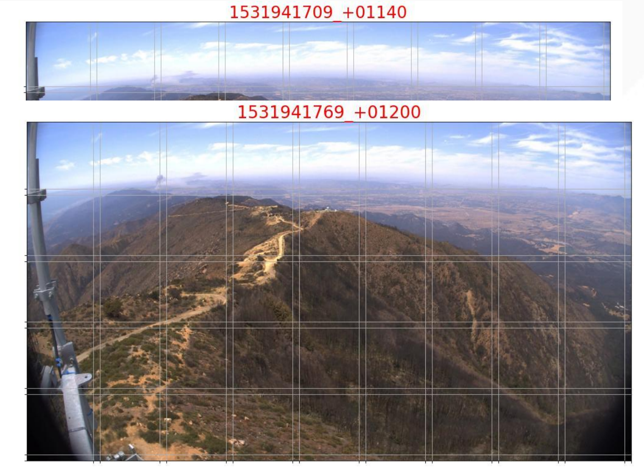
# Previous Work

- **Fire Ignition images Library (FIgLib) dataset**
  - 255 sequences of wildfire camera images
  - Each sequence consists of
    - 80 minutes of MP4 high resolution video feed
    - Fire sequence begins at the 40th minute
  - Time range:  3 July 2016 to 12 July 2021
- **SmokeyNet [1]**
  - ResNet + LSTM + Vision Transformer
  - Outperforms contemporary models (Faster R-CNN, ResNet, Transformer, Video Vision Transformer)

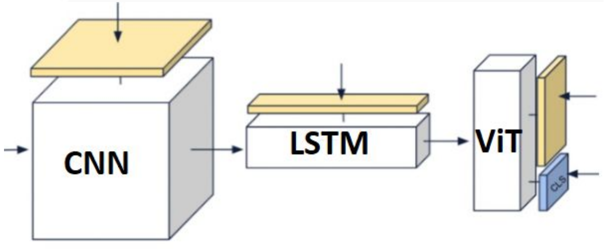


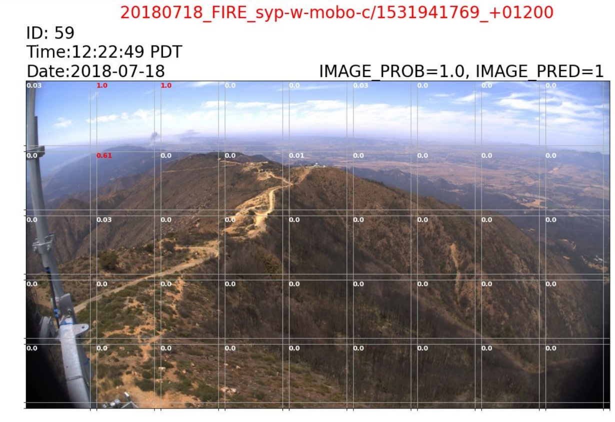

Dewangan, A., Pande, Y., Braun, H.W., Vernon, F., Perez, I., Altintas, I., Cottrell, G.W. and Nguyen, M.H., 2022. FIgLib & SmokeyNet: Dataset and Deep Learning Model for Real-Time Wildland Fire Smoke Detection. *Remote Sensing*, *14*(4), p.1007. doi:10.3390/rs14041007

# SmokeyNet




SmokeyNet




Tiled FigLib Input Sequence

Uses tile loss & image loss to train

Predicts tile & image probabilities

# Motivation

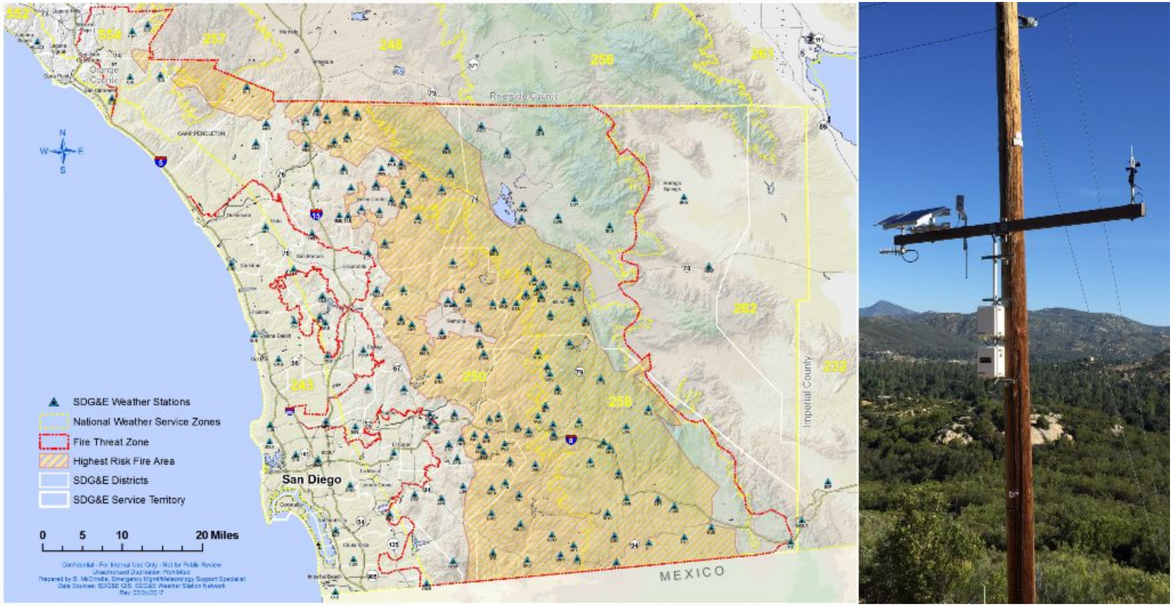
Can incorporating other types of data help performance?

Use multiple input data sources:

FIgLib images + **Weather Data**

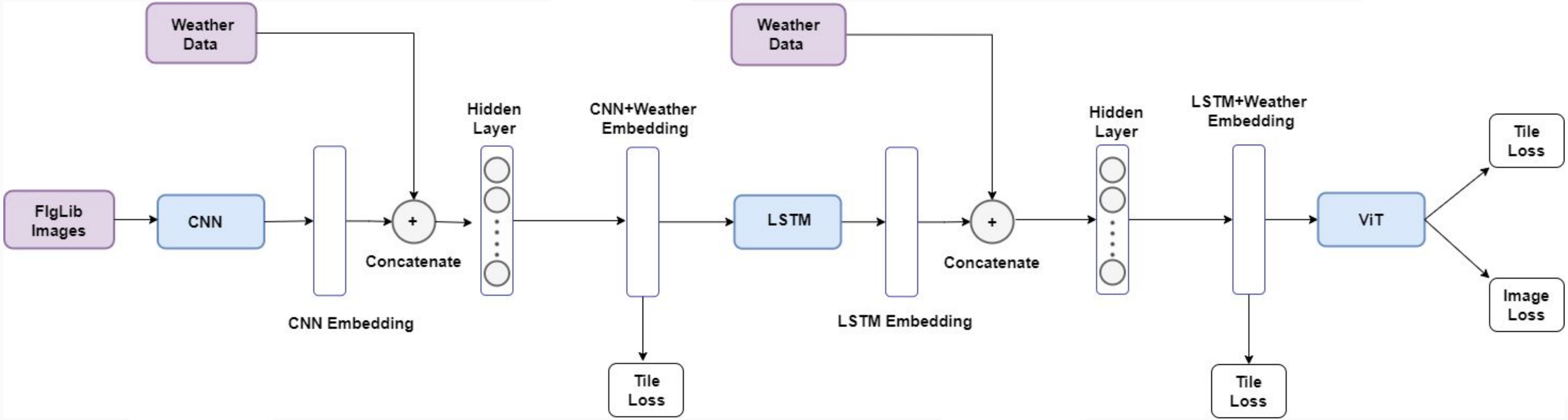
# Weather Data

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




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

# Multimodal SmokeyNet



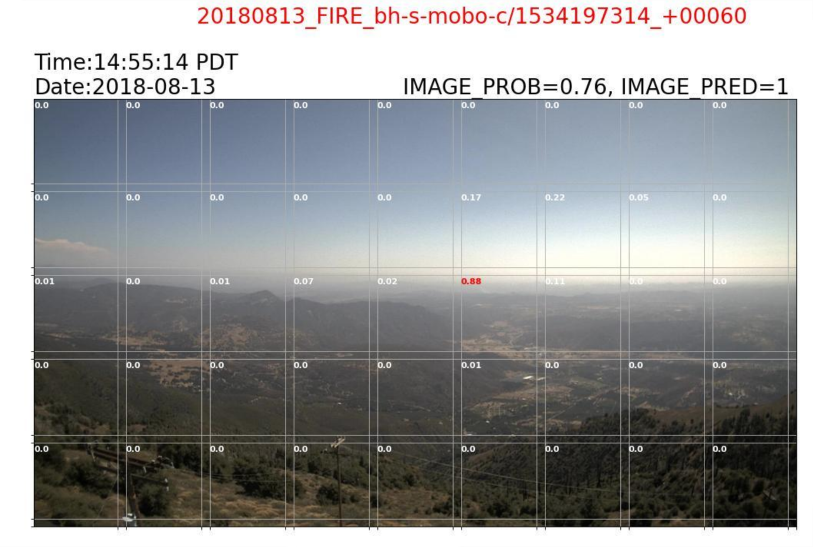
# Results

| Model | TTD | | Accuracy | | F1 | | Precision | | Recall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| SmokeyNet | 4.70 | 0.90 | **80.12** | 1.47 | 77.52 | 2.39 | **90.43** | 1.66 | 68.00 | 4.42 |
| SmokeyNet with Random Weather | 4.88 | 0.96 | 79.50 | 0.77 | 76.90 | 1.31 | 89.40 | 1.51 | 67.53 | 2.63 |
| SmokeyNet with Weather | **3.66** | 0.77 | 79.97 | 1.18 | **78.18** | 1.68 | 87.07 | 2.16 | **71.07** | 3.54 |

**Table 1.** Mean and standard deviation (SD) of Time-to-Detection (TTD), Accuracy, F1, Precision, and Recall metrics on the test set over 8 runs.

# Summary

- Extended SmokeyNet architecture to incorporate additional data types for multimodal wildfire smoke detection
- Results show trend in improvement in F1 and time-to-detection
- Future Work
    - Analyze results to gain insights into benefit of adding weather
    - Research ways to decrease false positives
    - Investigate use of unlabeled data to further improve detection
    - Explore methods to optimize model’s compute and memory resources
- Ultimate goal:  Deploy SmokeyNet on edge devices for real-time wildfire smoke detection




For this sequence, adding weather enables multimodal SmokeyNet to correctly detect smoke, which was ignored by the baseline SmokeyNet model.

# Co-Authors & Acknowledgements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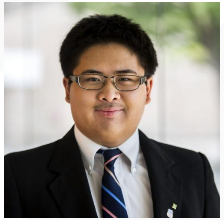
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