Early Detection of Wildfires Using Scalable AI Algorithms

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Background and Problem Statement

Wildfires are a rapidly increasing danger worldwide, causing loss of life and property in increasingly populated areas. For example, 7 million acres were burned in California alone in the decade 2009-2018, almost double the amount from 1979-1988 [1]. The average economic loss from wildfires in California during 2009-2018 was almost $1 billion, compared to $0.40 billion from 1999-2008 and $0.19 billion from 1989-1998 [2].

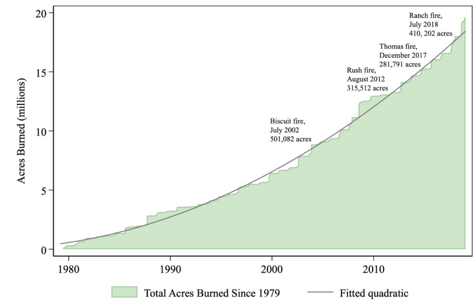

Figure 2. Cumulative Acres Burned, 1979-2018, for all Fires in California. Selected fires labeled for reference.

To combat wildfires, many governments are now deploying networks of video cameras that can detect fires much more quickly than satellite imaging. For example, the ALERTWildfire network in the Western US consists of 600 remotely operable, pan-tilt-zoom devices [7], which rely on human operators watching feeds and manually changing their direction to confirm and monitor fires. As networks grow, however, monitoring them solely with humans will become prohibitively expensive. A natural question is whether we can use AI to monitor camera networks. Unfortunately simply applying off-the-shelf ML models to this task is challenging for three reasons:

1. **Need for early detection:** Wildfires are much easier to contain if discovered early [10,11], but they are also hard to detect with high certainty when they are small. This creates a challenging tradeoff: when should the AI system notify human operators about a potential fire based on its certainty, or deploy other resources to confirm a fire, such as rotating other cameras?
2. **Computational cost:** Because of the need for fast detection, ML models will need to run continuously on hundreds or thousands of video streams. Unfortunately, the highest-quality computer vision models can only run at a real-time rate (30 frames/sec) for a single stream on a high-end GPU, potentially requiring massive computational resources that will only grow as networks add new sensors, such as IR cameras, UV flame detectors, and 360° fisheye cameras.
3. **Nonstationarity in wildfire risk:** Seasonal and long-term trends in wildfire risk due to global warming pose unique challenges for object detection. While off-the-shelf object detection systems can be highly accurate, they do not currently take into account the substantial variation in base rates across time. An effective approach to wildfire detection must allocate limited resources while accounting for the nonstationarity in the base wildfire risk.

Core Research Idea: Our goal is to design *statistical algorithms* and a *runtime system* that can aid human operators in monitoring a large camera network for wildfire detection, subject to both a *computational* and an *attention budget* (limited human attention to check alerts). If successful, this project could enable scaling wildfire detection networks to tens of thousands of cameras, greatly improving their efficacy. Designing effective algorithms for joint human-AI monitoring tasks fits in the Augment Human Capabilities theme of HAI.

Technical Contributions and Plan: Our research labs have done a wide range of work in efficiently querying large video datasets with ML, including cascading approaches that use a less expensive ML model to reduce the cost of accurate object detection in videos [3, 4, 5]. We have also done work in high-performance DNN inference [6] and worst-case performance for ML [8, 9] that can be used to implement an efficient and robust runtime system and monitor its quality. However, real-time wildfire detection imposes unique latency and resource constraints. We now describe the technical approach for each of the three key challenges outlined earlier.

First, we have developed algorithms to prioritize high-cost, high-latency resources (e.g., human attention or expensive DNNs) by using approximations called proxy models and subsequently debiasing errors that occur in the proxies [3, 4, 5]. As an example, consider a DNN trained to detect wildfires that returns a confidence per frame of video. Given these confidences, our prior work [5] selects a smaller subset of frames that is guaranteed to contain 90% of all wildfires and sends this subset to human volunteers for confirmation. While this work captures the core tradeoff between coverage and human annotation cost, it does not cover other tradeoffs in wildfire detection, such as allocating annotation budgets over different regions or zooming cameras to increase resolution at the cost of coverage. We can address these tradeoffs in a unified way by taking a decision-theoretic approach and quantifying the cost of latency and false positives in terms of the costs of the resulting fire. Our existing work on selection with statistical guarantees allows us to quantify the feasible space of actions, and a distributionally robust optimization problem can be used to get meaningful cost guarantees.

Second, in order to address the high costs of real-time ML analysis of videos, we have developed techniques for high-performance DNN inference over videos. This includes more efficient data input pipelines [6] and methods to efficiently train small DNNs that can approximate predictions from a larger target model [3, 4]. This past work operates on large, static video datasets. However, real-time video streams will pose additional challenges as naively running an ML model for each stream will still be exceptionally costly. We propose overcoming these challenges by building new systems that adaptively batches frames across multiple data streams to manage the processing cost.

Finally, most previous methods for using ML for object detection model data as stationary, so they would only work if wildfire risk were the same across all seasons and time. We will address this challenge in two parts: first, we will build detection models that can incorporate a prior base rate model and use this to account for trends, seasonal, and spatial nonstationarities. Even the most sophisticated base rate model is unlikely to fully account for nonstationarity, and thus our second point will be to build upon our earlier work on minimax-robust ML [7, 9] to make our predictions robust under small but possibly adversarial nonstationary base rates. This approach will allow us to control for known sources of nonstationarity, and also quantify the effects of unknown nonstationary structures.

We will evaluate our system using both existing resources and a prototype deployment at Jasper Ridge. We will use public video feeds from ALERTWildfire to evaluate the three challenges, including latency tradeoffs, multi-stream processing, and nonstationarities. To evaluate these factors in a real-world deployment, we will create a prototype system of several cameras at Jasper Ridge and test these using generated smoke during the rainy season.

Team: Our research team consists of Profs. Tatsunori Hashimoto and Matei Zaharia in computer science, Trevor Hebert, Technology Specialist at Stanford's Jasper Ridge Biological Preserve, and Daniel Kang, a graduate student in computer science. Prof. Hashimoto is an expert in robust machine learning and Prof. Zaharia is an expert in deploying deep learning systems at scale. Trevor Hebert will be deploying and testing the system at Jasper Ridge Biological Preserve. Daniel Kang will be the primary graduate student on the project, but we also want to hire another RA to help him.

Informal Sketch Budget: We are $65k for RAships and $10k to purchase several types of state-of-the-art camera equipment (including video, IR, and UV sensors), for a total of $75,000.

References

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