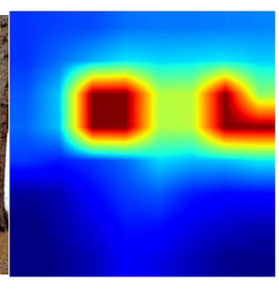
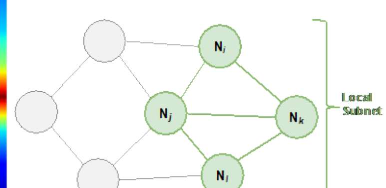
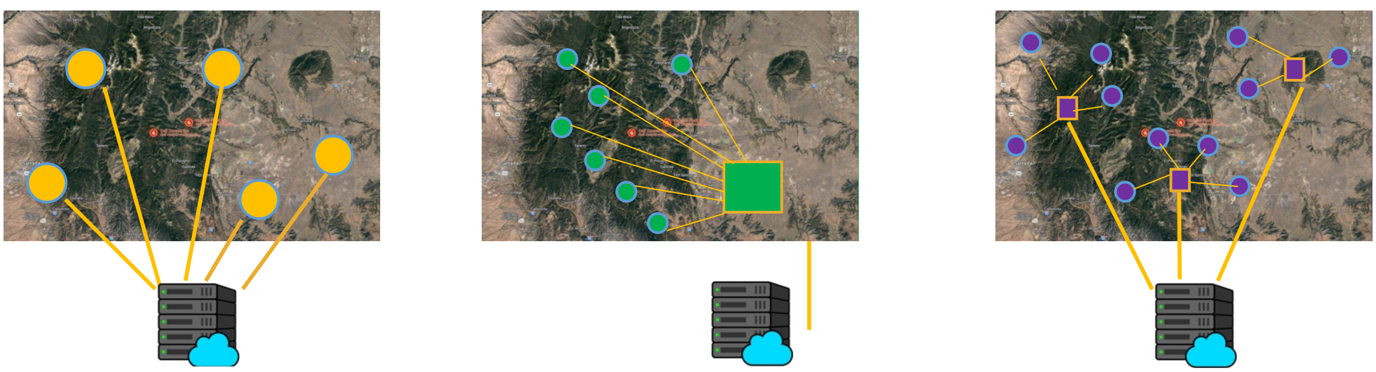
Machine Learning Models and Their Effectiveness for Autonomous Detection of Wildfires Utilizing Ground-Based Sensor Networks





Severe wildfires are becoming more common with large impacts on local economies, but also pose negative environmental impacts with global-scale effects from poor air quality to increased greenhouse gas emissions. With advancements in sensor technologies and new classes of machine learning methods, we now have new tool in our arsenal to deploy against this threat. Next generation of wildfire detection products and solutions will include multitude of sensing and implementation of artificial intelligence to provide real-time autonomous detection of ignition and predictive analytics. In this white paper we discuss the tradeoffs of various algorithmic approaches keeping in mind the resource requirements, namely energy, data bandwidth, implementation cost and operational requirements such as detection speed, false alarms, etc.

Three major categories of sensing and early-detection are 1) satellite based 2) camera based, and 3) ground-based sensor networks. Here we will consider innovative ML based methods that are being explored mainly in ground-based sensor networks (GSNs) and contrast them to camera and satellite imagery. Ground-based sensor networks typically are composed of many low cost and low power sensor nodes connected to a centralized server. These nodes continuously measure environmental data and send to a centralized location. Connection to the centralized location could be wired or wireless. In some architectures, all the data is sent to a centralized server to be processed either by humans or machines for example in camera-based systems. In other types of sensor networks, there could be some edge computation which reduces raw data into more relevant information packets that are then sent to the cloud for further processing.



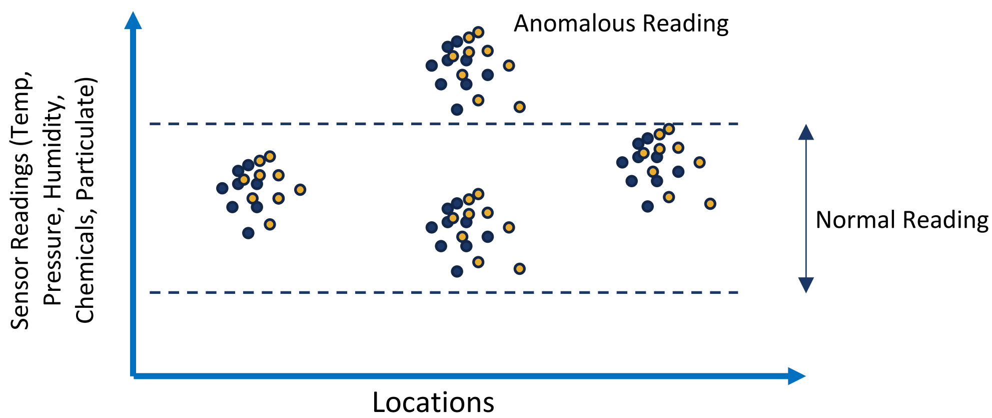
Individual Sensor Nodes Sending Data to the Server

Individual Sensor Nodes Sending Data a Gateway which in Turn Sends Data to the Server

Individual Sensor Nodes forming a Subnet Sending Data to a Gateway which in Turn Sends Data to the Server

Three different topologies of sensor networks are shown in the figure above. In all these topologies, edge processing can be implemented at the sensor node or at the gateway layer and can be combined with cloud-level processing. Different architectures represent tradeoff in latency, data load, response time, and false alarm rates. In topologies where data from each node (e.g., camera) is sent to a central location, high bandwidth communication links are needed. However, often areas prone to fire do not have high bandwidth connectivity solution such as LTE. Sensor networks that use edge processing can alleviate high data transmission requirements.

The main objective of any wildfire detection technology is fully autonomous 24/7 fire detection capability. Combination of machine learning (ML) methods with Camera and other ground-based systems can provide autonomous detection with low false alarm rates. Due to recent advances in ML methods and their cloud-based implementation, now is the perfect time to develop and deploy such capabilities. From machine learning perspective, autonomous identification of wildfires is an **anomaly detection** problem. The figure below represents conceptual anomaly detection using ground based-sensor networks. Sensor nodes at different locations are capturing environmental measurements, which normally would fall within certain thresholds, and measurements above such thresholds will then represent an anomaly. The purpose of ML models is to correctly identify these thresholds in various terrains, topographies, and macro environmental conditions and adjust accordingly to improve detection accuracy and reduce false alarms.



Deploying such wildfire detection sensor networks with ML represents the need to find energy and data efficient computing in a resource-constrained environment. With such networks measuring real-time data and fusing them with short-term and historical environmental and fuel data, we can train the ML models to not only detect but also predict the probability of ignition.

The table below summarizes key relevant data that can be used for detection and prediction of wildfires using ground-based sensor networks

Real-Time Measurements	Short and Long-Term Historical Data
Temperature	Average Rainfall for last 30 - 60 Days
Humidity	Average Humidity for last 30 - 60 days
Pressure	Avg High Temperature for last 10 days
Wind Speed	Fuel Type
Wind Direction	Fuel Level
Heat/IR Signature	
Chemicals	
Soil Moisture Level	
Lightning	

Measurement and utilizing of such different environmental parameters for detection of wildfires is a case of multimodal sensing. N5's wildfire detection product N5SHIELD™ uses such multimodal sensing technology. In N5SHIELD™ system, the edge algorithm benefits from the input of three separate sensing modalities -

1) Gas Sensing arrays – An array of gas and chemical sensors responsive to chemicals released during combustion. A change point detection algorithm is used to measure the overall array response magnitude in the presence of a changing environment. Wildfires result in increased rate of change in these chemical concentrations in the air. Our algorithm quantifies this change.
2) Particle Sensors – An optical-scattering based module measures a mixture of particulate sizes and their concentrations. Thresholding as well as change point detection allow us to identify particulate mixtures and behavior that are consistent with wildfire spread.
3) IR Heat Sensor – An Infrared sensor capable of measuring surface temperature provides a heatmap of the landscape. Changes and growth in hot spots are quantified as part of the edge detection algorithm.

The edge algorithm provides quantified severity measures for these modalities which are subsequently used in a network-based deep-learning aggregation model to provide robust wildfire likelihood estimation.

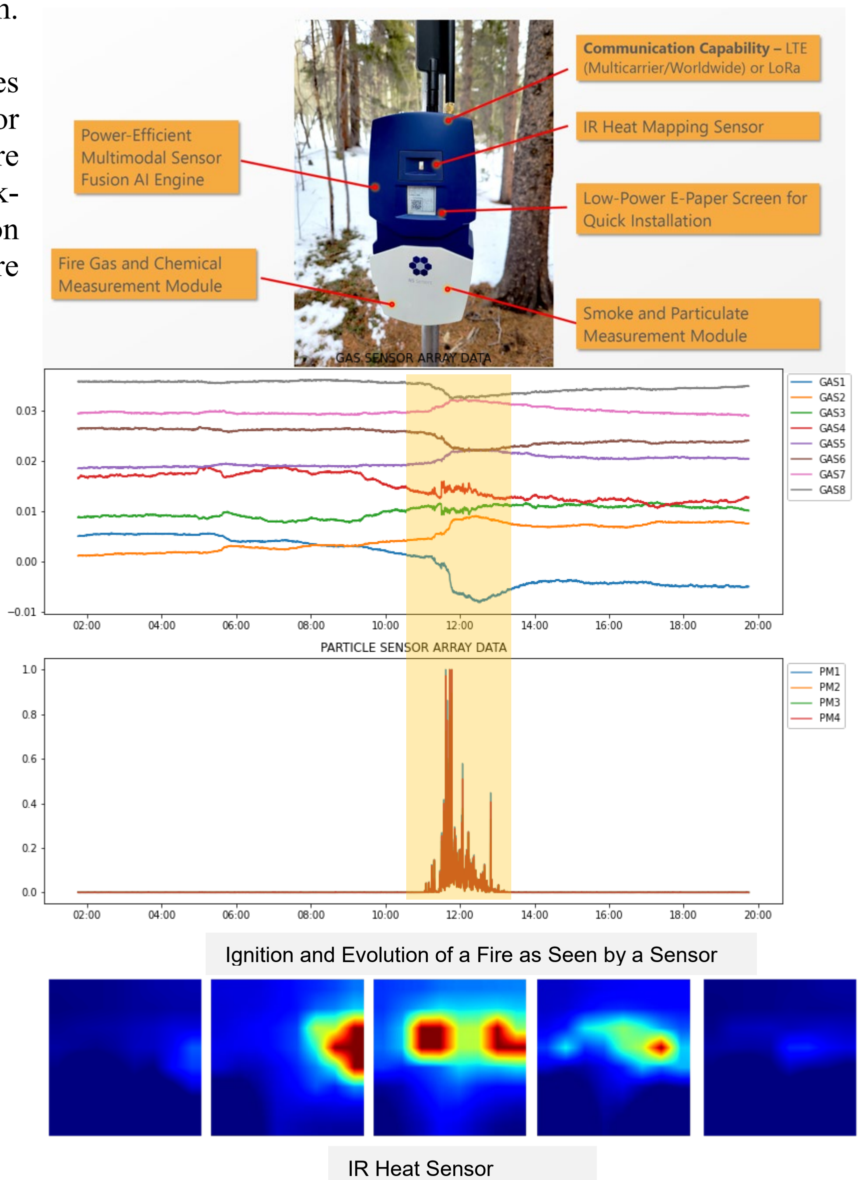
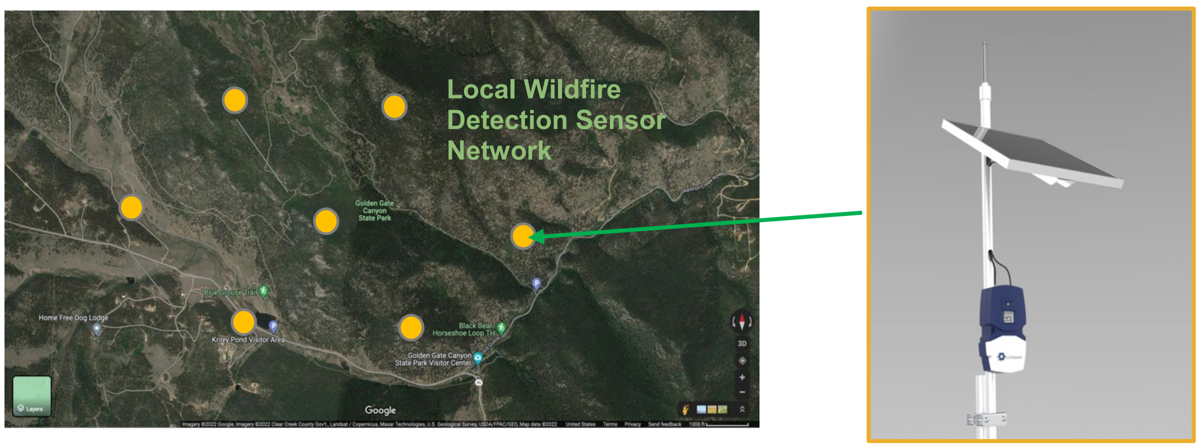


Fig. 1. Individual sensor node with multiple sensing modalities. Output from 3 different sensor modality during a fire event. The IR heat sensor shows an ignition with spreading. In addition, gas and particulate matter sensor reading show presence of obvious signatures of fire.

The true power of ML and sensor network comes into the picture when we distribute sensor Nodes forming a network and then utilize data from such network to make detection more accurate. As an example, we consider multiple Nodes are distributed across target geographical area as shown below.

Individual Sensor Node



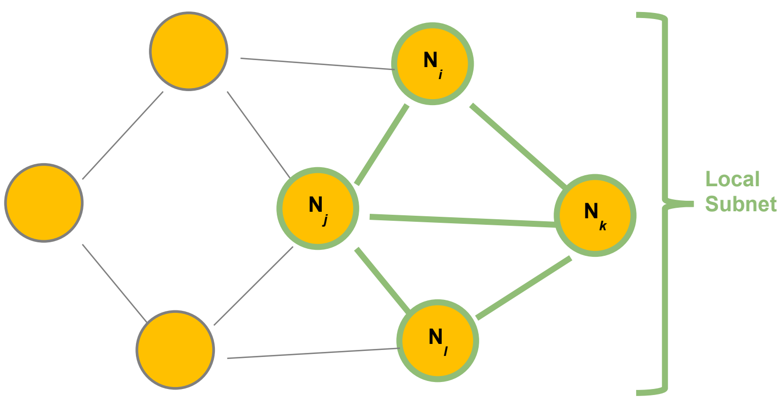


Fig. 2. Geographical representation of a sensor network, individual sensor Nodes are shown in the upper left. Graphical representation of the same network, with a smaller group of Nodes forming local subnet – lower left.

A **local subnet** represents nodes with a high degree of shared information —Nodes which are geographically closer to one another will have more shared information than those that are separated by greater distances. The **graph feature space** consists of each Node's edge algorithm outputs (Gas, Particle, IR model outputs), each node's geographical coordinates, and the graph edges and edge weights. This data is transformed into the **embedding space** via a graph neural network layer.

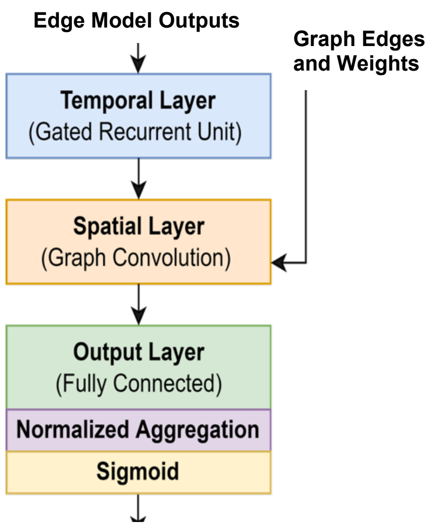


Fig. 3. Different layers in the multimodal deep learning Architecture used in N5SHIELD™

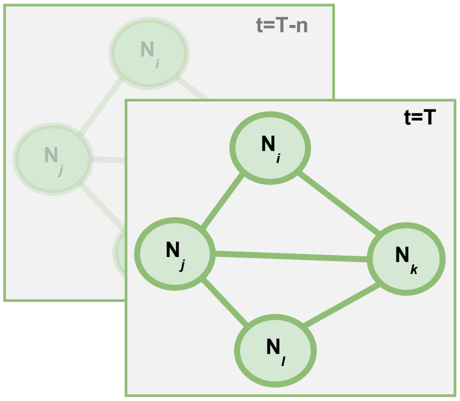


Fig. 4. Temporal evolution of graphical network, which is used as a model input.

This **Multi-Modal Deep Learning Architecture** takes a fixed cluster of N Node features as input. Subsequent layers (Graph Convolution, Gated Recurrent Unit) extract spatial and temporal information —how the gas, particle, and IR values change over time as a function of the sensor Node's spatial orientation. The model output is a predicted probability of active fire conditioned on a local cluster of Node units within a larger group deployed over a wider geographical area. The model is run simultaneously on disjoint or overlapping clusters of Node units. This allows for scalability across small or large deployments containing different numbers of deployed sensor Node units. A heat map of fire probabilities is produced and can be visualized in the cloud monitoring software and used to trigger an active fire alert if a probability threshold is exceeded.

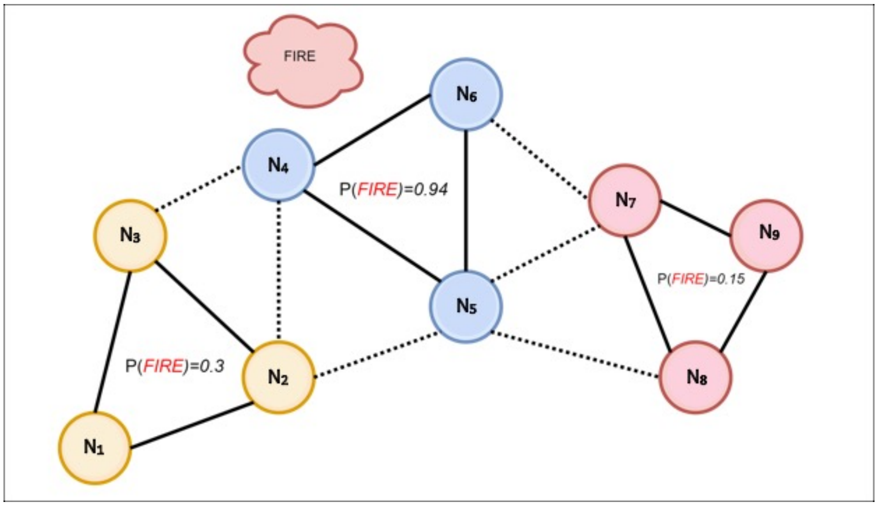


Fig. 5. Accurate estimation of location of fire using local subnets in network of sensors

The output of this network is a probability of fire detected by the input cluster of nodes, which also allows for localization of the fire event. It is an aggregation function of the node embeddings in the final layer. The framework provides the end-user with an interface that includes relevant temporal and spatial information about the fire risk which may offer useful insight in addition to a binary fire classification. The outputs can also be used to identify fire risk conditions

Such Deep Learning based multimodal detection using sensor network has some unique advantages compared to camera-based systems. One of the challenges of implementing any type of ground-based sensor network with deep-learning based ML models is the data bandwidth limitations in areas of deployment. For example, a typical camera system (Pan-Tilt-Zoom) requires about 24 Mbps of upload speed, whereas most typical upload speeds in 4G and 4G LTE are in the range of 20 Mbps. LoRa or other types on low-power long-distance radio communications have even lower bandwidths. Such multimodal sensing approach with ground-based sensor networks represents a paradigm shift in detection that is scalable and deployable in most geographical locations.

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