Developing an Unmanned Aerial Vehicle Module for Wildfire Detection Using Image Recognition

Grant Proposal

Samantha Wang

Massachusetts Academy of Math and Science at WPI

85 Prescott St, Worcester, MA 01605

Executive Summary

To decrease the hazardous qualities of abnormally destructive wildfires, this study designs an unmanned aerial vehicle (UAV)-based advance warning system for early detection of wildfires. Abnormally destructive wildfires have become increasingly prevalent in recent years. Existing systems for detecting these wildfires are not sufficiently effective. Early warning signs of wildfires often manifest as trailing indicators – distinguished by their rapid diffusion regardless of wind speed – which include the concentration of particulate matter in the air, carbon monoxide levels, and nitrogen dioxide levels. Object detection involves the use of algorithms to identify and categorize objects within an input image or video. Modern object detection algorithms leverage deep learning and convolutional neural networks. The widely-used You Only Look Once object detection algorithm was trained on a dataset of wildfire footage and deployed on a Raspberry Pi with a webcam. The signal of a carbon monoxide sensor was weighted based on testing data and combined with the output of the image recognition algorithm to produce a final probability. A global positioning system module was also added to provide location data. The long-term goal is to create a completely autonomous UAV-based system to identify, track, and communicate wildfire location data. The work proposed here is scalable to many instances, with communications interior to the system available. Depending on the number of instances, the system has the potential to support surveillance in a much greater quantity than existing solutions with equal or greater efficiency.

Keywords: Wildfire identification, object detection, image recognition, chemical sensors, autonomous systems, unmanned aerial vehicles, forest surveillance, smoke detection, warning system

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The increasing prevalence of wildfires worldwide underscores the urgency of implementing early detection methods to mitigate their devastating impact on ecosystems and human infrastructure. Considering this, the objective of this project was to design and develop a device capable of rapidly identifying wildfires through live footage acquired by an autonomous system. This technology aims to play a role in enhancing responses to these increasingly frequent natural disasters.

Wildfire Damage and Warning Signs

Wildfires are large-scale, destructive fires that spread quickly. While wildfires do not usually occur as a direct consequence of human involvement, anthropogenic climate change has greatly increased the rate at which wildfires occur, as well as the amount of area that is burned (Turco et al., 2023). This increase in wildfire severity necessitates a reliable and effective warning system for imminent wildfires, as abnormally destructive wildfires can cause significant damage to the environment and to human infrastructure. Therefore, a proactive warning system can be crucial in safeguarding lives, property, and ecosystems from the devastating impact of these increasingly severe wildfires. Early warning signs of wildfires often manifest as trailing indicators - abnormal trends that precede the transformation of a small flame into a large wildfire. These indicators – distinguished by their rapid diffusion regardless of wind speed – include the concentration of particulate matter in the air, carbon monoxide levels, and nitrogen dioxide levels (Bhowmik et al., 2023).

Object Detection

Object detection involves the use of algorithms to identify and categorize objects within an input image or video. These algorithms make predictions about bounding boxes to pinpoint the precise locations of each object. Traditional object detection techniques, such as Histograms of Oriented Gradients, relied on image processing methods that utilized filters to extract features from images (Dalal & Triggs, 2005). However, these methods faced challenges in capturing intricate details within an image, which are essential for distinguishing objects and enhancing accuracy.

In contrast, modern object detection algorithms leverage deep learning and convolutional neural networks. The majority of object detection architectures comprise two key components: a feature extractor and a meta-architecture. Initially, the feature extractor, which can be based on networks like VGG, MobileNet, Inception, or ResNet, processes the images through a convolutional neural network to extract relevant features. Subsequently, the data is forwarded through a meta-architecture, which outputs overall detection data of the image.

Region-Based Convolutional Neural Networks (R-CNNs) consist of a region proposal network (RPN) responsible for identifying potential regions where objects might be located. Then, an R-CNN utilizes a separate neural network to predict the bounding boxes and object classifications for each object (Girshick et al., 2014). On the other hand, Single-Shot Detector (SSD) models function as a single deep-learning neural network with additional convolutional layers to make predictions about bounding boxes and object classifications (Liu et al., 2016). SSD models generally offer quicker computational speed but may exhibit lower accuracy when dealing with smaller objects compared to R-CNN models (Huang et al., 2017).

Object detection models are often trained using transfer learning, a technique that involves fine-tuning a pre-trained model, initially trained on a large dataset, to specialize in a specific task. One widely used dataset for this purpose is the Microsoft COCO Dataset, containing over 200,000 labeled images and spanning 80 object categories (Lin et al., 2015).

Section II: Specific Aims

This proposal's objective is to develop a UAV (unmanned aerial vehicle) capable of detecting early warning signs of wildfires. Abnormally destructive wildfires post a significant risk to the surrounding ecosystem as well as any human populations nearby. Existing wildfire surveillance and monitoring systems are insufficient in providing satisfactory advance warning. The overall aim of this project is to engineer a device that can detect wildfires while surveilling an area of forest and provide alerts containing coordinates of the detected fire. The final product of this project is to be developed using YOLO, an object detection algorithm, and trained on collected wildfire data, which will be analyzed and tested to satisfy the specific aims discussed below.

Our long-term goal is to create a completely autonomous UAV-based system to identify, track, and communicate wildfire location data. The work we propose here will lead to the development of a system that yields greater safety and improved security for people inhabiting wildfire-prone areas. The proposed device will be scalable to a large number of instances, with communications interior to the system available. Depending on the amount of instances, the system has the potential to support surveillance in a much greater quantity than existing solutions with equal or greater efficiency.

Specific Aim 1: Use an image recognition algorithm to detect wildfires with at least 70% accuracy.

Specific Aim 2: Combine data from chemical sensors with the image recognition algorithm and detect wildfires with at least 85% accuracy.

Specific Aim 3: Be able to perform both of the above tasks using live footage from a UAV.

The expected outcome of this work is a system or device that is able to accurately detect wildfires using collated data from an image recognition algorithm and chemical sensors.

Section III: Project Goals and Methodology

Relevance/Significance

Advance warning of impending wildfires is crucial in maintaining the safety and security of human populations. Rapid mitigation of wildfire damage is also necessary to reduce the negative effect of excessive combustion on the surrounding environment. This study develops a system to identify wildfires and transmit location data. Additionally, this study contributes a unique implementation of integration of signals produced by chemical sensors and real-time object detection.

Innovation

In recent years, unmanned aerial vehicles (UAVs), commonly known as drones, have gained significant popularity in various fields, particularly in security-based surveillance. One such design involves a specific systems model for surveillance of heavily forested areas (Leng et al., 2014). Additionally, image recognition and object detection technology have progressed rapidly, corresponding with recent development in neural networks. Object detection algorithms have been adapted for the detection of forest fires from static images, showing their potential to be used in live identification (Sathishkumar et al., 2023). Similarly, chemical and particulate sensors for use in outdoor environments have been in use in different fields. There exist designs for outdoor smoke detectors that utilize chemical sensors to detect the presence of smoke particles (Wang, 2015). However, no system has been developed with a standalone, scalable UAV-mounted device that is capable of supporting a live image recognition algorithm and incorporating signal data from chemical sensors in the prediction. The proposed system aims to bridge this gap and provide a comprehensive and efficient solution for wildfire detection in heavily forested areas. This device will provide fast, accurate wildfire detection and be easily scaled into a large and comprehensive system, which will be one of the first of its kind.

Methodology

First, the object detection algorithm (YOLO) will be trained on a dataset composed of annotated images of wildfires. This training process will involve feeding the algorithm with a large number of images that have been labeled to identify the presence of wildfires. By analyzing these images and their annotations, YOLO will learn to accurately detect and localize wildfires in new, unseen images. Once the training is complete, the next step will be to deploy the trained YOLO algorithm on a Raspberry Pi. This small and portable device will serve as the platform for running the object detection algorithm in real-time. The Raspberry Pi's computing power and low energy consumption make it an ideal choice for this task. To assess the performance of the deployed system, it will be tested for both accuracy and speed. Virtual data, simulating various scenarios, will be used to evaluate how well the algorithm performs in different conditions. Additionally, a webcam will be used to capture live video footage, providing a physical representation of the data that the system will process. This testing phase will help fine-tune the algorithm and ensure it can detect wildfires accurately and quickly.

Next, a carbon monoxide sensor will be integrated into the system. The purpose of this sensor is to provide additional environmental data that can contribute to the overall accuracy of the system. By measuring the levels of carbon monoxide, a common byproduct of wildfires, the sensor will help validate the presence of a wildfire when combined with the object detection algorithm's output. To determine the weight or influence of the carbon monoxide sensor on the final result, the system will undergo testing using preconceived scenarios. These scenarios will involve controlled environments where the presence of wildfires and corresponding carbon monoxide levels can be accurately simulated. By analyzing the system's performance in these scenarios, the optimal weighting of the carbon monoxide sensor's data can be determined. Following the integration of the carbon monoxide sensor, the system will be tested again for accuracy and speed. This time, the testing will include the added factor of the carbon monoxide sensor's data. By evaluating the system's performance with both the object detection algorithm and the sensor, any improvements or changes in accuracy and speed can be measured.

Finally, a global positioning system (GPS) module will be added to the system. This module will enable the system to accurately determine its geographical coordinates. The combination of GPS data with wildfire detection and carbon monoxide sensing capabilities will provide valuable information about the location and potential severity of detected wildfires. The final output of the system will be a periodic transmission of three numbers: the coordinates of the system and the combined probability of a detected wildfire. These numbers will allow users or authorities to track the location of potential wildfires and assess their level of threat. The system's periodic transmissions ensure that the information remains up-to-date and can be used for real-time monitoring and response to wildfire incidents.

Specific Aim #1:

The first main objective of this project is to train an object detector that will rapidly and accurately detect wildfires in a dataset and through a webcam. The trained system will be at least 70% accurate in both the virtual dataset and through the webcam. As per this study, two different versions of the YOLO object detector have been trained. The YOLO architecture was chosen for its speed, accuracy, and relatively light load on computational resources.

Justification and Feasibility. The YOLO architectures are lightweight and portable, which makes them suitable for real-time detection, especially in outdoor environments with relatively small objects (Dewangan et al., 2023). As seen in Figure 1, a YOLOv5 architecture was able to achieve a mAP of about 0.95 in 150 epochs of training, on a dataset of approximately 1,500 images. Both versions will be trained on data taken from multiple datasets, which will be annotated and collated to produce a cohesive dataset that contains images of wildfires from multiple perspectives. Although it is infeasible to train the models for a large number of epochs, the quantity of dataset contained within the dataset should compensate for the lack of training time.

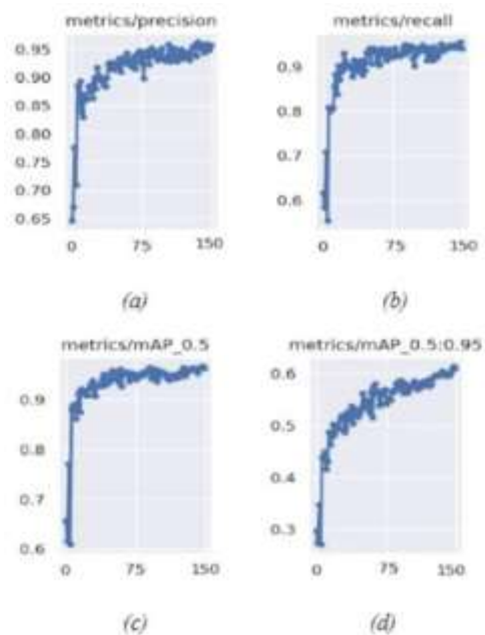

Figure 1. YOLOv5 Hue augmentation validation curves; (**a**) precision vs. epoch curve; (**b**) recall vs. epoch curve; (**c**) mAP score at 0.5 IoU threshold vs. epoch curve; (**d**) mAP (0.5:0.95) vs. epoch curve. Figure from (Dewangan et al., 2023)

Summary of Preliminary Data. As seen in Figures 2 and 3, the data indicates that, in general, the YOLOv5 model demonstrates greater consistency across training epochs when contrasted with the YOLOv8 model. Specifically, when comparing the two models, it is observed that the mean Average Precision (mAP) of the YOLOv5 model experienced a lesser decrease between epochs 4 and 5 in comparison to the mAP of the YOLOv8 model. This suggests that the YOLOv5 model exhibits more stable performance over the training epochs. Additionally, observed training time was much greater for the YOLOv8 model, which suggests a greater use of computational resources that a single-board computer (SBC), such as a Raspberry Pi, may not be able to handle. This quality may factor into the efficiency of the proposed system.

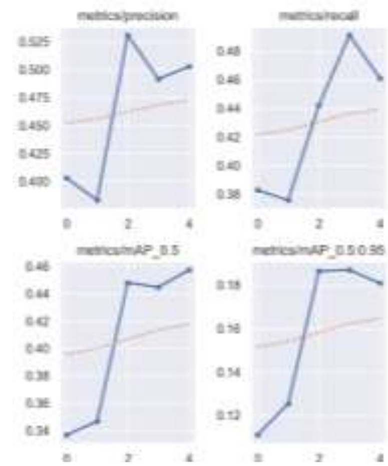

Figure 2. Graphs of 5-epoch training run on YOLOv5 model. Shows general precision and recall. Median average precision is denoted between 0.5 and 0.95 Intersection over Union thresholds.

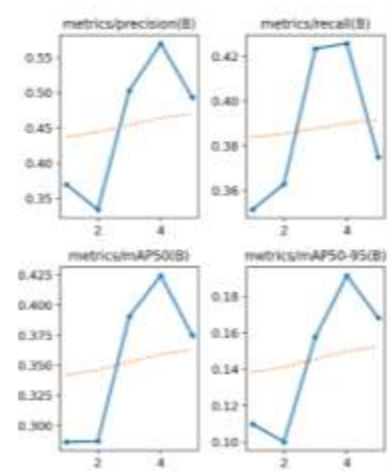

Figure 3. Graphs of 5-epoch training run on YOLOv8 model. Shows general precision and recall. Median average precision is denoted between 0.5 and 0.95 Intersection over Union thresholds.

Expected Outcomes. The overall outcome of this aim is to train an object detector to detect wildfires with at least 70% accuracy. The resulting data will be used to decide which version of YOLO will be used in the final system.

Potential Pitfalls and Alternative Strategies. The size of the dataset may be inadequate to sufficiently train the models. If the quantity of data is insufficient, the images can be duplicated and processed to have different attributes, which imitates the effect of a larger dataset. Additionally, data in the form of videos can be broken down into individual frames, which can be added to the dataset.

Specific Aim #2:

The second main objective of this project is to test a carbon monoxide (CO) sensor and a global positioning system (GPS) module. The CO sensor will be able to detect the relative amount of CO in the surrounding air and output a proportional resistance. The sensor should be able to achieve consistent results over a period of time. The GPS module will be tested on reliability and accuracy. The module should be accurate to a 15 meter radius while outdoors.

Justification and Feasibility. Carbon monoxide is an easily detectable trailing indicator of wildfires (Bhowmik et al., 2023). An increase in the relative frequency of CO in the air is sufficiently suggestive of a wildfire when combined with the object detection algorithm. While the sensor may not be effective in urban areas due to air pollution containing CO, the device will be deployed in remote areas. The GPS module is necessary because the device must be able to communicate the location of a detected wildfire.

Section IV: Resources/Equipment

Current equipment that has either already been obtained or is available for use are a Raspberry Pi, an Arducam OV5647 webcam, an MQ-7 carbon monoxide sensor, and a GPS module. Furthermore, basic computational resources for object detection training are available through Google Colaboratory. Open-source datasets can be obtained and annotated through Roboflow.

Section V: Ethical Considerations

This project will not involve animal subjects or human participants. Potential safety concerns would include live testing with carbon monoxide. To address this concern, the sensor would be tested with carbon monoxide testing spray in a sealed container in a well-ventilated area.

Section VIII: References

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