Toward a Deep Learning-guided Air-to-Ground Fire Extinguishing System for Wildfire Response

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***Abstract*— This extended abstract presents a deep learning–guided fire extinguishing system aimed at mitigating wildfires under adverse conditions such as strong winds, nighttime, drought, and smoke. The system combines a YOLO-based object detection algorithm with a unique Nona Filter to enable real-time recognition and priority-based target tracking of fires and smoke. In controlled experiments, the GFED system successfully identified and tracked fire sources at distances up to 30 meters, maintaining consistent performance even when multiple fire and smoke instances appeared in the same frame. The current work will target aerial deployment under challenging environments like strong winds, nighttime, high altitude operations. Additional enhancements include computational fluid dynamics, 6-degree-of-freedom analysis, sensor integration, and further optimization of the Nona Filter. With continued development, GFED shows strong potential to evolve into a fully autonomous wildfire suppression solution.**

I. INTRODUCTION

Wildfires remain a serious threat throughout the world, causing immense destruction. A recent example is the Los Angeles wildfires, which destroyed over 16,000 homes and commercial properties in Pacific Palisades, Malibu, and Altadena. The resulting property and capital losses are estimated between $95 billion and $164 billion, with insured losses at approximately $75 billion [1]. Elsewhere, Canada, the Maui, and Korea's Uljin and Gangneung regions experienced rapid fire spread that overwhelmed standard containment efforts [2]–[4].

Beyond immediate devastation, wildfires have long-term profound environmental consequences. Thousands of carbon-absorbing forests are lost, releasing significant greenhouse gases that exacerbate climate change. This, in turn, creates hotter, drier conditions conducive to even more frequent and intense wildfires, forming a vicious cycle [5]–[7].

Current responses typically involve aerial water drops, ground-based fire crews, and controlled burns, methods that can be compromised under adverse conditions. Thick smoke reduces visibility and elevates the risk of midair collisions, while nighttime operations become nearly impossible due to limited vision. Furthermore, strong winds and drought conditions can decrease the effectiveness of water-based suppression tactics, delaying containment efforts, and putting firefighters and nearby communities at risk.

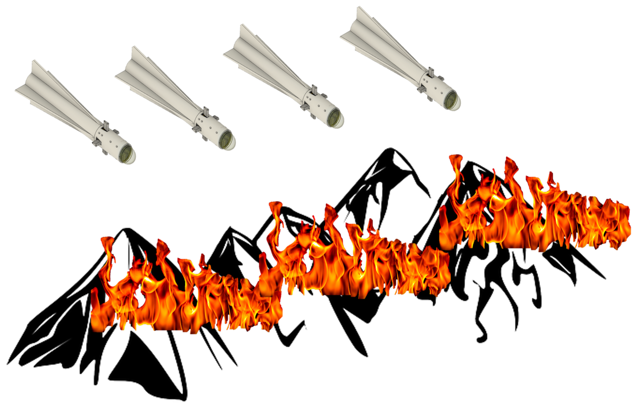

Fig. 1: Notional concept of the proposed system: Deployed from the air or the ground, autonomously navigate to the wildfire zone, and deliver a precisely targeted extinguishing payload—similar to a firefighting bomb—directly onto the flames.

In robotics, wildfire response has been studied for decades. For example, the Trinity Fire Fighting Robot competition has run for years at the international level [8]. Most of researchers focus on computer vision for wildfire detection, using deep learning algorithms and diverse training methods [9]–[13]. Some researchers extend these methods to mobile robots for real-time data gathering, aiming to speed up firefighting operations [14]–[17].

However, most systems have been limited to detection tasks or small indoor fires. So far, no solution has addressed large-scale outdoor wildfire suppression in harsh conditions. This gap highlights the need for an integrated approach that not only identifies and monitors wildfires but also engages in active suppression, even under strong winds, low visibility, or drought.

To address these gaps, this research proposes a deep learning-guided air-to-ground fire extinguishing system to strengthen the response to wildfires in harsh environments (See Figure 1). By employing deep learning algorithms for real-time fire detection and autonomous guidance controls, the system aims to localize outbreaks more accurately and optimize the deployment of extinguishing agents. Ultimately, such technology can improve response speed, protect human

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lives, and mitigate the growing environmental impact of wildfires.

Section II describes the current state of the system design. Section III demonstrates the work in progress; wildfire detection performance. Finally, Section IV concludes and discuss the future work.

II. SYSTEM DESIGN

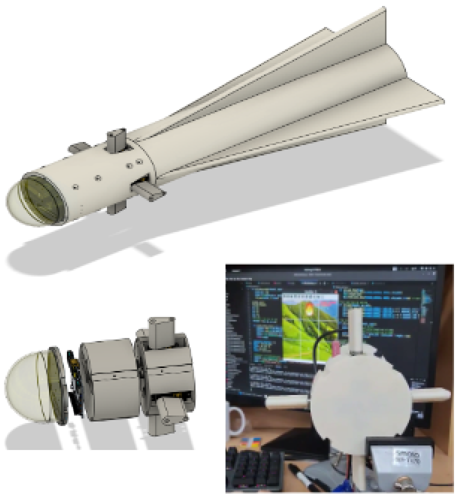

Fig. 2: Current system prototype

Figure 2 shows the current system prototype. It is considered aerodynamics, including a center of gravity at 43.1% forward and a center of pressure at 50.3% forward. The total mass is 14 kg, and it can carry up to 10 kg of fire-fighting agent. Polycarbonate and biodegradable polylactic acid (PLA) were used for the body materials. The front "head" holds an NVIDIA Jetson Nano and an 8 MP CCD camera module with a 160-degree FOV and a 12x zoom telephoto lens, both shielded by fireproof materials. Four motorized wings in the middle enable the system to navigate toward the fire target. The elongated rear section carries the extinguishing material.

III. WORK IN PROGRESS

A. Nona Filter

The Nona Filter is a portmanteau of "Nona," referring to the Greek numeral for nine. As shown in Figure 4, it continuously tracks the optimal target among multiple targets and outputs intuitive control in nine directions. The algorithm tracks the target with the highest Total Value by multiplying the object value, confidence value, and pixel square of each detected target.

The system utilizes Nona Filter-based guidance control to enhance the accuracy of fire suppression. The Nona Filter processes data received from the deep learning model, filtering out noise and identifying the most relevant fire and smoke sources. This filtering process allows the guidance control system to make more reliable and efficient adjustments on the position and orientation of the proposed system, minimizing unnecessary movements while accurately targeting the fire.

B. Model Training

Fig. 3: Data pipeline for global wildfire detection model training: multi-language keyword searches, automated bounding-box labeling, and dataset unification.

To ensure the wildfire detection model accurately reflects diverse global conditions, we gather international image data and update the existing deep learning framework. Figure 3 illustrates the process: keywords in various languages—such as Skogsbrand (Swedish), Waldbrand (German), and Incêndio florestal (Portuguese)—are first searched on worldwide video platforms, and the resulting videos are classified by country. A pre-trained model then identifies fire and smoke instances, automatically generating bounding box coordinates (x, y, width, height). These labeled images are combined into a unified dataset that captures a range of vegetation, climate, and lighting conditions. Finally, the data are used to retrain the deep learning model, improving its accuracy in detecting fire and smoke under diverse environmental scenarios.

The resulting dataset comprises 8,030 training images, 1,057 validation images, and 542 test images, achieving a mean average precision (mAP) of 88.0%, a precision of 90.3%, and a recall of 85.3%—indicating a notable improvement in the model's performance.

C. Test and Evaluation

To test and evaluate the current system, we conducted an experiment focusing on B Class 1 Unit fire detection at a range of approximately 31 meters, as recommended by our sponsor (KFIRE) to align with practical requirements. As illustrated in Figures 5, a 44.7 cm B Class 1 Unit fire model was projected rather than igniting a real flame. The distance was measured with a 100-meter measuring tape, and the detection. This setup allowed us to safely assess the Nona Filter's ability to detect and track flammable-liquid fires at a distance, providing insights into both the system's effectiveness and potential limitations. The result shows a

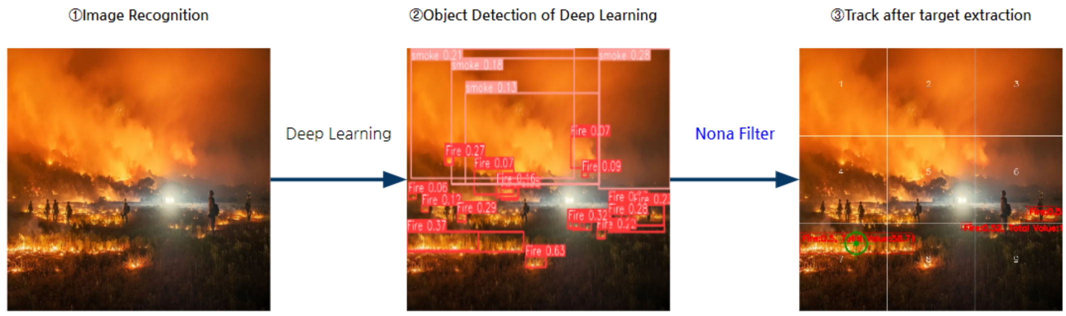

Fig. 4: Target tracking procedure with Nona Filter

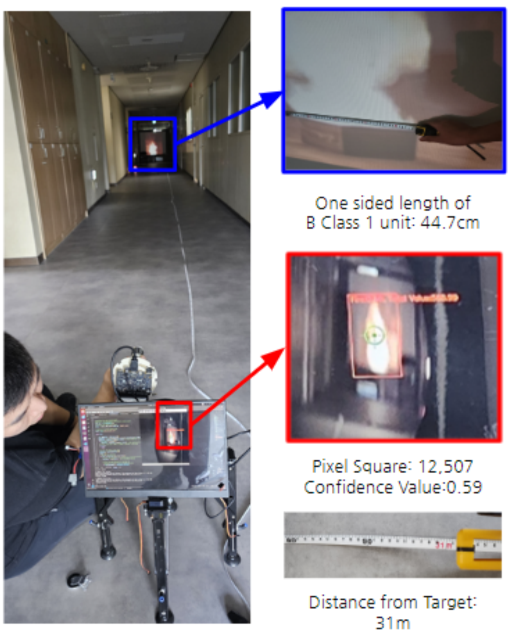

Fig. 5: Test and evaluation setup

Pixel Square of 12,507 and a Confidence Value of 59%. One could also find that for a B Class 1 Unit simulated fire model at a 30-meter distance, the Nona Filter required a minimum pixel area of 2,000 pixels to detect the fire reliably.

IV. Conclusions and Future Work

This extended abstract shows the system development and its preliminary evaluation. The Nona Filter with the YOLO object detection model demonstrated the ability to track the optimal target among multiple B Class 1 fires and smoke sources.

Future works will involve six degree-of-freedom (6-DOF) aerodynamic analyses for the robust control in the air, development of a spray sensor for the extinguishing agent, and validation and verification under dynamic conditions. Additionally, we plan to mount the proposed system on drones operating at altitudes of around 100 meters to refine drop accuracy and gather real-time data for wildfire response.

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