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Implementation of Deep-Neural-Network-based Unmanned Aerial Vehicle Platform for Fire Smoke Response: Wildfire Smoke Description Experiments

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A deep neural network (DNN) is a machine learning tool that mimics the functioning of the neurons in the human brain. DNN can detect smoke and thus provide early warnings regarding wildfires before they occur. In many cases, the initial response to wildfires is inadequate, which leads to large-scale fire damage. The goal of this study was to enable prompt response to wildfires. Unmanned aerial vehicles (UAVs) are unmanned and fast and can efficiently reach the source of wildfire smoke. They can also fly for long periods to perform wildfire detection. The UAV platform is a combination of deep neural networks and cyber–physical systems. The platform enables nonspecialists to understand the underlying science and technology by interacting with the builtin mechanisms—DNNs and cyberphysical systems (CPS). The results of this study demonstrate the potential of the UAV platform as a tool to pre-empt wildfires. The findings can serve as an important reference for the advancement of wildfire response strategies.

1. Introduction

Forest environments contain resources that are vital to human life. Deforestation also elevates wildfire risk by increasing fuel loads, fragmenting landscapes, and altering microclimates, thereby creating conditions conducive to ignition and spread. Unfortunately, with the rapid urban and industrial development worldwide, deforestation is becoming a growing threat to forest environments.[(1)] Wildfires, which cause soil erosion, chemical modification, and climate change, represent the most serious and widespread threat to Mediterranean forests.[(2,3)] Wildfires are highly complex phenomena affected by numerous interdependent variables, the causes of which are constantly diversifying;[(4)] thus, wildfire management is becoming increasingly important.[(5)] Wildfire management is implemented in three phases: prevention, detection, and

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suppression. Fire prevention involves using various methods to pre-empt the potential triggers of wildfires.[6]

In the 20th century, UAVs, also known as drones, were primarily used for military purposes. In recent years, the civilian use of UAVs has increased, with research organisations, universities, and industries showing a strong interest in studying UAV technology.[7] Specifically, UAVs have also been used for wildfire prevention and detection.[8–19] Additionally, advances in counter-UAV (c-UAV) solutions have led to the development of multisensor systems for protecting critical assets through ground situational awareness.[10]

Multisensor c-UAV applications constitute a prime example of the use of data fusion techniques. Data fusion is the collection of data from one or more sensors and the independent use of the collected data within a single system, with the expectation that independent sensing with multiple sensors will provide results better than those of a single sensor. In the data fusion field, artificial intelligence (AI) and a deep neural network (DNN) are the most effective methods for data representation.[5–20]

Early fire detection is important to limit the extent of fire damage. Wildfire smoke occurs when a fuel source is heated to ignition temperature, releasing flammable gases (smoke). The time needed by a DNN to detect a fire is the basis for determining the allowable time for initial wildfire response. DNNs must be able to clearly distinguish smoke produced by a fire from regular objects with similar appearances, such as clouds, in order to be used as a wildfire smoke detection tool. The first plume of smoke from a fire has the greatest impact on the effectiveness of wildfire smoke detection. Smoke is difficult to clearly distinguish when it is dense and has a hazy or cloud-like appearance.

Wildfire detection in Korea relies more heavily on people, such as mountain managers from the Korea Forest Service or local fire departments, than on computer systems.

Aerial support, such as that provided by UAVs, is an important firefighting tool as UAVs can help reconstruct an overview of wildfires.[11] The effectiveness of these aerial resources varies depending on cost, flight speed, flight range, response time, manoeuvrability, tank capacity, and fluid type. For example, the type of fluid may include fire extinguishers or water supplied from a nearby lake. There is also the method of providing indirect assistance by dropping fire hoses. The ability to have a drone deliver a fire hose to a desired location without the need for people to move the fire hose is a great help in fighting wildfires.

Unfortunately, few studies have focused on practical UAV-based platforms for wildfire prevention and suppression.[7,12] For example, ideas on how UAVs can be used in firefighting applications have been suggested, especially in areas that are difficult to access for humans.[13–15] One method involves using a self-organised fleet of drones, each carrying 120 kg of water, with a coordination mechanism based on a forgetful particle swarm algorithm. A second method involves using a rotary-wing UAV with a payload-dropping mechanism that can carry and release fire-fighting balls into the fire. Drones equipped with fire-extinguishing balls have been proposed to complement traditional firefighting methods.[16] To address the high temperatures in firefighting environments, aerial robots constructed from fire-resistant materials have been developed to reduce the risk of damage to electronic equipment directly exposed to flames.[17] Separately, a new lithium-ion battery design has been developed to withstand the ultrahigh thermal shocks experienced by fire-fighting UAVs.[18]

We propose the use of a swarm of collaborative UAVs that can carry large quantities of fractional fire-extinguishing liquids and release them at the fire front to simulate rain.

Even the most capable UAV will have limited effectiveness as firefighting tools if their operators do not understand their function clearly. The platform introduced in this study can serve as a guideline for operating UAVs and provide users with basic operation and troubleshooting methods to understand the systems discussed below.

The U.S. government is implementing a multipronged effort to respond to fire disasters and training programs that introduce new systems. In 2019, the "John D. Dingell, Jr. Conservation, Management, and Recreation Act" was passed in the United States, allowing federal agencies to promote the use of drones in wildfire management and suppression.(19)

Small unmanned aircraft systems are used in three phases of wildfire management and suppression, which are typically fire detection, confirmation, and observation.(20) General UAV users not trained in firefighting face significant issues in understanding and using UAV-based firefighting technologies. Thus, fire prevention using modern technology is difficult to achieve for disaster-related organisations. Since existing disaster-prevention systems cannot provide continuous technical support to users, encouraging users to recognise the importance of such systems and participate more actively in using them is difficult. The rapid growth and expanding applications of UAV technologies have been widely reported in recent market analyses.(21,22)

The platform introduced in this study detects smoke in real time through the combination of a computer and a camera installed on a UAV. The platform can detect forest-fire–induced smoke across any radius within its observable field of view. The platform can transport fire hoses to where they are needed to fight fires.

As shown in Fig. 1(a), the fire hose used in Korea is 15 m long and 40 mm thick. A typical fire hose weighs 4 kg per bundle. In the event of a wildfire, firefighters often have difficulty transporting firefighting equipment and fire hoses across mountains. As shown in Fig. 1(b), the platform detects smoke in real time, and the UAV drops the fire retardant near the fire. The UAV's mission equipment or gripper can transport three fire-retardant bags to a point near where smoke has been detected. Recent incidents involving UAV operations have highlighted both their potential impact and the importance of effective deployment in real-world environments.(23)

(a)

(b)

Fig. 1. (Color online) (a) Fire hose and (b) UAV platform.

The platform must be able to move to the correct location to enable reliable firefighting operations. However, locating fire lakes is often inconvenient because visibility is limited by the smoke. In such cases, the UAV's GPS coordinates can be transmitted to inform the firefighters of the locations of the UAV and the fire lake. Such capabilities can be further enhanced through multisensor data fusion techniques to improve situational awareness and positioning accuracy.(24)

During fires, authorities must provide firefighters with accurate descriptions and easy access to the relevant data. Analyzing disparate data to maximize its utility is a concept related to data science. AI mimics the manner in which humans learn and analyze and interpret data similarly to humans.

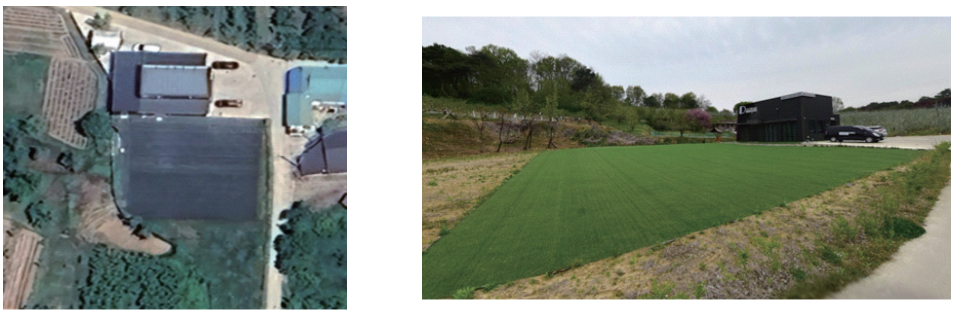
Recent contributions have advanced smoke and wildfire detection on drones by introducing lightweight YOLO variants, multisensor fusion, and segmentation approaches suitable for onboard inference. YOLO-based models achieve high mAP and real-time speed for smoke localization, while the multisensor fusion of RGB, thermal, and SAR improves robustness under poor visibility. Reviews also highlight the need for early-smoke sensitivity and cross-domain datasets, motivating the edge-oriented platform proposed here.(25–30)

2. Data, Materials, and Methods

The study site was an airfield in South Korea with an area of 625 m^2. The airfield is visually unobstructed from a UAV perspective and is covered in grass. As shown in Fig. 2, the airfield consists of a clearly defined landing area and surrounding terrain. For drone experiments, flight licenses and flight permits are required. The experiments were conducted by meeting both requirements. A dataset was created with support from the High Performance Wireless Research and Education Network (HPWREN) of the National Science Foundation.

Because of the absence of unnecessary obstructions, the generation of smoke and changes in its state, as well as the use of smoke bombs, can be detected without external disturbances. Therefore, at this airfield, fires can be predicted by measuring changes in smoke generation under controlled conditions. Traditional fire detection and prevention systems have fundamental limitations, such as the need for human intervention, the possibility of network failures, and the potential mislocalization of fires.

Recently, UAVs have been increasingly used in various applications, such as surveillance, precision agriculture, reconnaissance, environmental monitoring, and wildfire prevention and detection.(8,9) In the previous study, IoT-based forest-fire-detection systems detected forest fires



(a) (b)

Fig. 2. (Color online) (a) Airfield satellite image and (b) ground-level view of the airfield.

through sensor-based information processing. The system proposed in this study can detect forest fires through AI data analysis based on visual information. This can detect forest fires more accurately at a lower cost than existing sensor-based systems. However, the application of complex IoT technologies to forest resources has been challenging owing to the difficulty of installing and maintaining the necessary equipment in large forest areas. Recent technological advances in AI have enabled the potential automation of detecting disasters, such as of fires and earthquakes.

AI is a powerful tool that has replaced human decision-making as it can render accurate judgments based on data. Additionally, 5G-based transmission and reception facilitate accessible and cost-effective fire monitoring. By examining the correlation between training data related to forest-fire–induced smoke and actual smoke, we confirmed the possibility of detecting forest-fire–induced smoke using AI. However, detecting and responding to fires is difficult without complex and sophisticated technologies. Therefore, overcoming these technical limitations is essential to ensure the reliability of the proposed platform. In this study, these challenges were addressed through the methods described in Sect. 2, including the integration of UAV-based sensing, DNN algorithms for smoke detection, and system-level safety procedures.

To solve the aforementioned problem, we tested the reliability of a complex platform integrating various technologies. Additionally, we configured a platform that can detect forest fire smoke by transmitting data to a server in real time in conjunction with UAV featuring mission equipment, to enable initial responses to fire disasters.

2.1 Wildfire smoke detection

As wildfires occur over large areas, multiple fires must be monitored simultaneously. Typically, a fire starts with ignition, goes through a growth period, reaches its peak temperature, and then dies out. During this process, smoke is produced. To minimise the damage caused by wildfires, promptly detecting and extinguishing wildfires is crucial. To this end, research is being actively conducted on rapid fire-detection systems, with a particular focus on computer-vision–based techniques. However, colour-based fire detection methods suffer from high false-alarm rates caused by objects with fire-like colors, such as sunlight reflections or bright artificial lights, and challenges in accurately responding to fire owing to issues like missed detections in complex backgrounds or under varying lighting conditions. The phenomena caused by fire must be clearly identified to enable effective fire detection. As heat, gases, and light are commonly observed even in the absence of fires, additional research is needed to improve the accuracy of fire-detection systems.

The accurate detection of the smoke produced during a fire is essential for early fire detection. While most fires are reported after a plume of smoke is visually confirmed, manual on-site verification across large forest areas would be cost-prohibitive. Nonetheless, most reporting and verification of fires in the mountains rely on people. To evaluate the performance of the proposed smoke detection system, we used smoke bombs at the airfield, as shown in Fig. 3(b). Smoke detection was achieved by training a DNN on wildfire smoke data. The experiment was conducted under strong daylight, and green grass was used to simulate a mountain.

(a) (b)

Fig. 3. (Color online) (a) Platform configuration. (b) Installation of smoke bomb.

2.2 Configuration of platform

For a disaster-prevention system to be widely accepted, the platform must be easily and quickly accessible to most users. As UAVs can fly, they represent the fastest option to reach the location of a fire. However, rather than simply flying to the fire location from the platform, UAVs are required to render complex judgments through a trained DNN to perform the physical actions necessary for combating the fire.

By connecting multiple devices to a single platform, we implemented a system that can respond to fires in real time by tracking data on the ground and in the air. This unified platform is organically connected to a DNN, remote systems, a UAV, mission equipment, sensors, and monitoring devices. The platform is centred on a comprehensive control system composed of the following subsystems: flight control system (FCS), disaster prevention AI system (DPAIS), air traffic control (ATC), and ground control software (GCS). The systems included in the platform have inconsistent software and hardware on different operating systems. The platform implements a heterogeneous network where other systems are based on a single network.

Different hardware requires a unified protocol for communication across different environments and a platform control system (PCS) to control them in an integrated manner. In particular, the platform connects different systems into a single network and can be flexibly changed for various purposes by modifying parts of each system. Figure 4 illustrates the configuration of the proposed platform.

The system was designed to be modular to ensure that it could be easily modified for different purposes. Additionally, GPS and video data were transmitted to the server in real time to allow major smoke patches to be immediately identified on the platform. The data flow across the platform is illustrated in Fig. 5.

3. Results

3.1 DNN for wildfire smoke detection

A DNN was used to detect wildfire smoke by learning related data. A comparative performance evaluation among YOLO, Faster-RCNN, Retin-Net, Corenr-Net, and Center-Net showed that YOLO is the most suitable model for wildfire smoke detection.

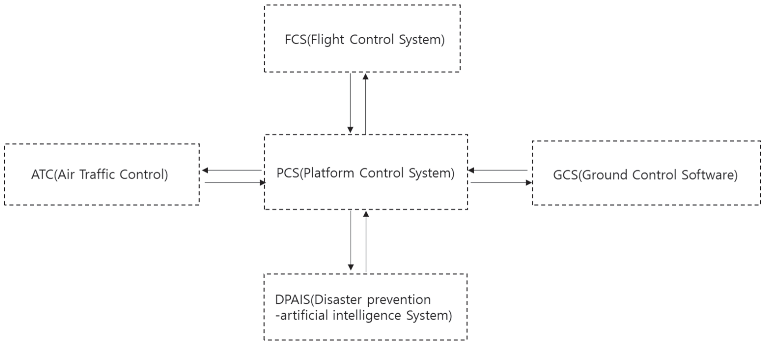


Fig. 4. Platform configuration.

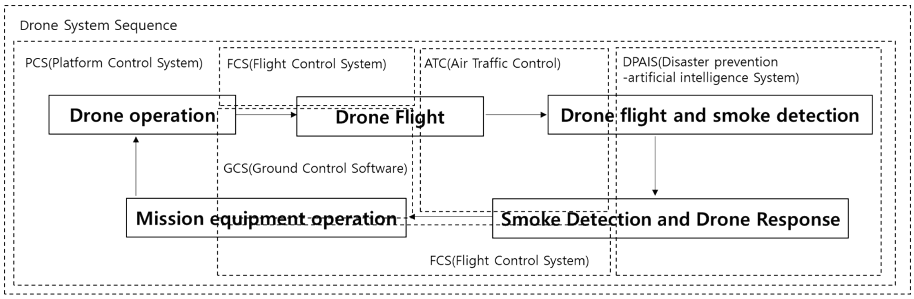


Fig. 5. Data flow across platform.

Therefore, we used the YOLO model in this study. Figure 6 shows graphs of precision, recall, and F1 score, which were used as the evaluation metrics, while Fig. 7 shows the detailed results of the data analysis for forest fire smoke detection. The DNN-based model used in this study exhibited strong performance, with a precision of 0.91 and a recall of 0.912. The model could process four images in 1 s because it needs 0.02 s to process one image, i.e., it can process 50 frames per second. This level of accuracy is satisfactory for real-time wildfire smoke detection.

3.2 DNN-based wildfire smoke detection platform with UAVs

In this study, UAVs were integrated into an embedded system environment to detect the locations of forest fire smoke using a DNN. The primary objective was to build a platform that combines various systems to observe and report real-time changes during forest fires and thus enable early responses. By combining various systems, a unified platform was implemented.

To control the entire platform together, we configured the graphical user interface (GUI) using PyQt5. For the heterogeneous network, we used Python's Paramiko library to allow access to multiple systems through Secure Shell (SSH). A key enabler of this integration is the use of the Paramiko Python library, which implements the SSHv2 protocol to provide encrypted remote communication. Paramiko allows the PCS to securely access and control multiple subsystems simultaneously without requiring direct manual login to each device. Through centralized credential management and encrypted channels, Paramiko ensures that all subsystems—FCS, ATC, GCS, and DPAIS—can exchange data reliably within a heterogeneous

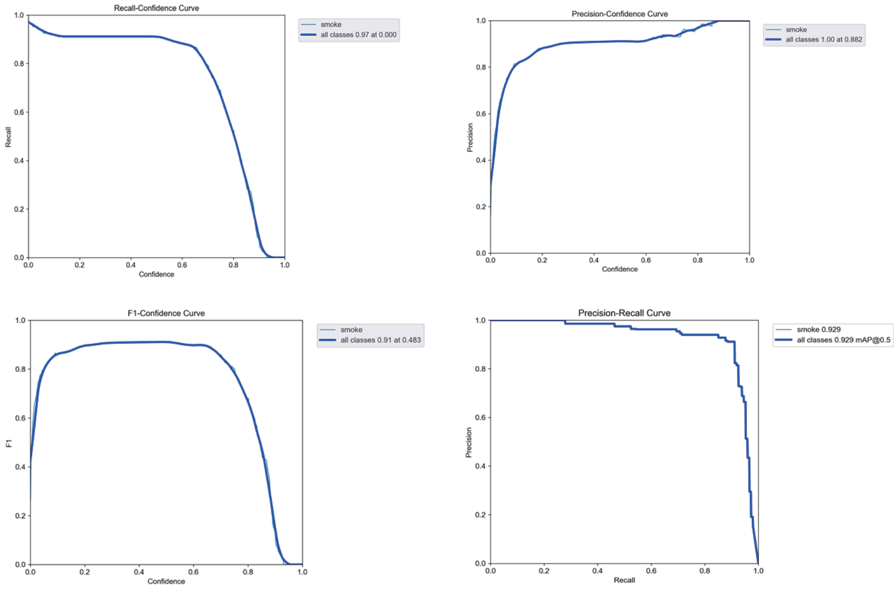


Fig. 6. (Color online) DNN performance evaluation graph (precision, recall, and F1 score).

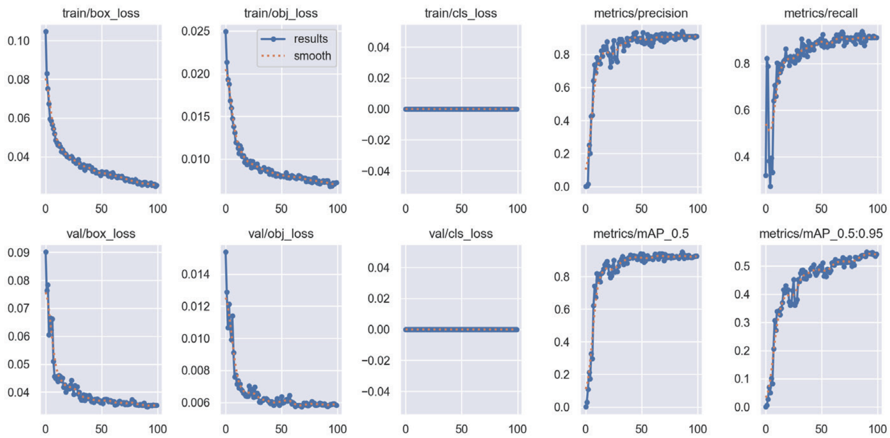
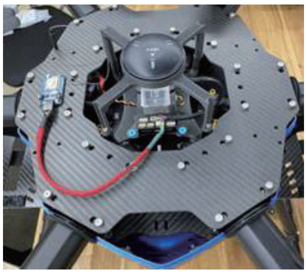


Fig. 7. (Color online) DNN analysis graphs.

network. This approach simplified integration, enhanced operational security, and enabled robust real-time coordination across the platform. To enable server–client communication between the different subsystems, a 5G-based web communication system was created, and the remote flight control of the UAV was via MAVProxy communication based on Pixhawk hardware, as shown in Fig. 8(b). The PCS created in this study allows any user to easily modify and distribute the code, and the platform can also be implemented with only the functionality essential for operation. Moreover, all systems are modularized and can be easily transformed for different purposes.



(a)

(b)

Fig. 8. (Color online) (a) UAV internal structure and (b) UAV external structure.

The DPAIS employed a DNN to detect smoke, as illustrated in Fig. 9(a). A Jetson Orin module was selected as the primary microcontroller, providing sufficient computational capacity to support continuous situational assessment and the execution of real-world missions. Integrated with the overall platform, the FCS and ATC subsystems directly controlled flight operations on the basis of the DNN's data-driven decisions, enabling autonomous UAV responses during smoke detection experiments.

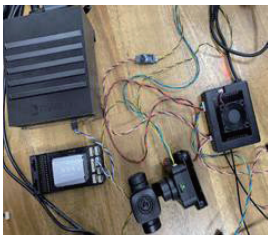
The FCS was implemented using a Pixhawk flight controller, as illustrated in Fig. 8(a). The Pixhawk integrates essential functions such as power monitoring, inertial measurement (IMU), GNSS-based positioning, and flight mode management within a single platform. It also supports standardized flight control protocols, map-based navigation, and safety mechanisms, which ensured the stable and reliable autonomous operation of the UAV during the smoke detection experiments.

The ATC subsystem coordinated air traffic when two or more UAVs operated simultaneously. For the experiments, a six-rotor Hexa UAV was employed. The UAV platform measured 945×542 mm^2 with the arms folded and 945×848 mm^2 in flight configuration, with a maximum take-off weight of 17.9 kg, providing sufficient payload capacity for onboard AI modules and mission equipment.

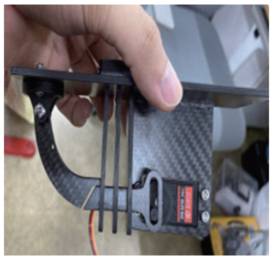
The GCS received real-time status reports from the FCS and ATC on the ground, and mission equipment such as the grapple holding a fire hose [Fig. 9(b)] could also be controlled via the GCS. All of these functions were executed automatically under the supervision of the PCS, which unified subsystem operations through secure SSH-based remote access. This configuration allowed the continuous monitoring of all processes, while the DNN enabled real-time smoke detection and the UAV responded autonomously to hazardous situations. These implementations demonstrate the feasibility of integrating AI and a cyber-physical system (CPS) into disaster prevention platforms.

3.3. UAV platform experiments

After validating the AI system, the embedded systems, and the UAV flight system, we conducted scenario-based testing on the UAV platform. The tests were conducted at the airfield mentioned earlier, with guidance from experienced pilots and on-site support in the event of a potential accident.



(a)



(b)

Fig. 9. (Color online) (a) DPAIS environment and (b) mission equipment (gripper).

Large UAVs must be operated with extreme caution as accidents can cause considerable damage to both property and human lives. To test the platform's practical effectiveness, we generated smoke artificially, as shown in Fig. 10, and verified that the systems function as intended. Smoke canisters are designed to produce smoke when ignited, making them ideal for creating a smoky environment and reconstructing fire or other incident situations.

The experiments were conducted at a private airfield with permission to fly, accompanied by a licensed pilot, and sufficient time was allotted to conducting pre- and postflight safety checks.

The simulation involved 12 steps in detail, which can be summarized into six steps, focusing on the features that can be visually observed. These six steps are UAV launch, smoke detection, smoke confirmation, UAV take-off, grapple operation and fire lake drop, and UAV landing. The simulation results confirmed the platform's ability to detect smoke from real wildfires and its utility in disaster preparedness education.

4. Discussion

In recent years, a wave of innovation has transformed embedded computing and AI. Current research focuses on platforming systems that use different hardware, software, and operating systems, as well as AI technologies. In particular, platforms are the next generation of technologies that have the potential to revolutionize not only online education and remote work, but also specialized fields such as disaster prevention and management in urban and mountainous areas.

All procedures on the platform are performed by the system itself without human assistance, based on AI. AI was once considered necessary only for certain industries. However, in recent years, the potential use of AI to replace humans has expanded its applicability to almost every field.

Currently, the most prominent subset of AI technology is the DNN. A DNN can judge spatial information in real time by learning data on the space it observes, similar to human perception. The proposed platform applies data fusion by integrating a CPS with a DNN. This enables wildfire smoke detection with quantitative visualization, one of its foremost advantages. Using pretrained datasets, the system can establish baseline conditions before ignition, thereby minimizing false alarms. Real-time detection data further support continuous wildfire monitoring.

Fig. 10. (Color online) Activated smoke canisters.

In our implementation, the smoke data identified by the DNN were transmitted to both the UAV and the ground control system to enable real-time monitoring. This workflow integrated the FCS, ATC, GCS, and DPAIS subsystems, which exchanged information via a 5G communication link and a heterogeneous network architecture. Through this design, all components were able to detect changes synchronously and respond without delay.

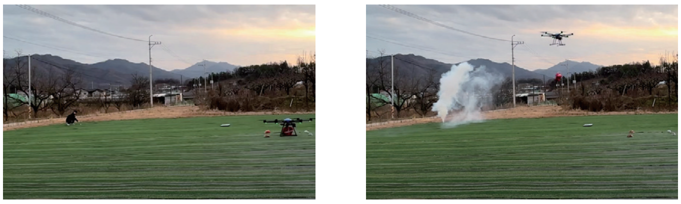
As shown in Fig. 11, (a) illustrates the UAV in a standby state, while (b) shows the UAV performing its mission, where smoke can be detected in real time. Normally, smoke is not detected unless it is generated, so we can see that the smoke detection from the fire is within the expected behavior. All smoke detected in real-time monitoring can be visualized using data. This is valuable for disaster response resources.

In the proposed platform, the smoke data obtained by the DNN are transmitted to the UAV and ground control system to enable the real-time monitoring of forest fires. The platform features FCS, ATC, GCS, and DPAIS, each of which can communicate with the others. The data are transmitted to the server in real time via 5G, and all components within the platform can detect changes. The changes mentioned above are identified from sensor information acquired from each system, and based on this, it is possible to determine whether smoke is present.

As shown in Fig. 12, the status of external smoke can be checked in real time. In normal circumstances, no malfunctions, such as recognizing clouds as smoke occurred, and smoke due to fire were detected accurately. Any smoke detected during real-time monitoring can be visualized, which is valuable for timely disaster response.

Further research is needed to generalize the data fusion and cyber–physical techniques used in this study. In previous studies, deep learning was used to track the fire status in real time. Systems featuring real-time tele-coordination with unmanned vehicles other than UAVs have also been developed. However, in previous UAV studies, platforms that integrated multiple systems were not designed, but many systems were applied to a single platform. Additionally, the entire system was not operated using a single controller for different system platform configurations.

In this study, we implemented a complete platform on which all systems can be controlled with a single controller. However, we could not test the platform in a real-world disaster environment. Despite the limitations of this study, we believe that the proposed platform can be used directly to make the concepts of complex technologies more familiar and understandable.



(a) (b)

Fig. 11. (Color online) (a) UAV mission standby and (b) UAV Operation Fire Detection and Fire Hosing.

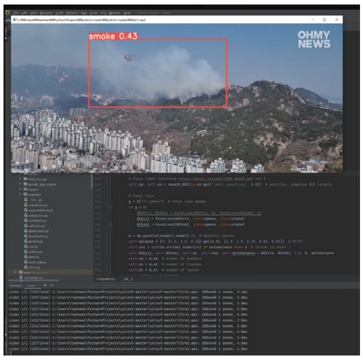


Fig. 12. (Color online) Real-time smoke detection using a DNN, including the detection interface and results.

If such a platform is introduced into university curricula, students will be able to apply AI and unmanned control technology to various fields and diagnose and solve various real-world problems. In addition, It is predicted that substantial results can be achieved in detecting forest fire smoke by responding to disaster prevention through an automated system instead of having humans respond directly whenever smoke occurs.

This study validated the integrated platform using controlled smoke canisters at a private airfield rather than in active wildfire environments. Consequently, generalization to varied topography, lighting, and atmospheric conditions (e.g., haze, low-contrast early plumes, and cloud–smoke confusion) remains untested. The training data also focus on specific sensor suites and geographies, which may introduce dataset bias; cross-site validation with multi-sensor data (RGB, thermal, and SAR) is needed. In addition, end-to-end latency depends on backhaul availability; 5G connectivity may be intermittent in mountainous terrain, impacting real-time responsiveness. Finally, onboard compute constraints and power budgets limit model size; lightweight models must balance accuracy and speed for reliable deployment on UAV.

Future work will expand data collection to diverse biomes and seasons, incorporate thermal and multispectral streams, and evaluate recent lightweight detection and segmentation models on-board UAVs. We will benchmark state-of-the-art YOLO-family and transformer-based models optimized for edge devices, perform ablation on attention mechanisms, and explore self-supervised pretraining to improve early-smoke recall. Additionally, we plan to implement robust multi-UAV ATC with collision-avoidance and cooperative tracking, integrate fail-safe behaviors for GNSS-denied conditions, and quantify end-to-end latency under varying network conditions. We will also conduct field trials with firefighting agencies to assess operational impacts (time-to-confirm, false-alarm rate, and workload) and release high-resolution figures and code to facilitate reproducibility.

5. Conclusions

To our knowledge, this was the first demonstration of a firefighting UAV that can be used in a real-world wildfire environment. It is a dedicated UAV platform that allows direct external mechanical control by AI on a nonpiloted device.

The fuselage of the UAV measures 1720 × 1500 × 556 mm. Six 600-mm-diameter propellers were used to achieve stable flight under wind speeds of 4–12 m/s. The DNN detected forest fire smoke with an accuracy of 0.91 and a recall rate of 0.912, thus demonstrating strong performance. On the proposed platform, the UAV can fly 16.67 km at a maximum speed of 50 km/h. The flight time is approximately 20 min, which is sufficient to identify and reach the source of a wildfire within 30 min from the average ignition time.

The flight stability of the UAV was verified through wind resistance tests, which confirmed that the UAV could reach the fire source without any issues. These results verify that the UAV can reach the target even in the presence of strong winds. On the basis of previous studies, typical UAVs struggle to monitor and reach their target location over extended periods, with lithium-ion batteries lasting less than 30 min and the flight times of hydrogen-fuelled UAVs lasting less than 2 h. These problems were overcome in this study by using a UAV with a combination of wired and wireless power sources.

The proposed platform is expected to contribute to early fire assessment and facilitate firefighting by using a DNN to detect abnormal smoke, enabling managers to handle the fire promptly by deploying a UAV. This platform can be implemented without prior knowledge of UAV and AI technologies and is valuable as a tool for learning the principles of mechanisms through technology implementation. It eliminates development issues such as software and hardware that arise when combining various systems. The results of the wildfire imaging experiment showed that the platform can detect the location of wildfire smoke in advance and thus enable 24 h automated wildfire detection. In this study, we utilized AI, UAV, and other representative technologies of modern industry to create a tool for detecting smoke. It is expected to be an important reference for the advancement of existing disaster systems and for use as a disaster management tool.

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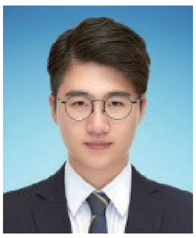

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