



Vision-based fire management system using autonomous unmanned aerial vehicles: a comprehensive survey

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Abstract

In recent years, the intensity and frequency of fires have increased significantly, resulting in considerable damage to properties and the environment through wildfires, oil pipeline fires, hazardous gas emissions, and building fires. Effective fire management systems are essential for early detection, rapid response, and mitigation of fire impacts. To address this challenge, unmanned aerial vehicles (UAVs) integrated with advanced state-of-the-art deep learning techniques offer a transformative solution for real-time fire detection, monitoring, and response. As UAVs play an essential role in the detection, classification and segmentation of fire-affected regions, enhancing vision-based fire management through advanced computer vision and deep learning technologies. This comprehensive survey critically examines recent advancements in vision-based fire management systems enabled by autonomous UAVs. It explores how baseline deep learning models, including convolutional neural networks, attention mechanisms, YOLO variants, generative adversarial networks and transformers, enhance UAV capabilities for fire-related tasks. Unlike previous reviews that focus on conventional machine learning and general AI approaches, this survey emphasizes the unique advantages and applications of deep learning-driven UAV platforms in fire scenarios. It provides detailed insights into various architectures, performance and applications used in UAV-based fire management. Additionally, the paper provides detailed insights into the available fire datasets along with their download links and outlines critical challenges, including data imbalance, privacy concerns, and real-time processing limitations. Finally, the survey identifies promising future directions, including multimodal sensor fusion, lightweight neural network architectures optimized for UAV deployment, and vision-language models. By synthesizing current research and identifying future directions, this survey aims to support the development of robust, intelligent UAV-based solutions for next-generation fire management. Researchers and professionals can access [the GitHub repository](#).

Keywords Fire management system · Fire detection · Computer vision · Artificial intelligence · UAV · Vision-based system

List of symbols

ML	Machine learning
DL	Deep learning
FLAME	Fire luminosity airborne-based machine learning evaluation
FLAME2	Fire detection and modeling: aerial multi-spectral image dataset infrared
AIDER	Aerial image dataset for emergency response application
IR	Infrared
RGB	Red green blue
DC	Data cluster
Seg	Segmentation
Cls	Classification
Det	Detection
YOLO	Only look once
GAN	Generative adversarial networks
ViT	Vision transformers
RNN	Recurrent neural networks
CNNs	Convolutional neural networks
UAV	Unmanned aerial vehicles
DNN	Deep neural network
UGVs	Unmanned ground vehicles
CCTV	Closed-circuit television
ECP-LEACH	Enhanced consumed energy-leach protocol
SegNet	Segmented neural network
FRN	Feature refinement network
FWSRNet	FForest wildfire and smoke recognition network

1 Introduction

Disaster management has attracted considerable attention from researchers across various domains, including computer engineering, health sciences and environmental engineering, highlighting its interdisciplinary significance and the need for integrated approaches. Disasters are broadly classified into natural and technological categories, with technological disasters including nuclear plant accidents, acts of terrorism, and hazardous material incidents, whereas natural disasters encompass floods, earthquakes, and fires. Fire is one of the most perilous disasters characterized by its rapid spread and destructive nature, making it challenging to control within a short time frame. Fires are primarily caused by individual activities, such as cooking in buildings, road construction, and smoking in forested areas, as well as natural factors like thunderstorms and global warming (Feng et al. 2019). Uncontrolled fires can have a profound impact on human life, businesses, ecology, and the environment at both global and local levels. In recent years, climate change has exacerbated the incidence of large-scale wildfires and hazardous fires across diverse landscapes, including forests, urban areas, and industrial sites (Dabous et al. 2024). This intensification is driven by rising global temperatures, prolonged heatwaves, earlier snowmelt, and altered precipitation patterns, all of which significantly increased the frequency, duration, and severity of wildfires across diverse ecosystems. These climatic shifts expand the availability of dry vegetation

(fuel), reduce soil and atmospheric moisture, and intensify fire-conducive conditions such as heatwaves and strong winds. Studies indicate that these factors have contributed to a marked increase in fire-prone days and an extension of fire seasons worldwide, particularly in Mediterranean and boreal regions (Farid et al. 2024; Bolan et al. 2025). The synergistic effects of these environmental stressors have resulted in more frequent mega fires, which are harder to control and more destructive to both ecological and human systems. Therefore, timely detection and effective fire intelligence systems are essential for successful firefighting and disaster response; however, these challenges continue to pose significant difficulties for society. **Fig. 1** gives detailed statistics on the various causes of fires.

Fire is one of the most dangerous disasters and has diverse impacts on both the environment and human life. In terms of environmental impact, it disrupts the ecological balance, reducing forested zones and increasing air pollution, including emissions of CCO_2 and CO , causing soil erosion and changing the global climate. On the other hand, it also affects human life, health, and property. It damages the vegetation sourced from the forest and breaks the tread route, putting the local communities in trouble. It's noteworthy that only 3 to 5% of forest fires are responsible for 80 to 90% of the total burned area (Calkin et al. 2005; Short 2014). In general, fire has a large impact on human life and economics, locally and globally. Hence, early fire detection and control are crucial to mitigating the human health, wealth, and environmental impacts of fire.

Traditional methods and tools have been applied in the last few decades, such as scalar sensor-based techniques for fire detection, including flame, particle, heat, and smoke sensors

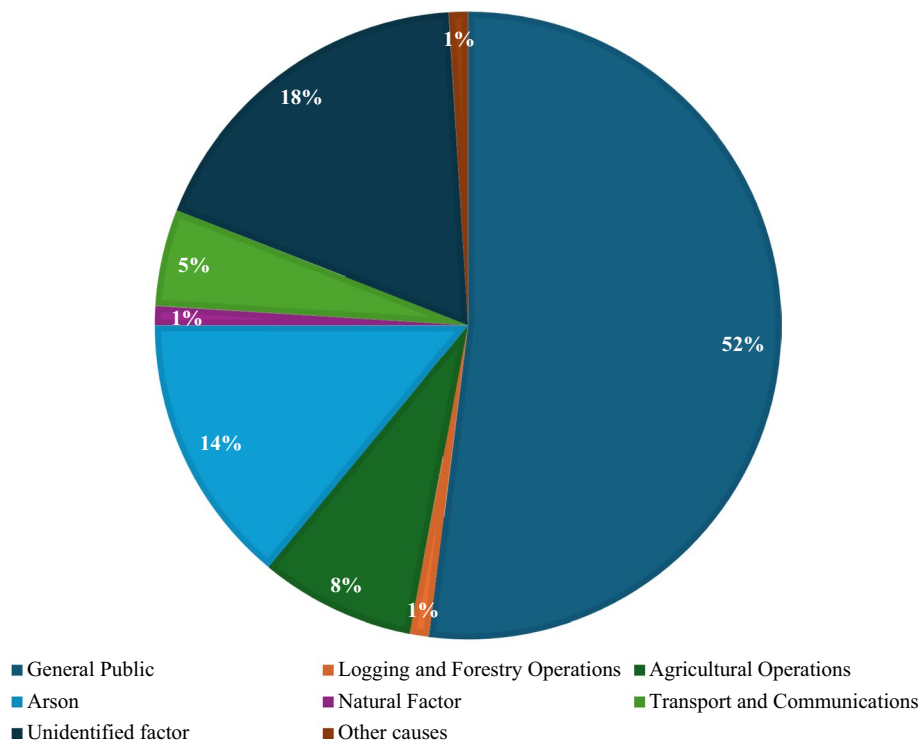


Fig. 1 Statistical information about the causes of fire (Arshad et al. 2022)

(Zhu et al. 2025b; Kuznetsov et al. 2024). Scalar sensor-based fire detection systems have several advantages, including cost-effectiveness, rapid fire detection, capabilities of early warning, ease in implementation and integration with other fire safety systems (Khan et al. 2022). Furthermore, sensor-based systems can provide nonstop environmental monitoring, minimizing the risk of undetected fires and allowing for early evacuation. However, sensor-based systems have certain limitations, such as generating false alarms due to smoking, steam, dust or cooking (Fonollosa et al. 2018). Sensors-based system response time to fire detection increases over time. Moreover, it is challenging to detect fires in the initial stages if the fire is far from the sensor-based system or growing slowly. Ensuring early fire detection accurately and precisely is essential for fire management, and an alternative approach, such as a fire intelligence system, is required to overcome the limitations of sensor-based systems, such as false alarm rates.

To tackle these challenges of a scalar sensor-based system, such as false alarms from steam, dust, or cooking emissions, an intelligence vision-based fire detection system was proposed, which provides wide coverage, requires no human intervention, offers a prompt response, and is ecologically robust. A vision-based fire detection system, such as closed-circuit television (CCTV) offers broad coverage and real-time fire detection using visual fire indicators, including flames and smoke (Ahn et al. 2023; Zhang and Geng 2024). This type of vision sensor verifies fire incidents and makes it easier to take action against fires (Li and Sun 2024). Nevertheless, it has also reduced the number of false alarms generated by scalar-based sensor systems (Li et al. 2024b). Despite this advantage, CCTV still has some limitations, the most important being limited area coverage and a fixed direction.

To overcome this limitation, researchers are interested in finding the optimal solution for fire detection. Advancements in AI technology can assist in early fire detection and tackle the drawbacks of traditional vision-based methods. These advancements reduce the impact of fire on individual lives, financial losses, and ecosystem damage. UAVs have been proposed as optimal technology for vision-based fire management systems due to their enormous potential (Liz-López et al. 2024). UAVs integrated with advanced artificial intelligence technologies are emerging as transformative tools in wildfire management. These AI-powered UAVs enable rapid, autonomous aerial surveillance, allowing early fire detection through real-time thermal imaging, smoke segmentation, and computer-vision techniques. Furthermore, UAVs can fly to high-risk spots without the intervention of human beings and provide confirmation of fire with real-time updates for accurate planning and monitoring during firefighting, without threatening human lives (Afghah et al. 2019; Zhu et al. 2025b). For example, Pesonen et al. proposed a lightweight segmentation model trained using bounding box-guided supervision and foundation models, capable of detecting wildfire smoke at pixel-level accuracy and 25 frames per second using onboard UAV computing resources, which is ideal for remote areas lacking mobile connectivity (Pesonen et al. 2025).

Beyond detection, predictive modeling has advanced significantly. The probability of fire (PoF) model, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), integrates vegetation dryness, lightning activity, and human presence to forecast fire risk with greater spatial and temporal precision than traditional indices (Di Giuseppe et al. 2025; Centre 2025). These models, when deployed via UAVs, enhance situational awareness and support dynamic fire-spread simulations. Furthermore, integrated AI frameworks such as Cerberus and CAL FIRE AI combine UAV surveillance, IoT sensor networks, and machine learning algorithms to optimize resource allocation and reduce response times

(Lehmer and Anguelov 2025; Agrawal 2025). The emergence of domain-specific large language models, such as WildfireGPT, further supports decision-makers by transforming climate projections and scientific literature into actionable wildfire risk assessments (Xie et al. 2024). Collectively, these innovations represent a paradigm shift in wildfire preparedness and response, offering scalable, intelligent solutions to mitigate the growing threat posed by climate-driven wildfires.

UAV-based fire detection has been rising as a new research hot spot due to its various capabilities, including the clear capturing of fire images from challenging, diverse landscapes and environments, and object tracking (Xu et al. 2025; Haider et al. 2024; Jung et al. 2024). Vision-based fire management systems using UAVs can enable different functions, such as real-time fire detection, estimating the spreading rate, the direction of fire flow utilizing real-world data, and providing cost-effective solutions for firefighting in high-risk areas (Zhang and Jiang 2008; Ma et al. 2024). **Table 1** represents an overall overview of fire, its factors and challenges, the impacts of fire, solutions for safe firefighting using drones, and its advantages compared to human firefighters.

Although numerous surveys have explored fire detection and monitoring systems, many remain limited in scope, focusing primarily on specific applications (e.g., forest fires only), traditional scalar sensors, or traditional machine learning approaches. As summarized in **Table 4**, most prior works lack coverage across multiple fire domains (urban, rural, vehicle), omit essential computer vision tasks such as segmentation, or focus exclusively on conventional models like CNNs while exploring recent advancements in deep learning. In contrast, this survey offers a comprehensive and structured analysis of UAV-based vision systems for fire detection, explicitly categorizing contributions across detection, classification, and segmentation tasks. Unlike previous works, we cover a wide range of deep learning architectures, including CNNs, YOLO variants, GANs, RNNs, attention mechanisms, and Vision Transformers and discuss their relative strengths and challenges faced by researchers using these models. As shown in the model coverage matrix, our survey is the only one that simultaneously addresses all major fire domains (forest, urban, rural, and vehicle fires), and all major deep learning model families, providing both technical breadth and application depth. We also highlight practical considerations such as real-time feasibility, deployment constraints, and edge computing readiness, which are often underrepresented in prior reviews. Furthermore, we emphasize the importance of dataset diversity and modality, as summarized in **Table 5**. While most earlier surveys are limited to RGB data, this work includes a curated evaluation of thermal and infrared datasets, which are an essential factor for robust fire detection in variable environmental conditions. We provide dataset links and metadata to enhance accessibility and reproducibility for future researchers. Finally, this survey introduces an important future direction through the integration of vision-language models (VLMs) (Danish et al. 2025). Although the current literature has not yet explored their use in fire management, we outline their potential to bridge visual UAV inputs with textual fire incident data to enable intelligent, context-aware decision-making. In summary, our work stands out for its unified coverage of deep learning models, multimodal datasets, practical deployment insights, and forward-looking AI directions, all within the focused context of UAV-enabled, vision-based fire detection and response. These distinctions are further explained in **Tables 3, 4 and 5**, which compare our contributions against recent major surveys and clearly demonstrate the novelty and relevance of our approach. Overall, this

Table 1 Fire behaviors, factors, impacts, and solutions using UAVs

Behaviours	Factor	Challenges	Impacts	UAV-based solution	Advantages
Combustion	Fuel	Rapid fire spread	Air quality degradation	Aerial surveillance	Rapid deployment
Combustion	Fuel	Rapid fire spread	Air quality degradation	Aerial surveillance	Rapid deployment
Release heat	Oxygen	Limited resources	Environmental destruction	Early detection	Enhanced safety
Flame formation	Heat	Terrain and accessibility	Soil degradation	Firefighting support	Cost-effectiveness
Spread	Ignition source	Urban interface	Water quality impacts	Environmental monitoring	Flexibility and versatility
Smoke	Weather conditions	Evacuations and sheltering	Carbon emissions	Safety and risk assessment	High accuracy
Size and intensity	Topography	Health and safety risks	Economic losses	Communication and coordination	Access to remote areas
	Human activities	Climate change	Displacement of communities	Search and rescue	Aerial surveillance
		Public awareness and education	Human health impacts		Minimize human risk
		Post-fire recovery and rehabilitation	Psychological and social impacts		Environmental monitoring
			Long-term recovery challenges		High-resolution imaging

survey aims to provide comprehensive insights to the research community in the realms of fire detection and UAVs. The contributions of this survey paper are outlined as follows:

- To the best of our knowledge, this is the first survey to offer a comprehensive overview of UAV-based vision systems for fire management systems across diverse environments, including commercial buildings, smart cities, residential areas, and wildland environments. It systematically examines deep learning model variants and publicly available datasets, while directly addressing gaps identified in prior surveys and related literature, thereby offering actionable insights for the vision-based fire management research community.
- The survey includes an in-depth analysis of multimodal sensor data (RGB, infrared, and thermal), sourced from both static and dynamic platforms. We also provide direct links to datasets, emphasizing the role of sensor diversity in improving detection robustness across varying environmental conditions.
- Unlike existing works that focus on specific fire types or traditional models, we organize the literature by deep learning model families such as CNNs, RNNs, GANs, YOLO variants, Vision Transformers, and attention mechanisms. This model-centric organization highlights the unique capabilities, advantages, and limitations of each architecture, helping researchers identify suitable approaches.
- The survey introduces the emerging research direction of integrating vision language models into UAV-based fire systems, a novel contribution not addressed in prior surveys, showing their potential in fusing visual data with contextual textual cues for more intelligent, situation-aware fire response.
- Lastly, the paper presents key technical and ethical challenges, such as dataset imbalance, environmental variability, and privacy concerns, alongside forward-looking research directions, including federated learning, edge computing, adaptive UAV architectures, and interdisciplinary collaboration to guide future innovation.

The rest of the paper is arranged as follows: Sect. 2 highlights the overview of AI in UAV based fire management system, Sect. 3 presents the research question, Sect. 4 highlights the application of UAVs in fire detection and monitoring, while Sect. 5 reviews related work, and Sect. 6 details various deep learning models. Section 7 Describe the management of various types of fire using a Drone. Section 8 describes the different datasets used in fire detection research. Section 9 discusses open research limitations and future directions. The paper is concluded in Sect. 10. Figure 2 shows the complete content of the survey paper.

2 Overview of artificial intelligence for UAV-based fire detection

Artificial intelligence encompasses computational methods that enable machines to perceive, learn, and act in ways that approximate intelligent behaviors. Within this broad field, machine learning refers to algorithms that infer predictive functions from data rather than relying on hand-crafted rules, while deep learning constitutes a subset of ML that employs multi-layer neural networks to learn hierarchical representations from high-dimensional signals such as RGB and thermal imagery acquired by UAVs. In the context of vision-based fire management, this hierarchy is not merely taxonomic. It maps directly onto the evolu-

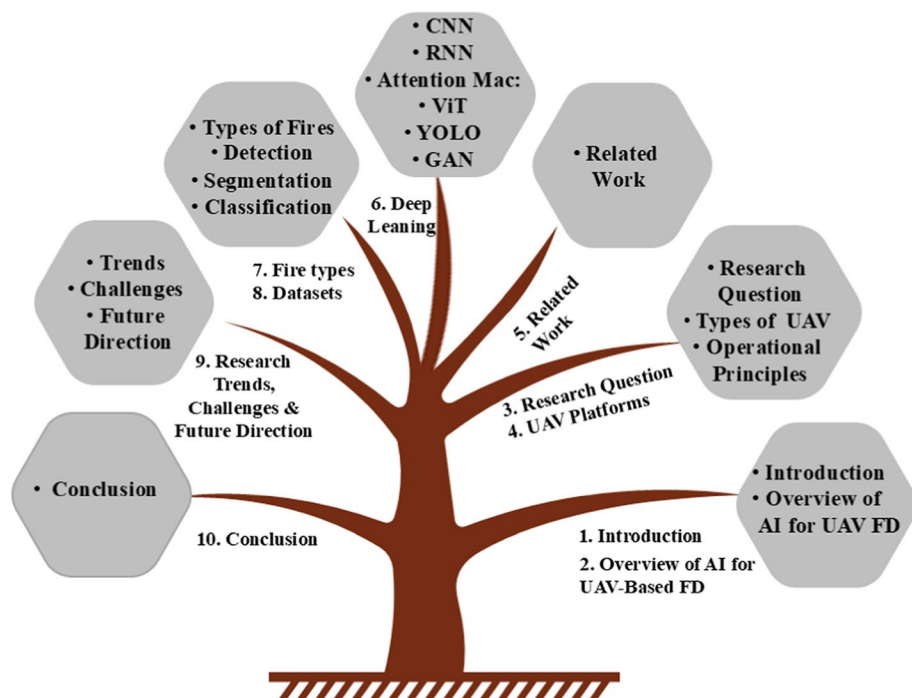


Fig. 2 The structure of a survey paper: an overview of key components and their organization

tion of practical systems. Early UAV solutions relied on traditional ML models, including support vector machines (SVM), random forests (RF), k-nearest neighbors (k-NN), and decision trees, and were trained on engineered descriptors that encode color ratios, motion or optical-flow patterns, texture such as LBP, shape and perimeter features, or simple thermal gradients. These pipelines were attractive for their modest computational cost and are still valuable for edge-constrained platforms and as ensemble components, yet their dependence on manual feature design and their limited robustness to illumination changes, haze, occlusions, and cluttered backgrounds constrained generalization in real wildfire scenes. DL addresses these limitations by learning features jointly with the task objective, thereby reducing the need for hand-crafted descriptors and improving robustness across environments. The fundamental structures of modern DL models include convolutional layers with local receptive fields and parameter sharing, non-linear activations, normalization layers for training stability, and down and up-sampling operations to form multi-scale feature pyramids. Attention mechanisms can be embedded to modulate channel and spatial responses, and temporal modules, LSTM/GRU, ConvLSTM, or video transformers capture inter-frame dynamics characteristic of smoke onset and flame propagation. Supervised learning dominates, with cross-entropy or focal losses for classification and detection and Dice or IoU losses for segmentation; transfer learning and semi/self-supervised strategies are frequently employed to mitigate limited annotation in fire datasets.

Within this landscape, convolutional neural networks remain the primary feature extractors for all three perception tasks surveyed here. As backbones such as ResNet, EfficientNet, MobileNet, CNNs feed task-specific heads for classification of fire and non-fire, while

encoder-decoder designs such as U-Net and DeepLab produce pixel-accurate segmentation masks that delineate smoke and flame regions for situational awareness and impact assessment. For real-time detection, one-stage YOLO variants are widely adopted on UAV platforms because they deliver single-pass localization with favorable accuracy, latency trade-offs and improved sensitivity to small, distant objects. Attention modules including SE, CBAM, self-attention further suppress distractors such as clouds, glare, and terrain highlights while amplifying discriminative cues like flame cores and thin smoke. Building on attention, transformer architectures for example ViT/Swin backbones, DETR-style decoders, introduce global context that benefits thin-smoke delineation and long-range consistency. In practice, hybrid CNN-transformer designs are often preferred to balance accuracy, memory footprint, and throughput on embedded hardware. Temporal reasoning strengthens operational reliability and supports short-horizon fire-spread prediction. RNN-based modules and video transformers, attached to CNN or transformer features, stabilize detections across frames and reduce false alarms from transient artifacts or camera motion. Generative adversarial networks (GANs) complement these discriminative models by synthesizing rare conditions for data augmentation and by enabling cross-modal fusion or translation e.g., RGB to thermal, thereby improving performance under low-light or heavily occluded scenes. For deployment on-board, quantization, pruning, knowledge distillation, and mixed-precision inference are commonly used to meet size, weight, and power constraints without sacrificing real-time operation. Putting these elements together, a typical UAV perception pipeline ingests multi-modal video (RGB, thermal, multispectral), applies minimal pre-processing and optional registration, and passes the stream to a backbone such as CNN or transformer. Task heads then generate georeferenced bounding boxes (detection), pixel masks (segmentation), and labels (classification); temporal modules refine these outputs before alerting and response. Figure 3 summarizes the relationships between AI, ML, and DL and shows how specific architectures such as CNNs, attention mechanisms, YOLO detectors, transformers, RNNs, and GANs contribute to the three perception tasks within a UAV fire-management system. By eliminating the need for handcrafted features and enabling real-time inference. These models show superior performance in detection accuracy, scalability, and adaptability across diverse fire scenarios, including forest fires, urban fires, and multispectral contexts. This survey emphasizes the recent paradigm shift toward deep learning and vision-based systems, which is particularly important for early fire detection using UAVs, which plays a critical role in reducing harm to human lives and economic losses. This distinguishes itself from earlier reviews that primarily focused on image processing, traditional machine learning, or limited applications of deep learning. In contrast, this survey provides a technically focused and updated analysis of UAV-enabled, vision-based fire management systems by covering an extensive range of deep learning architectures such as CNN, YOLO variants, attention-based networks, Vision Transformers (ViTs) and GAN. We also distinguish our work by highlighting multimodal datasets, including RGB, thermal, and multispectral data, which are essential for training robust and generalizable models in real-world conditions. A curated list of such datasets is provided along with detailed metadata and direct links to facilitate future research.

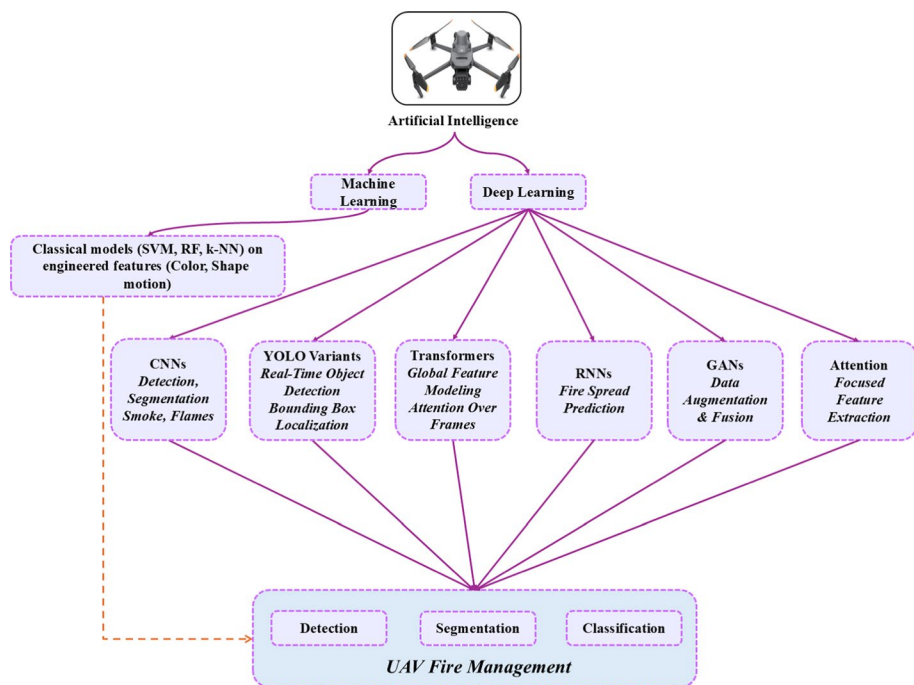


Fig. 3 Overview of artificial intelligence (AI) approaches for UAV-based fire management. The diagram illustrates the subset of machine learning and deep learning techniques, including CNNs, RNNs, GANs, transformers, and attention mechanisms, used for key tasks such as detection, segmentation and classification. Specialized models like YOLO variants and attention-based transformers enhance real-time detection and global feature modeling for effective fire response

3 Research questions

To guide our comprehensive survey on UAV-based detection, segmentation, and classification, we formulated the following research questions:

- A What are the current artificial intelligence and deep learning methodologies and technologies used in UAV-based fire detection, segmentation, and classification? This question aims to identify and evaluate the various techniques, algorithms, and tools utilized in this domain, including computer vision, deep learning, and remote sensing technologies.
- B How are different types of fires (e.g., forest fires, urban fires, rural fires, vehicle fires) detected and managed using UAVs? This question explores the application of UAV-based technologies across various fire scenarios, highlighting specific challenges and solutions for each fire type.
- C What datasets are available for training and evaluating UAV-based fire detection, segmentation, and classification models? This question focuses on identifying the datasets used in existing research, their characteristics, and the extent to which they support the development and validation of fire detection models.

These research questions will guide our analysis and synthesis of the existing literature, providing a structured framework to understand the current state, challenges, and future opportunities in UAV-based fire detection, segmentation, and classification.

4 UAV platforms for fire detection and monitoring

UAVs, commonly referred to as drones, have emerged as pivotal tools in fire management, particularly in tasks involving fire detection, classification, segmentation, and real-time monitoring. Their ability to deploy quickly, access remote or hazardous zones, and transport diverse sensor payloads makes them indispensable in both pre-fire risk assessment and active fire response (Wang et al. 2025b). UAVs are increasingly used not only to detect fires but also to track their progression and to provide live situational awareness to firefighting teams. Typically, UAVs deployed for fire management follow a systematic operational workflow, beginning with rapid launch and autonomous navigation along predetermined or adaptive paths. During these missions, UAV-based fire management systems typically integrate multiple sensors. High-resolution RGB cameras are used to visually detect flames or smoke, and thermal infrared cameras identify heat signatures even in low-visibility conditions, such as smoke or nighttime (Muksimova et al. 2024). In more advanced configurations, LiDAR sensors are also deployed for terrain mapping or structural analysis, supporting navigation and post-fire damage assessment. These multimodal sensors support the detection of diverse fire types, including forest fires, building fires, vehicle fires, and industrial incidents, allowing accurate identification across varied operational contexts. Real-time data analysis, either through onboard edge computing or immediate transmission to ground-based processing stations, enables prompt detection and precise geolocation of fire threats. These capabilities provide actionable insights directly to firefighting teams and incident commanders, enhancing coordination and response effectiveness (Shamta and Demir 2024).

The data collected during UAV missions are increasingly processed in real-time using onboard edge computing units. Deep learning models, such as CNNs, YOLO-based object detectors, and vision transformers, are employed to automatically recognize fire patterns, localize fire regions, and classify fire intensity. In advanced systems, generative adversarial networks are also used to enhance or fuse visual and thermal data (Ciprián-Sánchez et al. 2023). This AI-driven processing allows UAVs to function as intelligent aerial platforms, delivering accurate, low-latency analyses and enabling prompt decision-making during emergencies. UAVs can be deployed autonomously or in coordination with firefighting crews, supporting integrated surveillance and response operations.

This section categorizes UAV platforms based on their mechanical architecture and operational characteristics, emphasizing their suitability for various fire-related missions. Fig. 4 illustrates the primary UAV types relevant to fire applications, including fixed-wing, multicopter, and single-rotor UAVs. Each type offers distinct trade-offs in terms of flight endurance, payload capacity, maneuverability, and deployment logistics. Table 2 presents representative models with technical specifications and mission profiles.



Fig. 4 Common types of unmanned aerial vehicles (UAVs) employed in fire management

4.1 Fixed wing UAVs

Fixed-wing UAVs are designed with fixed wings that generate aerodynamic lift, allowing efficient long-range and high-speed flight. These platforms typically offer the longest flight durations, often exceeding 240 min, and operational ranges that can extend beyond 50 kms. Such characteristics make them excellent for large-area surveillance, perimeter mapping, and pre-fire fuel-load assessment. Fixed-wing UAVs can transport substantial payloads, supporting advanced sensors such as high-resolution RGB cameras, thermal infrared imagers, and hyperspectral systems. However, their deployment is often constrained by the need for specialized launch and recovery systems, such as launchers or runways, which may limit their use in rough or forested terrain. Notable examples include the WingtraOne GEN II, which features vertical takeoff and landing (VTOL) capability and high-accuracy mapping using PPK or RTK GNSS (Wingtra 2024), another example is the Quantum Systems Trinity F90+, optimized for long-endurance missions in adverse conditions (Quantum-Systems 2024); and similarly, the Insitu ScanEagle 3, a military-grade platform designed for persistent surveillance and strategic fire-line monitoring (Insitu 2024).

4.2 Multicopter UAVs

Multicopter UAVs, encompassing quadcopters, hexacopters, and octocopters, are widely deployed in fire operations due to their vertical takeoff and landing capabilities and exceptional maneuverability. These UAVs are especially efficient for close-range tasks, such as fire detection, active fire-front monitoring, and post-fire damage assessment. Their flight endurance is generally shorter, ranging from 20 to 60 min, and their operational range is limited to approximately 5 to 15 kms, primarily due to battery energy density constraints. Multicopter excels in precision hovering and agile navigation through complex terrain. They can carry payloads from 0.4 kgs to 15 kgs, allowing them to be equipped with high-resolution cameras, thermal imagers, LiDAR, and gas sensors for close-range detection (DJI 2024a, b). Representative models include the DJI Mavic 3T, a compact and foldable UAV equipped with integrated thermal and visual cameras for initial fire detection and hotspot identification (DJI 2024a). The DJI Matrice 300 RTK is an industrial-grade platform supporting mid-fire monitoring, gas detection, and real-time incident support, with hot-swappable batteries and multiple payloads (DJI 2024b). The Freefly Alta X is designed for initial fire detection in tight and obstacle-rich environments, offering stable flight for high-resolution imaging and supporting advanced sensor deployment for fire-behavior research (Systems 2024).

Table 2 Representative UAV platforms for wildfire management applications

UAV model	Category	Primary mission	Payload (kg)	Flight time (min)	Range (km)	Speed (km/h)	Key Sensors/ remarks
WingtraOne GEN II	Fixed-Wing	Pre-fire mapping and large-area fuel assessment; VTOL capability for remote deployment	0.7 to 2	59	100+	57	VTOL, PPK GNSS, high-accuracy mapping (Wingtra 2024)
Quantum-Systems Trinity F90+	Fixed-Wing	Long-range surveillance and post-fire damage assessment	Up to 1.5	90	100+	72	VTOL, robust in adverse conditions (Quantum-Systems 2024)
Insitu ScanEagle 3	Fixed-Wing	Strategic overview and persistent surveillance of remote fire lines	Up to 50	240+	150+	139	Catapult launch, military-grade endurance (Insitu 2024)
DJI Mavic 3T	Multicopter	Initial fire detection and hotspot identification in confined areas	0.4	45	15	54	Integrated thermal and visual cameras (DJI 2024a)
DJI Matrice 300 RTK	Multicopter	Mid-fire monitoring, gas detection, and real-time incident support	Up to 2.7	55	15	82.8	Hot-swappable batteries, multiple payloads (DJI 2024b)
Freefly Alta X	Multicopter	Initial fire detection in tight spaces and obstacle-rich environments; supports advanced sensor deployment for fire research.	Up to 15.8	20- to 35	5	80	Custom sensor integration, research use (Systems 2024)
Yamaha Fazer R G2	Single Rotor	Large-area surveillance and targeted suppression in rugged terrain	35 (spray) / 10 (sensor)	90 to 100	30	72	Gasoline-powered, adaptable for wildfire ops (Yamaha Motor Co 2024)
Swiss-Drones SDO 50 V2	Single Rotor	Persistent monitoring and communication relay over active fire zones	Up to 45	180+	100+	60	Turbine-powered, long-range reconnaissance (SwissDrones 2024)

4.3 Single rotor UAVs

Single rotor UAVs resemble traditional helicopters and offer a balance between endurance, payload capacity, and maneuverability. These platforms typically support flight durations of 90 to 180 min and operational ranges of up to 100 kms. Their design allows for large payloads, often exceeding 45 kgs, making them suitable for heavy-duty surveillance and precision operations. While they provide excellent hovering capabilities and relatively high speeds, they are generally technically more complex and costlier to operate than multicopters (Yamaha Motor Co 2024; SwissDrones 2024). Examples include the Yamaha Fazer R G2, a gasoline-powered UAV originally developed for agricultural spraying but adaptable for wildfire surveillance and targeted suppression (Yamaha Motor Co 2024). Another example is the SwissDrones SDO 50 V2, a turbine-powered UAV capable of persistent monitoring and communication relay support over large fire zones (SwissDrones 2024).

It is important to note that selecting a suitable UAV model depends on several factors such as payload capacity, sensor compatibility, and mission requirements. Considering these factors carefully can support informed decision-making when choosing the most appropriate UAV for fire-related tasks.

4.4 Operational principles and real-time capabilities of UAVs

Modern UAV-based fire detection systems are progressively deployed across a wide range of fire scenarios, including wildfires, industrial fires, urban fires, and transportation-related incidents. These systems are designed not only to capture high-resolution visual and thermal data but also to process and transmit actionable fire intelligence in real time, enabling rapid and informed responses across diverse environments. A typical setup involves an autonomous UAV equipped with a stabilized gimbal camera system, typically integrating dual RGB and thermal sensors and onboard computing hardware for edge AI processing. These UAVs can be preprogrammed to navigate designated surveillance zones via GPS-defined waypoints or dynamically adjust their flight paths using AI-guided mission planning, while continuously transmitting live video streams to ground control stations or conducting onboard inference. Recent advancements have enabled the integration of compact yet high-performance processors, such as NVIDIA Jetson modules, which support real-time deep learning inference directly on the UAV. For instance, a quadcopter system was demonstrated with a Jetson Nano running a YOLOv5 or YOLOv8 model to detect forest fire flames and smoke in real time, sending fire location coordinates and images to a command center (Shamta and Demir 2024). This onboard intelligence allows the drone to autonomously identify fires and trigger alerts without relying on slow remote servers, achieving detection within a few milliseconds per frame in flight (Pesonen et al. 2025). In more sophisticated deployments, coordinated multi-UAV systems are employed to enhance coverage and precision. For instance, a high-altitude fixed-wing UAV or tethered aerial platform may conduct broad-area thermal surveillance, and upon identifying anomalous heat signatures, dispatch a lower-altitude rotary-wing UAV to perform detailed inspection using high-resolution sensors. Such collaborative UAV frameworks have been validated in experimental settings, demonstrating the efficacy of multi-perspective data fusion for robust fire confirmation and situational monitoring (Qiao et al. 2024). Across all configurations, the UAV platform's functionalities, including autonomous navigation, operational adaptability, and real-time

communication, are crucial. UAVs can access high-risk zones and track fire evolution continuously with no risk to human life, all while providing live data for decision-makers. The integration of rapid aerial data collection with onboard deep learning inference enables early detection of fires, accurate localization of fire boundaries, and even predictive modeling of fire spread, thereby greatly augmenting traditional ground-based or satellite fire monitoring methods in both forest and urban fire scenarios. As a result, UAVs function not merely as passive imaging tools but as intelligent, real-time sensing agents that support rapid and informed decision-making in firefighting operations.

5 Related work

In recent years, vision-based fire detection using UAVs has gained considerable attention in the research community. To ensure transparency and reproducibility, a systematic literature search was conducted across five major academic databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and SpringerLink. The search covered publications from 2018 to 2025, using keyword combinations such as “forest fire”, “urban fire”, “rural fire”, “vehicle fire”, “wildfire”, “UAVs”, “drones”, “computer vision”, “deep learning”, “remote sensing”, “detection”, and “monitoring”. An initial pool of research articles was collected and screened based on title and abstract relevance. Then a full text analysis was performed to evaluate diverse fire scenarios, methodological depth, technical contributions, and applicability to UAV-based fire detection, classification, or segmentation. The final selection includes peer-reviewed papers that demonstrate the use of deep learning architectures (e.g., CNNs, YOLO, GANs, RNNs, and Transformers) in fire-related applications. A key gap identified in prior surveys is their primary focus on forest fires, often ignoring other critical scenarios such as building fires, vehicle fires, industrial zones, and urban or rural fire contexts. In contrast, this survey adopts a broader scope, aiming to capture UAV applications across multiple fire domains and thereby offering a more inclusive and versatile perspective. The Fig.5 represents the graphical representation of the research paper collection and analysis while Algorithm 1 describes the pseudocode of the survey paper.

Require: Search in academic databases

Ensure: Relevant research papers from 2018 to 2025

```

1: while keywords Fire AND (UAV OR Unmanned Aerial Vehicles OR Drone) do
2:   while keywords Forest Fire OR Urban Fire OR Rural Fire OR Vehicle
     Fire OR Wild Fire do
3:     if paper discusses Deep Learning Models (CNN, RNN, YOLO, Attention
       Mechanism, or GAN) then
4:       Include paper for analysis
5:     else
6:       Exclude paper from analysis
7:     end if
8:   end while
9: end while

```

Algorithm 1 Research paper selection and processing criteria

Akhroufi et al. (2020) conducted a comprehensive study of UAV applications in wildland fire management, focusing on sensor technologies, fire perception algorithms, and operational strategies for both airborne UAVs and unmanned ground vehicles (UGVs). They

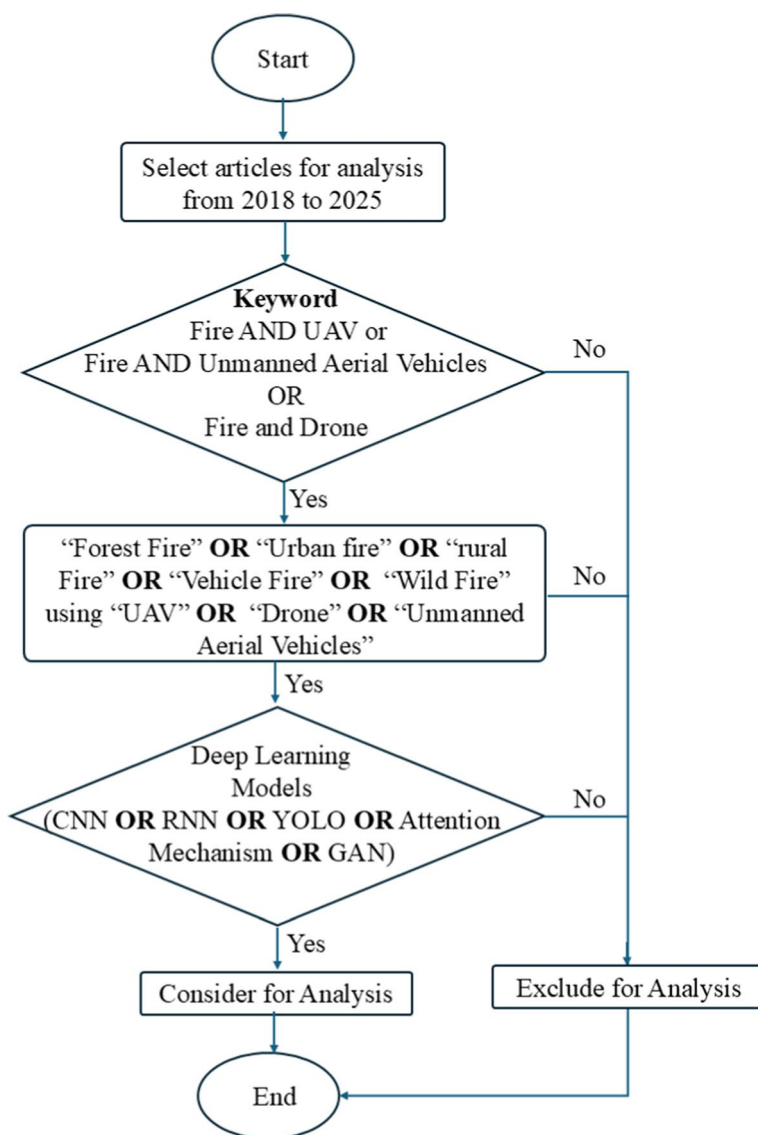


Fig. 5 The graphical representation of the research papers collection and analysis

identified drawbacks in autonomy, trustworthiness, and fault tolerance, with minimal coverage of deep learning techniques and dataset availability for fire detection and classification via UAVs. Another study (Partheepan et al. 2023) discussed various UAV types, obstacle detection, search and rescue techniques, and machine learning-based fire detection methods (Liu and Zhuang 2024), but lacked detailed descriptions of DL-based approaches and comprehensive coverage of fire detection techniques.

In a survey (Barmpoutis et al. 2020), optical remote sensing networks for early fire and smoke detection were investigated, emphasizing both traditional and deep learning methods

across terrestrial, airborne, and satellite platforms. The survey identified the strengths and weaknesses of existing fire detection frameworks but primarily focused on detection methods, omitting classification and segmentation techniques as well as detailed discussions on wildfire datasets. Roldán-Gómez et al. (2021) proposed robotic technology-based UAVs for forest firefighting, focusing on detection and prevention but providing limited coverage of fire segmentation, classification using deep learning, and dataset details. A review (Moumgiakmas et al. 2021) of vision-based UAV systems for wildfire detection discussed software algorithms and hardware implementations but lacked comprehensive coverage of UAV technologies, detailed wildfire datasets, and specific detection methods like reinforcement learning and fusion-based frameworks. Similarly, another survey (Yuan et al. 2015) examined UAVs for forest fire monitoring and detection, highlighting various UAV models and sensors used, but lacked technical reviews of UAVs, detailed discussions on vision-based methods like DL and reinforcement learning, and comprehensive coverage of relevant datasets.

A more recent survey (Li et al. 2023) reviewed advancements in UAV-based technologies for wildfire management but did not sufficiently cover fire detection, monitoring, or UAV-based remote sensing approaches. It also lacked explanations of DL models and datasets used in this context. In a related study (Hossain et al. 2019), UAV technologies for wildfire detection and monitoring were reviewed, emphasizing fire behavior and diagnosis but lacking insights into recent deep learning techniques and fire datasets. Finally, a comprehensive review (Bouguettaya et al. 2022) compared various AI and deep learning frameworks for UAV-based fire detection, highlighting benefits and limitations but omitting detailed comparative analyses of algorithms, UAV-specific datasets, and exploration of reinforcement learning techniques. The review focused predominantly on forest fires, with limited coverage of other fire types and ML models beyond CNN-based and YOLO-based approaches. Dhall et al. (2020) conducted a survey on forest fire disaster management, emphasizing rescue operations, fire localization, and victim assessment but offering limited coverage of fire-related datasets.

These surveys collectively highlight the advancements, limitations, challenges and research gaps in vision-based fire detection systems using UAVs for fire classification, detection and segmentation, and emphasizing the need for further exploration of deep learning and computer vision techniques and comprehensive datasets across various fire scenarios beyond forest fires to support the research community. Tables 3, 4 and 5 provide a concise summary of the application, domains, details of deep learning models mentioned, dataset details, strengths and limitations of the existing survey.

6 Deep learning approaches

In the current era, artificial neural networks have led to the development of deep learning and computer vision models. To manage massive amounts of tagged analog data, including text, audio, video, and images, these models create complex neural networks. CNNs, which are frequently utilized in image processing, and recursive neural networks, which are valuable for modeling dynamic temporal phenomena, are two of the many layers of hidden information that make up a deep neural network (DNN). When designing DNNs, various hyperparameters are critical, such as layer number, activation function types, and node con-

Table 3 Comparative analysis of UAV-based fire management survey papers: key strengths and limitations

References	Strength	Limitation
Akhloufi et al. (2020)	● Aboard sensor tool, fire perception methods, and coordination approaches tailored to specific applications. ● Introduced recent frameworks for UGVs.	● Shortage of detailed facts about the DL techniques for fire detection. ● Lack of dataset information and focus only on forest fires.
Partheepan et al. (2023)	● Discusses UAV obstacle detection, search and rescue, and types of UAVs. ● Discusses TML methods and general DL and AI-based detection of fire.	● Absence of detailed data about the DL techniques for fire detection. ● Few fire datasets and classification techniques mentioned.
Barmpoutis et al. (2020)	● Covers flame and smoke detection using optical remote sensing, including terrestrial, aerial, and satellite-based systems. ● Discusses TML methods and DL-based detection techniques.	● Focuses solely on detection methods, omitting classification, segmentation, and the latest DL-based and RL-based forest fire methods. ● Lacks information on wildfire datasets, UAVs, and sensors.
Roldán-Gómez et al. (2021)	● Mainly focused on forest fire detection, prevention, and firefighting.	● Lacks DL-based methods for UAV fire detection, classification, and segmentation. ● Missing information on datasets and their types.
Moumgiakmas et al. (2021)	● Classification of Unmanned Aerial Vehicle types, cameras, models, and weight categories. ● Forest fire facts, datasets, frameworks, fire detection vision-based hardware, and AI-based software techniques.	● Provides a fundamental overview of UAVs without covering important concepts and does not discuss all accessible videos and images of forest fire datasets. ● Offers only a brief mention of a few AI-based methods for wildfire detection.
Yuan et al. (2015)	● Technologies utilizing UAVs for detecting, monitoring, and combating forest fires. ● Conceptualization, types, classifications, characteristics, and sensors of UAVs. ● Vision-based methods for detecting and monitoring forest fires.	● Lacks technical information concerning UAVs, datasets, and sensors. ● DL and RL-based methods for fire monitoring and detection are not addressed. ● Mentions outdated methods.
Li et al. (2023)	● Utilization of UAVs, their technologies, sensor capabilities, and data collection methods. ● Techniques involving image processing, segmentation, and classification, alongside the application of remote sensing and ML techniques.	● Excludes UAV classification, models, and their characteristics. ● Lacks information on detection techniques and omits many recent computer vision DL-based methods.
Hossain et al. (2019)	● Development of drone technologies for fire detection, monitoring, and firefighting. ● Fire behavior and diagnosis.	● No information about recent developments in DL techniques, fire datasets, and only focused on forest fires.
Bouguettaya et al. (2022)	● UAV remote sensing techniques and general deep learning vision models. ● Image detection, classification, segmentation techniques, forest fire characteristics, datasets, and evaluation metrics.	● Excludes UAV models, characteristics, and architectures. ● Lacks active fire monitoring methods, such as RL techniques, and mentions only a few fire datasets.
Dhall et al. (2020)	● Fire and victim localization, fire behavior and spread, victim health assessment, pain estimation, and firefighting and rescue procedures.	● Limited fire datasets and detection. ● Does not explore DL techniques for segmentation and classification. ● Focused only on forest fires.

Table 3 (continued)

References	Strength	Limitation
Our paper	• Unmanned Aerial Vehicles, their types, and advantages in fire management. • Discussed latest DL and computer vision-based techniques for fire detection, classification, and segmentation. • Fire datasets, types, and statistical information. • Multimodal dataset focus (RGB, thermal, IR) and Discussed Suitability of dataset for UAV-based early fire detection. • Analyzes current challenges and explores potential solutions. • Discussed case studies	• Limited to vision approaches and not cover other like gas-sensing • Operational constraints (battery, bandwidth) not quantified. • Lacks cost analysis and deployment case studies. • Not discussed the ML techniques.

nectivity. Regardless of their architecture, deep learning models are generally trained by passing data through network layers and activation functions to generate an output. By comparing the output with labeled training data, error metrics are utilized to evaluate the efficiency of the model in supervised environments. Deep learning models have significantly advanced UAV-based fire detection, classification, and segmentation (Özyurt 2024; Mozaffari et al. 2023). These models leverage sophisticated neural network architectures to process and analyze large volumes of aerial data, enhancing the capabilities of UAV systems in the fire management systems.

This section explores various deep learning and computer vision approaches tailored for UAV-based fire-related tasks, citing recent studies in the field. Table 6 gives the overall summary of the DL model for UAV-based fire classification detection and segmentation.

6.1 Convolutional neural networks (CNNs)

CNNs are vital to image processing and are widely used in the segmentation, classification, and detection of fires using unmanned aerial vehicles. CNNs consist of multiple convolutional layers that apply learned filters to input images which automatically extract hierarchical features, such as edges, textures, and patterns relevant to fire detection. In UAV systems, these features include smoke, flames, and heat signatures, which allow UAVs to identify and classify fires based on their visual properties. The activation functions (typically ReLU) introduce non-linearity, allowing the network to represent complex visual patterns. Pooling layers downsample the feature maps, reducing computational load, preserving important information and enhancing the network's ability to generalize. The fully connected layers then aggregate the learned features to classify the input, such as identifying whether a fire is present or not. In segmentation tasks, CNN-based encoder-decoder structures such as U-Net produce dense pixel-wise masks that identify fire-affected regions. These models excel at recognizing spatial dependencies in images, making them perfect for classifying and identifying fire incidents from aerial video. For example, Zhang et al. (2020) and Talaat and ZainEldin (2023) show how effective CNNs are for UAV-based fire monitoring and detection. Moreover, various scholars have investigated different CNN based models for fire detection, segmentation, and classification, leading to advancements in UAV-based fire management (Gewali and Panday 2022; Khan and Khan 2022; Wang et al. 2023c; Islam et al. 2023; Zhao et al. 2018; Namburu et al. 2023; Sathishkumar et al. 2023; Bahhar et al.

Table 4 Existing survey paper summary of targeted area and application domain

References	Application			Domain			Deep learning Model								
	Det	Cls	Seg	Forest Fire	Urban Fire	Rural Fire	Vehicle Fire	CNN	Attention	ViT	RNN	GAN	Yolo	G.DL	ML
Akhloufi et al. (2020)	✓	-	✓	✓	-	-	-	✓	-	-	-	-	-	✓	-
Partheepan et al. (2023)	✓	✓	-	✓	-	-	-	✓	-	-	-	-	-	✓	✓
Barnpoutis et al. (2020)	✓	-	-	✓	-	-	-	✓	✓	-	-	✓	✓	-	✓
Roldán-Gómez et al. (2021)	✓	-	-	✓	-	-	-	-	-	-	-	-	-	✓	-
Moungiakmas et al. (2021)	✓	-	-	✓	-	-	-	✓	-	-	-	✓	✓	✓	-
Yuan et al. (2015)	✓	✓	✓	✓	-	-	-	-	-	-	-	-	-	-	✓
Li et al. (2023)	✓	✓	✓	✓	-	-	-	-	-	-	-	-	-	-	✓
Hossain et al. (2019)	✓	-	-	✓	-	-	-	✓	-	-	-	-	-	✓	✓
Bouguettaya et al. (2022)	✓	✓	✓	✓	-	-	-	✓	-	-	-	-	✓	-	✓
Dhall et al. (2020)	✓	-	-	✓	-	-	-	✓	-	-	✓	-	-	✓	✓
Our paper	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-

Det Detection, Cls classification, Seg segmentation, CNN convolutional neural network, RNN recurrent neural network, YOLO you only look once, ViT vision transformer, GAN generative adversarial network, G.DL general deep learning, ML machine learning

2023; Ahmad et al. 2023; Tamilselvi et al. 2023; Nadeem et al. 2023; Jonnalagadda and Hashim 2024; Rahman et al. 2023; Ibraheem et al. 2024; Vishwakarma and Deshmukh 2025; Khan et al. 2025; Ali and Kurnaz 2025; Wu et al. 2023; Yar et al. 2024) and El HOFFY et al. (2023). Fig. 6 illustrates the use of CNNs for fire management systems.

Challenges in CNNs In fire detection, classification, and segmentation, CNNs show better performance compared to traditional machine learning methods but still face some limitations and challenges, including a high rates of false negatives and false positives, high computational costs inhibiting real-time performance, environmental variability, overfitting, and trouble in detecting early-stage fires which is essential for vision-based fire management systems (Buriboev et al. 2024; Zhao et al. 2024b).

6.2 Recurrent neural networks (RNNs)

RNNs are particularly useful for tasks involving temporal dependencies, such as predicting the spread of fire over time. Unlike CNNs, which are designed primarily for spatial feature extraction, RNNs can retain past information through their hidden states, which makes them well-suited for processing sequential data like video frames or time-series data from UAV sensors. In UAV-based fire management systems, each video frame is first passed through a CNN to extract spatial features. These features are then input into the LSTM sequence model, which maintains a hidden state that updates over time. The memory gates in LSTMs help capture the progression of fire behavior, such as growing flames or moving smoke. This temporal information is critical for understanding how fire dynamics and enabling predictive analysis of fire spread. Furthermore, the LSTM's output is mapped to a final classification or regression layer, allowing the system to forecast important variables such as the direction and rate of fire spread. This capability is essential for supporting real-time, data-driven fire management decisions. Research (Jain et al. 2020) demonstrates how RNNs can be used to model fire dynamics using UAV imagery. Furthermore, other scholars have studied various RNN models for fire detection, classification and segmentation that contribute to the development of UAV-based fire management (Mashraqi et al. 2022; Li et al. 2021; Mahaveerakannan et al. 2023; Ghosh and Kumar 2022; Shamta and Demir 2024; Cao et al. 2019; Wang et al. 2023d; Fang et al. 2025; Cao et al. 2024; Valarmathi and Ramkumar 2025; Dhir et al. 2023). Fig. 7 shows the application of the LSTM network in fire detection, where the RCNN is used to determine the suspected region of the fire and the LSTM gathers the local features inside the bounding boxes to determine a fire in a short period of time (Kim and Lee 2021).

Challenges in RNN RNNs are highly effective for fire classification, detection, and segmentation using UAVs. This is achieved by processing sequential data, preserving temporal information, incorporating multiple types of input, adapting to fire behavior, and supporting real-time analysis. However, RNNs face challenges, including difficulties with long-term dependencies, extensive training requirements, susceptibility to noise, restricted spatial feature extraction, potential for overfitting, and heightened architectural complexity (Al-Selwi et al. 2024).

Table 5 Existing survey paper summary of dataset types

References	RGB	Thermal	IR
Akhloufi et al. (2020)	✓	-	✓
(Partheepan et al. (2023)	✓	-	✓
Bampoutis et al. (2020)	✓	-	✓
Roldán-Gómez et al. (2021)	-	-	✓
Moumgiakmas et al. (2021)	✓	-	-
Yuan et al. (2015)	✓	-	✓
Li et al. (2023)	-	-	-
Hossain et al. (2019)	-	-	-
Bouguettaya et al. (2022)	✓	-	-
Dhall et al. (2020)	✓	-	-
Our paper	✓	✓	✓

6.3 Attention mechanisms

Attention mechanisms enhance the performance of deep models by allowing them to selectively focus on critical spatial or channel-wise features in UAV imagery. Spatial attention mechanisms, such as the convolutional block attention module (CBAM) and squeeze-and-excitation (SE) blocks, highlight relevant regions like flames or dense smoke plumes, while channel attention assigns greater importance to feature maps that capture fire-related patterns. These weights are then applied to the feature tensors, enhancing the contribution of salient features during classification, detection, or segmentation. This method works especially well for drone images where smoke or foliage may partially obscure flames. Recent advancements in attention-based architectures have significantly advanced UAV-based fire detection systems. Mowla et al. (2024a) introduced the adaptive hierarchical multi-headed convolutional neural network with modified convolutional block attention module (AHM-HCNN-mCBAM), which effectively addresses challenges related to multiscale feature extraction, spatial dependencies, and temporal context modeling in aerial wildfire imagery. Their model, evaluated on both the UAVs-FFDB and FLAME datasets, achieved state-of-the-art accuracy and demonstrated substantial improvements in precision, recall, and model efficiency through the integration of GRU, BiLSTM, and explainable AI techniques. Mowla et al. (2024a) have demonstrated how attention mechanisms with another deep learning model can enhance the performance of fire detection using UAV data. Moreover, numerous researchers have studied methods for attention techniques fire detection, segmentation, and classification using UAV-based fire monitoring (Kong et al. 2024; Islam et al. 2023; Hussain et al. 2022a; Aral et al. 2023; Jiang et al. 2023; Li et al. 2024a; Kim et al. 2024a; Pang et al. 2023; Wang et al. 2023a; 2025a; Wu et al. 2024). Han et al. (2024) proposed the LUFFD-YOLO model using an attention technique and hierarchical feature fusion methods where GhostNetV2 is used to reduce parameters, an ESDC2f module for small fire detection, and an HFIC2f module to improve feature extraction and fusion, as shown in Fig. 8.

Challenges in attention mechanism The overall efficiency of the attention-based model over the CNN in fire classification, detection and segmentation is remarkable. They enable models to focus on relevant features, integrate contextual information, allow dynamic feature selection, and reduce computational costs through targeted processing. However, it has some limitations like high complexity, huge data for training, and reduced interpretability, risk of overfitting (Guo et al. 2022, 2023; Saleh et al. 2024).

Table 6 Overview of deep learning models for UAV-based fire detection, classification, and segmentation

References	Method	Categories	References	Method	Categories
Gewali and Panday (2022)	VGG16, VGG19, InceptionV3	CNN	Ibraheem et al. (2024)	Intermediate Fusion VGG16 ECP-LEACH	CNN
Khan and Khan (2022)	FFireNet	CNN	Islam et al. (2023)	EfficientNetB7-ACNet	CNN
Wang et al. (2023c)	Reduce-VGGNet	CNN	Zhao et al. (2018)	DCNN FireNet	CNN
Namburu et al. (2023)	X-MobileNet	CNN	El HOFFY et al. (2023)	UAV-Net	CNN
Sathishkumar et al. (2023)	LwF-Inception-V3	CNN	Rahman et al. (2023)	CNN	CNN
Bahhar et al. (2023)	BCN-MobileNet-V2	CNN	Ahmad et al. (2023)	FireXnet	CNN
Tamilselvi et al. (2023)	RBFN-AISR	CNN	Jonnalagadda and Hashim (2024)	SegNet	CNN
Li et al. (2021)	FNU-LSTM	RNN	Mahaveer-akannan et al. (2023)	RLSTM-NN	RNN
Ghosh and Kumar (2022)	RNN	RNN	Shamta and Demir (2024)	CNN-RCNN	RNN
Dhir et al. (2023)	CNN, RNN	RNN	Cao et al. (2019)	ABi-LSTM	RNN
Wang et al. (2023d)	SA-EX-LSTM	RNN	Reddy et al. (2024)	RNN-WO	RNN
Mashrafi et al. (2022)	DIFFDC-MDL	RNN	Sheng et al. (2024b)	FSA	RNN
Kong et al. (2024)	ADE-Net	Attention	Islam et al. (2023)	ACNet	Attention
Hussain et al. (2022a)	DMFA-Fire	Attention	Aral et al. (2023)	Lightweight Model Attention Base CNN	Attention
Jiang et al. (2023)	UAV-FDN	Attention	Li et al. (2024a)	P-DenseNet-A-TL	Attention
Pang et al. (2023)	FuF-Det	Attention	Wang et al. (2023a)	BrantNet	Attention
Kim et al. (2024a)	YOLOV5, Spatial attention, GTP	Attention, YOLO	Han et al. (2024)	LUFFD-YOLO	Attention, YOLO
Ghali et al. (2022)	TransUNet-R50-ViT	ViT	Wang et al. (2024a)	FWSRNet	ViT
Haldorai et al. (2024)	ViTM	ViT	Ghali et al. (2021)	TransUNet, MedT	ViT
Wang et al. (2024b)	FireViTNet	ViT, CNN	Ghali and Akhloufi (2023)	CT-Fire	ViT, CNN
Tong et al. (2024)	FireFormer	ViT, CNN	Yuan et al. (2024)	Swin Transformer	ViT
Lin et al. (2022)	STPMSAH	ViT, CNN	Kumar et al. (2024)	Deeplabv3	ViT, CNN
Shahid et al. (2023)	FFS-UNet	ViT	Zheng et al. (2023)	Lightweight ViT, CNN	ViT, CNN
Tong et al. (2024)	FireFormer	ViT, CNN	Yar et al. (2024)	Modified ViT	ViT

Table 6 (continued)

References	Method	Categories	References	Method	Categories
Xiao et al. (2023)	FL-YOLOv7	YOLO	Abramov et al. (2024)	YOLO	YOLO
Luan et al. (2024)	YOLO-CSQ	YOLO	Avazov et al. (2021)	YOLOv8, CNN-RCNN	YOLO
Wang et al. (2023b)	YOLOv5	YOLO	Zhao et al. (2024a)	FSDF	YOLO
Sheng et al. (2024a)	YOLOV8, LSTM	YOLO, RNN	Daoud et al. (2024)	YOLO3	YOLO
Zhang (2024)	YOLOV8	YOLO	Yun et al. (2024)(	FFYOLO	YOLO
Gonçalves et al. (2024)	YOLOv8s	YOLO	Yandouzi et al. (2024)	Mask R-CNN and YOLO V5,7,8	YOLO
Yang et al. (2023)	Yolov5	YOLO	Chan et al. (2024)	YOLOV4, YOLOV5, YOLOV7, YOLOV8, and Faster RCNN	YOLO
Silva et al. (2024)	YOLO	YOLO	Li and Yu (2021)	Yolo-Edge	YOLO
Jiao et al. (2020)	YOLOv3	YOLO	Zheng et al. (2024)	FireDM	GAN
Mozaffari et al. (2024)	Generative AI	GAN	Ciprián-Sánchez et al. (2021)	FIRE-GAN	GAN
Kacker et al. (2023)	GAN	GAN	Park et al. (2020)	CycleGAN	GAN
Jayagopal et al. (2024)	MGANs	GAN	Zhikai et al. (2019)	ACGAN	GAN
Park et al. (2022)	GAN	GAN	Boroujeni and Razi (2024)	IC-GAN	GAN
Qin et al. (2022)	FGL-GAN	GAN	Qiao et al. (2020)	GAN	GAN
Boone et al. (2023)	AttentionGAN	GAN	Shawly and Alsheikhy (2024)	NDGANs	GAN

6.4 Vision transformers

Vision transformers apply the transformer architecture, which was originally developed for natural language processing (NLP). ViTs process UAV-based fire images by dividing them into fixed-size patches, which are flattened and linearly embedded into vectors. These vectors are fed into transformer encoder blocks where self-attention layers represent inter-patch relationships. Unlike CNNs, which rely on local filters, ViTs capture global dependencies, enabling them to identify subtle or widely dispersed fire indicators. Each self-attention head computes the similarity between patches, enabling the model to infer spatial patterns, such as the shape and distribution of fire or smoke, across the landscape. In segmentation applications, ViTs output class probabilities for each patch, enabling UAVs to precisely delineate fire regions, even in complex terrains. Vision transformers have been investigated by Dosovitskiy et al. (2020) and Yang et al. (2022) for different image analysis applications, including UAV-based fire classification and detection. Additionally, other researchers have applied a vision-transfer-based DL model for fire detection, classification, and segmentation

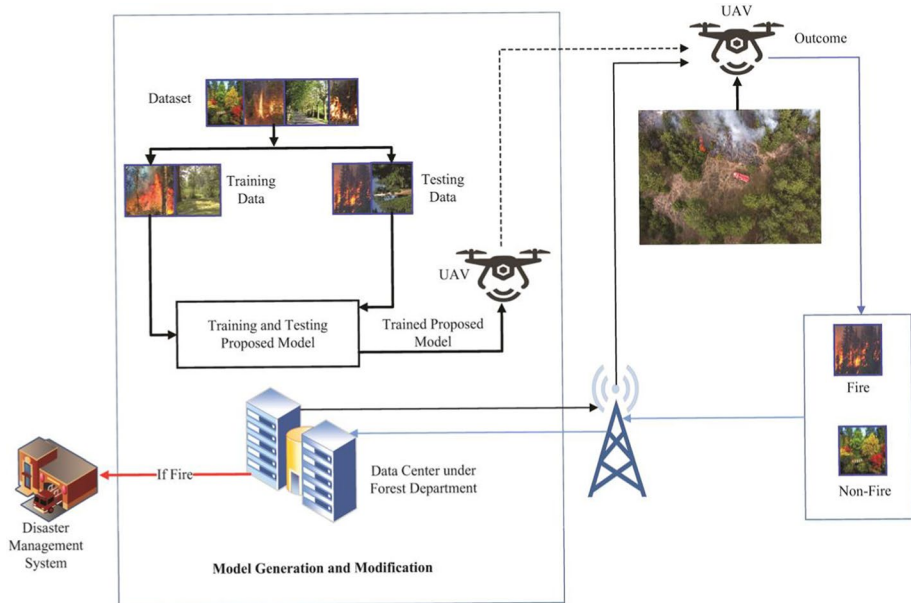


Fig. 6 Forest fire management system using CNN (Rahman et al. 2023)

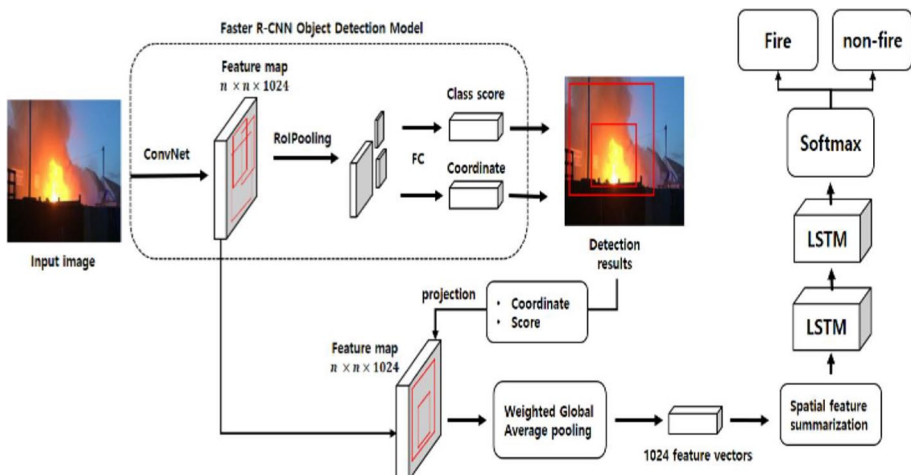


Fig. 7 Application of the LSTM network in fire detection, the RCNN is used to identify the suspected fire region and the LSTM gathers the local features inside the bounding boxes to decide a fire in a short time (Kim and Lee 2021)

using drones (Bakirci 2024; Wang et al. 2024a, b; Shahid et al. 2023; Haldorai et al. 2024; Ghali et al. 2021; Ghali and Akhloufi 2023; Lin et al. 2022; Zheng et al. 2023; Yar et al. 2024; Tong et al. 2024; Kumar et al. 2024; Yuan et al. 2024; Saxena et al. 2025; Feng et al. 2025; Chaturvedi et al. 2025). The author modified and enhanced deep learning techniques for early fire detection by introducing a novel deep ensemble learning methodology that

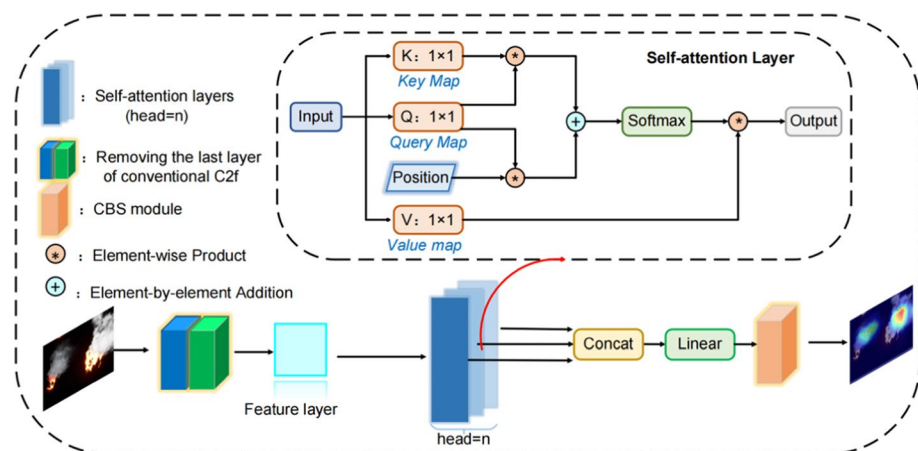


Fig. 8 LUFFD-YOLO model using an attention mechanism and hierarchical feature fusion techniques where GhostNetV2 is used to reduce parameters, an ESDC2f module for small fire detection, and an HFIC2f module to improve feature extraction and fusion (Han et al. 2024)

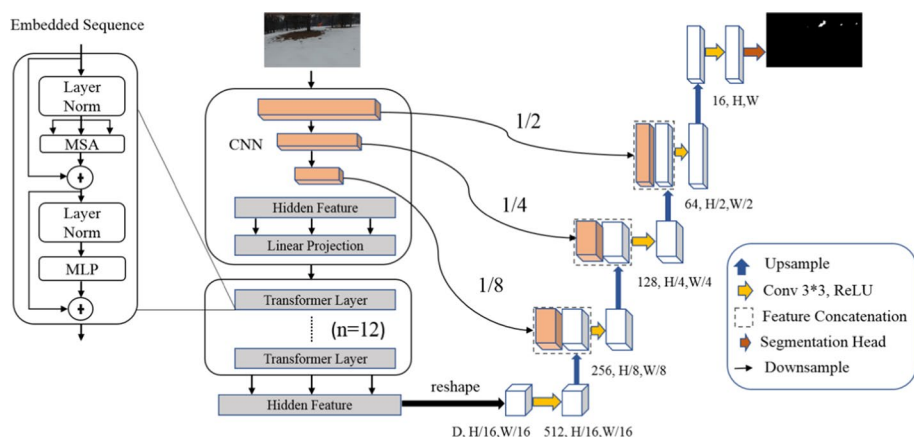


Fig. 9 The proposed TransUNet architecture using ViT (Ghali et al. 2022)

integrates EfficientNet-B5 and DenseNet-201 models for detection and classification of fire from aerial images. Moreover, two vision transformers (TransUNet and TransFire) and EfficientSeg, a deep convolutional model, were utilized to segment and precisely delineate fire areas (Ghali et al. 2022). The whole process is shown in Fig. 9.

Challenges in ViT The transformers enhance the interaction between pixels by leveraging self-attention. The Transformers perform remarkably well in the detection, classification, and segmentation of fire images, improved feature representation, global contextual information and scalability, which are crucial for vision-based fire management systems using UAVs. However, they have some challenges and limitations, including requiring a large dataset to train (Kumari and Kaul 2023; Kumar et al. 2024; Vuppari et al. 2025).

6.5 You Only Look Once (YOLO) models

You Only Look Once (YOLO) models have emerged as a foundational deep learning framework for UAV-based fire detection due to their speed, accuracy, and architectural efficiency. These models enable fast detection and classification of fires with high temporal and spatial precision by processing entire images or video frames in a single feedforward pass. This capability is especially critical in wildfire emergencies, where rapid and accurate detection can significantly influence response time and containment strategies. YOLO models follow a one-stage object detection architecture that directly predicts bounding boxes and class probabilities from input UAV imagery. The input image is first processed by a backbone network, such as CSPDarknet, which extracts multilevel feature maps capturing essential fire-related patterns. These features are then refined through a neck module, typically a feature pyramid network (FPN) or path aggregation network (PANet), which enhances multi-scale representation to detect both small fire hotspots and large smoke plumes. The detection head then divides the image into a grid and predicts bounding boxes and class confidence scores for each grid cell in a single pass. Non-max suppression removes overlapping boxes, and the model outputs fire regions with associated certainty levels. YOLO's real-time performance allows UAVs to detect and track fire outbreaks dynamically during flight. Norkobil Saydirasulovich et al. (2023) and Shamta and Demir (2024) provide examples of how to apply YOLO models for quick and precise detection of fire. Additionally, other researchers have worked on fire detection, segmentation, and classification (Avazov et al. 2021; Alhasan and Yilmaz 2025; Sheng et al. 2024a; Daoud et al. 2024; Zhang 2024; Yun et al. 2024; Gonçalves et al. 2024; Yandouzi et al. 2024; Yang et al. 2023; Li and Yu 2021; Jiao et al. 2020; Chan et al. 2024; Wang et al. 2023b; Xiao et al. 2023; Abramov et al. 2024; Silva et al. 2024; Zhu et al. 2025a; Alkhamash 2025; Zhu et al. 2025a; Sun et al. 2025). FSDF improves fire detection by combining YOLOv8 and VQ-VAE (vector quantized variational autoencoders) for image segmentation and fire detection (Zhao et al. 2024a). The Fig. 10 shows the proposed framework of the FSDF.

Challenges in YOLO YOLO shows the best performance in a vision-based fire management system using UAVs for fire detection, end-to-end training, ease of implementation and single-stage architecture. However, YOLO models have certain limitations and challenges like handling class imbalances, differentiating overlapping objects, and effectively utilizing contextual information, which require large datasets for training (Hu et al. 2025).

6.6 Generative adversarial networks (GANs)

GANs are employed in UAV-based fire classification detection and segmentation for data augmentation and synthetic data generation to overcome the challenge of limited and imbalanced datasets. Training a generator network to generate realistic fire-related images and a discriminator network to differentiate between real and generated images. GANs enable the production of realistic fire scenarios, particularly those involving early-stage or rare incidents often missing from conventional datasets. GANs can improve the robustness and generalization capabilities of fire detection and segmentation models. The study by Kim et al. (2024b) and its applications in synthetic data generation for fire detection are particularly noteworthy. Other researchers have proposed using GANs for data augmentation and generation to enhance fire detection, classification, and segmentation (Zheng et al. 2024;

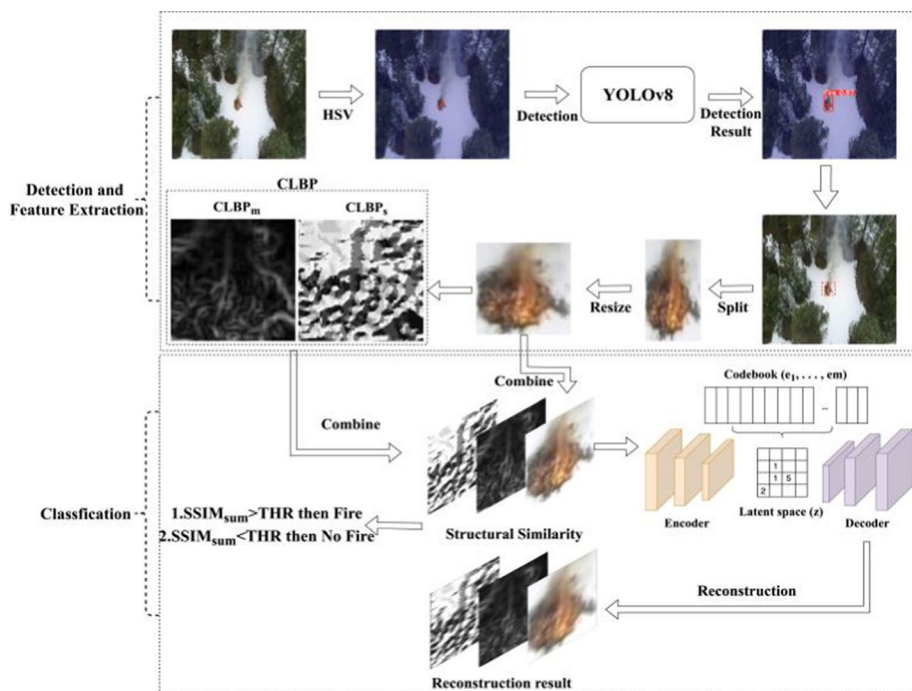


Fig. 10 The overall flowchart of the FSNet model using YOLOv8 (Zhao et al. 2024a)

Mozaffari et al. 2024; Ciprián-Sánchez et al. 2021; Zhikai et al. 2019; Park et al. 2022; Boroujeni and Razi 2024; Amin et al. 2025; Qin et al. 2022; Qiao et al. 2020; Kacker et al. 2023; Boone et al. 2023; Zeng et al. 2023; Wang et al. 2025a; Jayagopal et al. 2024). In this study, the issue of dataset imbalance was addressed using CycleGAN and DenseNet-based models, demonstrating enhanced performance relative to pre-trained models (Park et al. 2020) as illustrated in Fig.11 while Fig.12 shows a sample of the generated image of fire using GAN.

Challenges in GANs Generative adversarial networks in UAV-based fire detection, classification and segmentation have shown outstanding performance in data augmentation, enhanced feature learning, superior image generation, adaptability to various fire conditions, and unsupervised learning. However, they encounter challenges, including training instability, substantial data and computational demands, generalization difficulties, and restricted control over generated outputs (Pal et al. 2024; Saad et al. 2024).

7 Application of UAV-based technologies across fire types

Unmanned aerial vehicles have become increasingly significant in the detection and management of various types of fires, including forest, urban, rural, and vehicle fires. These advanced systems leverage a combination of sophisticated sensors and deep learning models to enhance fire detection capabilities, improve situational awareness, and facilitate real-time decision-making.

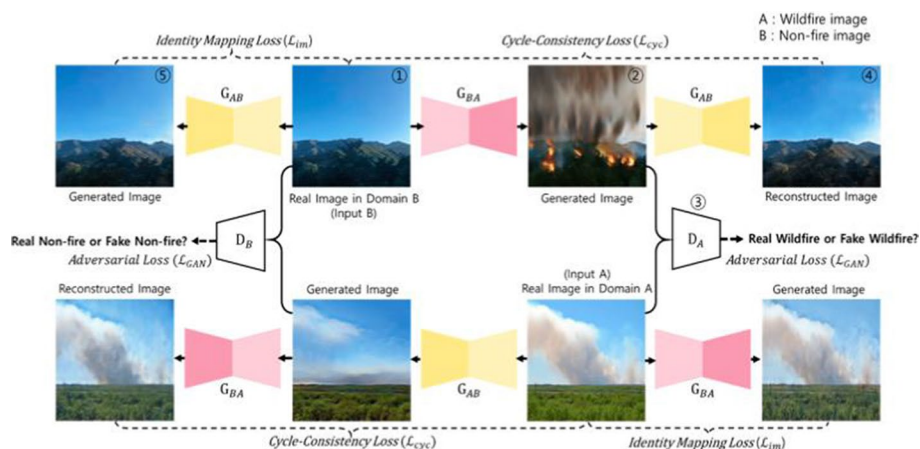


Fig. 11 The proposed DenseNet-based model addresses data imbalance by utilizing fire data generated by CycleGAN-generated (Park et al. 2020)



Fig. 12 Synthetic fire image generated by GAN (Park et al. 2022)

7.1 Forest fires

Forest fires, or wildfires, are increasingly frequent and severe due to climate change, posing significant ecological and economic threats. These fires can lead to long-term environmental degradation, including soil erosion and increased risks of landslides and flash floods.

UAVs equipped with thermal imaging, infrared sensors, and AI-based detection algorithms have proven to be effective in early-stage fire detection, even before visible smoke is present. Systems like IGNIS enable controlled burns from a safe distance, aiding in fire prevention and control strategies (Enterprise 2021). Recent advancements such as lightweight YOLOv5 models integrated with MobileNetV3 and semi-supervised knowledge distillation have significantly improved detection accuracy while reducing computational load, making them suitable for real-time deployment on UAV platforms (Zhou et al. 2024). These systems also support continuous monitoring and post-fire assessment, enhancing situational awareness and resource allocation during firefighting operations (Kumar 2025). UAV-based technologies, thus offer a scalable and proactive solution to manage forest fires in increasingly vulnerable ecosystems.

7.2 Urban fires

Urban fires are primarily associated with high population density and neglected infrastructure, particularly in areas with vacant housing (Hossain and Smirnov 2023). Rapid urbanization has increased the risk of fire incidents due to various factors, including improper disposal of materials and overcrowded living conditions. UAVs offer rapid situational assessment through aerial surveillance and thermal imaging, enabling emergency responders to evaluate structural hazards, locate fire hotspots, and identify trapped individuals. Recent developments have demonstrated the effectiveness of UAVs equipped with onboard cameras and sensors, using image classification and processing techniques such as SVM and YOLOv5 to detect fire-prone areas and assist in extinguishing efforts before fires escalate (Shashidhara et al. 2024). Smart firefighting drones have been developed to autonomously navigate complex urban landscapes and deliver extinguishing agents with high precision (Perez-Saura et al. 2023). UAVs have become integral to urban fire response systems, offering speed, precision, and enhanced safety in densely populated environments.

7.3 Rural fires

Rural fires are affected significantly by economic activities, such as agriculture and land-use practices (Hossain and Smirnov 2023). These fires are often exacerbated by human activities, such as land clearing for farming or failing to follow safety measures during agricultural burns. UAVs offer critical support in monitoring fire-prone landscapes, providing vital information about fire behavior, and assessing the impact of these fires on local ecosystems. Moreover, UAVs play a critical role in community-based early warning systems and post-fire ecological assessments, supporting sustainable land management practices. UAVs equipped with multispectral sensors and AI-based classification systems can differentiate between smoke, dust, and fire signatures, reducing false alarms, thereby improving response accuracy. Recent advancements in UAV-based fire detection have focused on enhancing sensitivity to small-scale fires common in rural environments. For instance, the integration of single-shot multibox detector (SSD) with MobileNetV2 has significantly enhanced real-time UAV-based agricultural fire and smoke detection capabilities while maintaining a lightweight architecture suitable for deployment in edge-computing environments (Abdusalomov et al. 2025a). Additionally, modified detection transformer (DETR) models incorporating ConvNeXt backbones and feature enhancement blocks (FEB) have demonstrated

superior performance in identifying small-scale fire outbreaks, achieving high precision and recall across diverse agricultural scenarios (Abdusalomov et al. 2025b). Multi-scale feature fusion and attention mechanisms have also been employed to improve detection accuracy in rural and smart city ecosystems, enabling UAVs to highlight critical fire regions through enhanced spatial and contextual feature representation (Hussain et al. 2022b). These systems support proactive fire management strategies, including early intervention, fuel load assessment, and ecological recovery planning, making UAV-integrated smart technologies a scalable and adaptable solution for rural fire safety.

7.4 Vehicle fires

Vehicle fires can occur for various reasons, including mechanical failures, collisions, or arson. Although the immediate detection of vehicle fires often relies on human observation or emergency services' reporting systems, UAVs can provide aerial surveillance in busy urban areas, rapidly identifying fires and assisting in directing firefighting resources to the incident site. Their ability to cover large areas and access difficult-to-reach locations makes UAVs a valuable asset in managing vehicle fire incidents effectively. A modified VGG16 model, optimized for UAV deployment, has demonstrated strong performance in identifying fire incidents while reducing computational complexity and resource demands (Yar et al. 2021). UAVs thus offer a fast, flexible, and low-risk approach to vehicle fire detection and response, particularly in high-traffic or hard-to-access zones.

Across all fire types, the integration of DL models with UAV platforms has significantly enhanced detection capabilities. DL algorithms process large volumes of sensor data to identify fire patterns, adjust UAV flight paths dynamically, and support predictive modeling for fire spread. These technologies not only improve detection accuracy, but also facilitate proactive fire management strategies. UAVs continue to evolve as essential components of integrated fire response systems, offering a versatile and adaptive approach to mitigating the growing threat of fires in diverse environments.

8 Datasets

Deep learning and computer vision techniques heavily depend on the quantity, quality, and diversity of the training data. As the demand for automated and UAV-integrated fire management systems grows, the availability of well-structured, annotated datasets has become essential for enabling accurate detection, classification, and segmentation of fire events. In recent years, a number of SOTA open-access datasets have been released to support the research community in developing and evaluating such models. These datasets are essential for advancing early fire incident detection, which plays a critical role in minimizing damage and safeguarding lives and property (Fig. 13).

In the context of UAV-based systems, particularly those intended for real-time operations and early-stage fire detection, specific characteristics are crucial. (1) high-resolution imagery suitable for aerial processing; (2) annotated instances of small or early-stage fires (e.g., smoke trails, ignition points); (3) multimodal sensor support for thermal or infrared mapping and (4) UAV-based perspectives. Datasets that lack such characteristics are often constrained in their utility for real-world UAV deployment. Among the datasets reviewed,

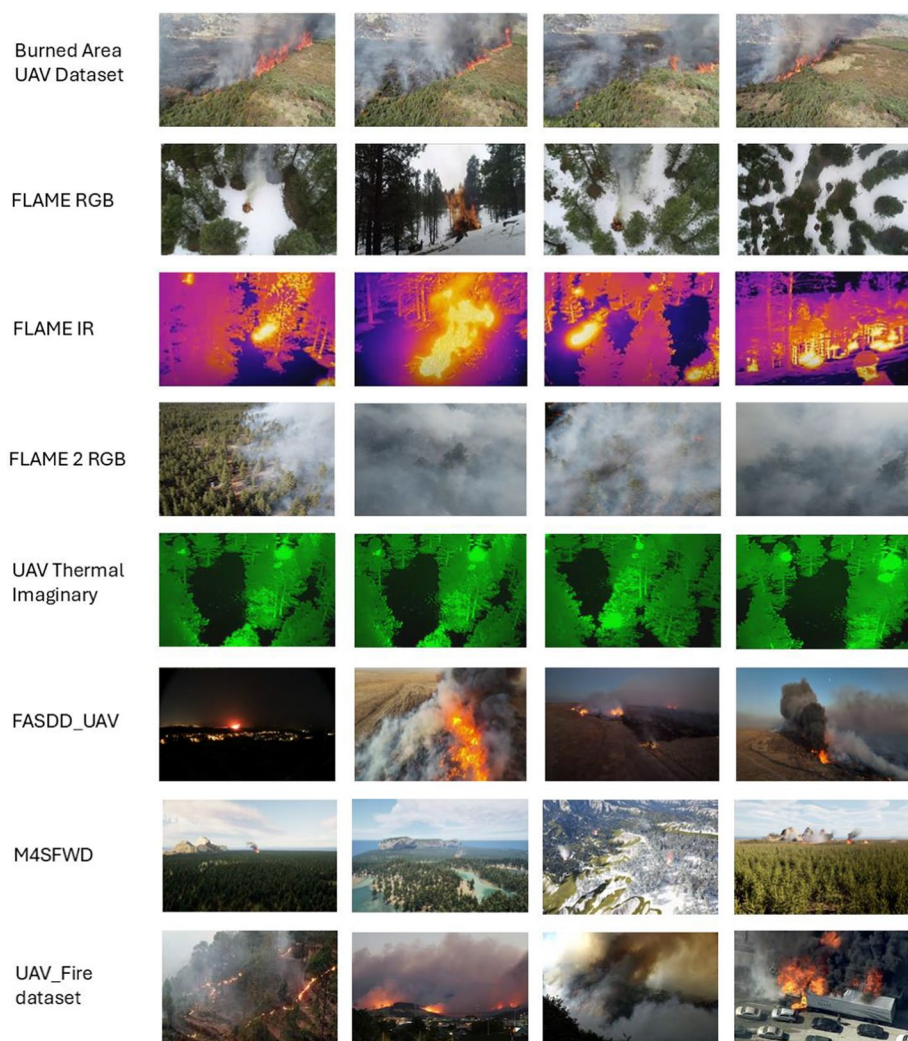


Fig. 13 Sample images collected from various UAV fire datasets

several stand out for their relevance to UAV-based fire detection: the FLAME dataset family [including FLAME (Shamsoshoara et al. 2020), FLAME2 (Chen et al. 2022), and FLAME3 (Hopkins et al. 2024)], M4SFWD (Han et al. 2024) and FASDD UAV (Wang et al. 2023b) have demonstrated particular value in supporting real-time UAV-based fire detection. These datasets feature UAV-captured imagery under varied lighting and environmental conditions and include critical samples of small-scale fires and smoke, a prerequisite for developing responsive early-warning models. For instance, FLAME3 (Hopkins et al. 2024) focuses on pile-burn detection using multispectral aerial footage, M4SFWD (Han et al. 2024) spans multiple weather and fire scenarios to enhance generalizability, and FASDD UAV (Wang et al. 2023b) provides thermal and RGB data tailored for lightweight CNNs suitable for edge deployment.

In contrast, several widely used datasets, such as DFire (Venâncio et al. 2022b), Mivia (Foggia et al. 2015), and FireNet (Farhadi and Redmon 2018), are limited by their emphasis on large-scale or fully developed fires. These datasets often lack sufficient representation of early ignition phases or temporal sequences and may suffer from class imbalance, with disproportionate numbers of intense fire events relative to subtle fire onsets. Consequently, models trained exclusively on such datasets may exhibit reduced sensitivity to early fire cues and perform suboptimally in UAV-based applications requiring fast detection and response. To overcome these limitations, future dataset development should prioritize early-stage fire imagery, include temporally coherent video frames to support fire progression modeling, and incorporate multimodal sensor alignment (e.g., RGB with synchronized thermal data). Furthermore, standardized annotations with metadata such as GPS coordinates, timestamps, and UAV altitude would significantly enhance the applicability of datasets for real-world UAV operations.

In summary, although the expanding collection of publicly available fire datasets has fueled significant advancements in the field, only a subset, namely FLAME (Shamsoshoara et al. 2020), M4SFWD (Han et al. 2024), and FASDD UAV (Wang et al. 2023b), are currently optimized for early-stage detection in real-time UAV deployments. This identifies an important research gap and underscores the need for continued dataset enhancement to meet the evolving requirements of autonomous fire management systems. A comprehensive overview of the commonly employed fire detection, classification and segmentation datasets is provided in Table 7 along with their download links. The table summarizes their distinguishing characteristics, including data type and the number of samples.

9 Research trends, challenges and future directions

This section critically examines the dynamic trajectory of research within the domain, highlighting current trends, remaining challenges, and emerging directions for future research. It aims to provide information on how the domain is progressing and what gaps and opportunities remain for further investigation.

9.1 Trends

The rising frequency and intensity of fires and advancements in deep learning and autonomous drone technology have sparked significant research interest in vision-based fire management systems, particularly in detection, segmentation, and classification. Recent studies highlight the integration of CNNs, RNNs, ViTs, and hybrid models to enhance real-time fire monitoring. These deep learning frameworks have shown promising results in detecting, segmenting, and classifying fire in aerial imagery and video streams, offering greater accuracy and efficiency than traditional sensor-based systems.

Another significant trend in recent developments is the creation of multimodal systems that integrate RGB, thermal, and LiDAR data to improve detection reliability. Research indicates that deep learning models utilizing fused sensory inputs perform better than those based on a single type of data, especially in complex fire environments with varying visibility conditions. Additionally, generative adversarial networks have become increasingly

Table 7 Detection, classification and segmentation datasets

Ref	Dataset name	Dataset types	Total
Ribeiro et al. (2023)	Burned Area UAV dataset	RGB	22,500
Shamsoshoara et al. (2020)	FLAME	RGB & IR	47,992
Chen et al. (2022)	FLAME2	RGB & IR	59,451
Hopkins et al. (2024)	FLAME3	RGB & IR	739
Kyrkou and Theodorides (2019)	AIDER	RGB	1000
DataCluster Labs (2024b)	DC Lab fire dataset	RGB	10,210
Khan and Hassan (2024)	Wildfire dataset	RGB	1900
Farhadi and Redmon (2018)	FireNet	RGB	502
Shah (2024)	Fire dataset	RGB	3225
Pande (2024)	Fire detection dataset	RGB	864
CA et al. (2019)	Furg fire	RGB	36,702
Foggia et al. (2015)	Mivia's fire dataset	RGB	62,690
Hu et al. (2023)	Firefly	RGB	19,273
DataCluster Labs (2024a)	Domestic fire dataset	RGB	5000
Phylake1337 (2024)	Fire dataset	RGB	999
Venâncio et al. (2022a)	DFire dataset	RGB	21,000
Roboflow (2024a)	Fire Smoke and Human Detector Dataset	RGB	9749
Roboflow (2024b)	Fire-Detection-Polygon	RGB	3010
de Almeida Pereira et al. (2021)	Activate Fire	Thermal	146,214
diye Ceran (2024)	UAV Thermal Imaginary	Thermal	3980
Mowla et al. (2024b)	UAVs-FFDB	RGB	15560
Leading India AI (2024)	UAVs-Fire dataset	RGB	2096
Venâncio et al. (2022b)	D-Fire	RGB	21,000
Wang et al. (2023b)	FASDD UAV	RGB	53530
University of Corsica (2024)	Corsican dataset	RGB	-
Han et al. (2024)	M4SFWD	RGB, GAN	35,526
Hu et al. (2025)	MTBS data	RGB-IR	6000

popular for augmenting training datasets, addressing the lack of fire-related images, and enhancing model generalization across a variety of fire scenarios.

Transformer-based networks, like swin transformers and TransUNet, have become promising alternatives to traditional CNN-based models for fire segmentation tasks. These models are particularly effective in capturing long-range dependencies within aerial images, thereby leading to more accurate delineation of fire boundaries. Furthermore, real-time

object detection models like YOLOv5 and YOLOv8 have been optimized for UAV-based fire monitoring, showing excellent performance in both detection speed and accuracy.

9.2 Challenges

Despite considerable advancements in technology, several challenges persist in developing reliable deep learning and computer vision-based fire detection systems using UAVs. These challenges span technical, operational, and ethical domains and significantly affect the reliability and scalability of UAV deployments in real-world fire situations. The following subsections outline the most critical issues organized by severity and propose corresponding solutions, drawing from recent research and practical deployments.

9.2.1 Dataset imbalance and early-stage fire detection

One of the foremost challenges is the lack and imbalance of publicly available fire datasets. Most existing datasets are skewed toward large, fully developed fires, offering insufficient representation of small or early-stage incidents. This imbalance impairs the ability of deep learning models to generalize, particularly in detecting subtle or nascent fire signatures in real-time scenarios (Sun et al. 2025). Consequently, these systems struggle in practice when visibility is limited or when fires are partially obscured.

Proposed solutions Data augmentation using generative techniques (e.g., GANs), synthetic dataset generation, and the use of transfer learning from large-scale pretrained models can alleviate these constraints. Additionally, incorporating balanced, scenario-rich datasets that capture varied fire intensities and backgrounds is vital for robust model performance.

9.2.2 Environmental variability and multi-modal sensor fusion

Environmental conditions, such as wind, fuel type, terrain complexity, and lighting, dramatically influence the visual and thermal characteristics of fire. These fluctuations often degrade detection accuracy, particularly in heterogeneous or smoke-obscured environments (Zhu et al. 2025a). Enhancing detection accuracy under such variability requires the fusion of RGB, thermal, and in some cases LiDAR data to capture complementary cues.

Proposed solutions Multi-modal sensor fusion can help improve system robustness, but it introduces technical complexity in terms of sensor calibration, temporal synchronization, and real-time data integration. Edge-computing architectures and optimized fusion pipelines are required to manage computational loads while maintaining responsiveness.

9.2.3 Real-time processing constraints

UAVs are inherently constrained by payload capacity, energy limitations, and processing power. Deploying computationally intensive deep learning models onboard is challenging, especially when high-resolution video feeds or multi-sensor data are involved. Lightweight models may reduce latency, but this often comes at the cost of detection accuracy (Abdusalomov et al. 2024).

Proposed solutions Optimized deep learning models, such as YOLOv5-tiny, MobileNet, along with model compression techniques (e.g., pruning, quantization), are currently being

adopted to mitigate these limitations. Alternatively, edge-cloud hybrid systems can balance the inference load while preserving near real-time responsiveness.

9.2.4 Balancing false positives and false negatives

A critical operational challenge is managing the trade-off between false alarms and missed detections. False negatives delay emergency responses, whereas false positives can lead to resource misallocation and unnecessary disruptions (Diaconu 2023).

Proposed Solutions: Fine-tuning detection thresholds, implementing ensemble models, and incorporating contextual reasoning (e.g., wind direction, prior fire maps) can help mitigate both types of errors. Rigorous validation under diverse conditions remains essential.

9.2.5 Privacy and ethical concerns

The deployment of UAVs in fire detection and monitoring introduces significant privacy and ethical considerations. UAVs, particularly when equipped with high-resolution cameras, may inadvertently capture images of individuals, private property, or sensitive locations during surveillance flights. This is especially problematic in the wildland when urban interface or post-fire damage assessments are conducted, where civilian infrastructure may be visible (Pal et al. 2024). Additionally, centralized training architectures further amplify these challenges by requiring the transmission of raw data to remote servers, increasing the risk of unauthorized access to data and raising further ethical and privacy concerns (Ceviz et al. 2025).

Proposed solutions To address these concerns, geofencing techniques can be employed to limit UAV operation over residential zones, and onboard anonymization tools, such as real-time blurring of faces or license plates can help protect privacy. Furthermore, the integration of data governance frameworks and adherence to regional privacy laws (e.g., GDPR, local aviation authority guidelines) is essential. Transparent communication with affected communities and obtaining necessary permissions also foster ethical deployment. Furthermore, the integration of federated learning offers a privacy-preserving alternative to centralized training. In this decentralized framework, UAVs process data onboard and share only model updates, not raw images or sensor data. This approach minimizes data leakage risks, supports compliance with privacy regulations, and leverages onboard computational capabilities for efficient and ethical AI deployment in fire monitoring operations.

Addressing these challenges requires a multi-faceted approach involving more comprehensive and balanced datasets, development of lightweight yet accurate models, real-time sensor fusion frameworks, improved interpretability, and robust error mitigation strategies. Continued research in these directions is essential to advancing the field toward scalable, trustworthy fire detection systems.

9.3 Future directions

To tackle the current challenges in vision-based fire management systems using UAVs, future studies must focus on several critical domains. These advancements should focus on addressing dataset limitations, improving real-time processing capabilities, enhancing

detection accuracy and advancing multidisciplinary collaboration to accelerate advancement in UAV-based fire detection and management systems.

9.3.1 Fire datasets

A major challenge in fire detection systems is the imbalance and lack of comprehensive fire datasets. Most existing datasets focus on large, fully developed fires, which hinder the ability of deep learning models to generalize to early-stage or smaller fires. To address this, large-scale, diversified, and well-annotated datasets that cover a range of fire intensities, habitats, weather conditions, and geographical landscapes are essential. Moreover, synthetic data generation methods, such as generative adversarial networks could be used to augment existing datasets and introduce diverse fire scenarios. This is critical for training models capable of handling diverse environmental conditions and fire stages. Further efforts should focus on ensuring data quality and variety to improve the robustness of fire detection models in real-world applications.

9.3.2 Lightweight and adaptive deep learning models

The real-time deployment of deep learning models on UAVs faces significant challenges due to limited payload capacity and processing power. Lightweight models like MobileNet, EfficientNet, and NAS-based architectures are increasingly being adopted to reduce latency while maintaining acceptable accuracy. Future research should focus on optimizing deep learning models for UAVs using techniques such as model pruning, quantization, and compression to meet these constraints without sacrificing performance. Furthermore, adaptive models capable of adjusting to real time fire situations, such as changes in fire intensity or wind patterns should be developed. This flexibility will ensure that the systems remain highly accurate in dynamic fire environments.

9.3.3 Real-time sensor fusion and edge AI deployment

To address challenges posed by varying environmental conditions (wind, terrain, etc.), multimodal sensor fusion (e.g., combining RGB, infrared, and LiDAR data) is critical for enhancing detection accuracy. However, multimodal fusion introduces technical challenges in sensor calibration, real-time data synchronization, and computational load. Future systems will require edge-AI solutions, that allow UAVs to process data locally, reducing dependency on bandwidth and allowing instantaneous decision-making. Edge-computing architectures equipped with optimized fusion pipelines will be crucial in managing these challenges without compromising system responsiveness.

9.3.4 Morphing-wing UAVs for adaptive fire monitoring

Morphing-wing UAVs represent a promising advancement in aerial fire detection systems, offering dynamic flight adaptability through the capability to transition between multirotor hovering and fixed-wing gliding modes. This hybrid mechanism enables UAVs to efficiently survey extensive fire-prone areas while maintaining the flexibility required for navigating complex and variable wildfire terrains. Their dual-mode operation renders them especially

effective for both strategic long-range surveillance and localized high-resolution hotshot evaluation. When integrated with artificial intelligence, these UAVs can optimize flight control and real-time decision-making based on environmental changes such as wind patterns or fire intensity. The incorporation of multi-sensor fusion techniques, involving thermal, infrared, and RGB data streams, further enhances the UAVs' ability to perform adaptive and context-aware monitoring. In particular, the deployment of edge AI facilitates onboard processing of sensor data, thereby reducing communication latency and improving responsiveness in time-critical wildfire scenarios. As discussed by Mowla et al. (2025), recent developments in compliant materials, morphing architectures, and AI-guided control systems have significantly advanced the operational feasibility of these UAVs. Their ability to modify aerodynamic structures during flight results in improved endurance, stability, and energy efficiency under challenging atmospheric conditions. In the context of vision-based fire management, the integration of morphing-wing UAVs with AI offers a transformative approach to wildfire detection and monitoring, enabling scalable, efficient, and adaptable systems that enhance aerial coverage, responsiveness, and operational endurance in dynamic fire environments.

9.3.5 Managing false positives and false negatives

Striking the right balance between false positives and false negatives rates remains a significant challenge. Future advancements should focus on fine-tuning detection thresholds and implementing ensemble models that can handle these trade-offs more effectively. Additionally, contextual reasoning (e.g., wind direction, fire history) should be incorporated to reduce false alarms and improve the accuracy of fire detection. Multimodal input from diverse sensors, such as thermal and optical cameras, can further enhance decision-making, enabling more precise and context-aware fire detection systems.

9.3.6 Integrating vision-language models

Vision-language models (VLMs) have the potential to revolutionize UAV-based fire detection by integrating visual data with natural language processing (NLP). Recent studies suggest that combining visual understanding with language could enhance the system's ability to interpret contextual information about fire behavior. For instance, VLMs could analyze real-time captions or voice commands from firefighting teams, interpreting textual descriptions of fire conditions such as "fast-spreading fire near the forest edge." This integration enables UAV systems to better understand and respond to dynamic fire situations by providing more contextual and actionable insights.

The feasibility of VLMs for fire detection applications is supported by recent work. Seidel et al. (2025) demonstrated that VLMs can generate structured descriptions of wildfire scenarios by fusing UAV images with fire-related metadata, providing improved situational awareness for responders. Similarly, CLIP-based models have shown promise in adapting to fire detection tasks by recognizing nuanced visual cues that traditional models might miss (Wu et al. 2025). By integrating VLMs, UAV systems could autonomously generate fire reports, including location, intensity, and spread patterns, aiding human responders with real-time decision-making. Additionally, VLMs could enable UAVs to operate based on

high-level semantic understanding, such as interpreting mission commands or contextual cues.

9.3.7 Interdisciplinary collaboration

Future UAV-based fire detection systems will require collaboration across multiple fields, including environmental science, engineering, computer vision, and aerospace engineering. The complexity of wildfire and other types of fire dynamics necessitates that experts from different domains work together to improve detection algorithms and model robustness. Additionally, collaboration between researchers, government agencies, and industry stakeholders will be essential to accelerate the development and deployment of UAV-based fire detection systems. Industry partnerships can help facilitate the integration of real-world constraints, such as regulatory requirements, public safety standards, and operational efficiency, into UAV systems.

In summary, to advance UAV-based fire detection systems, research should focus on the development of balanced datasets, real-time, context-aware models, and multi-modal sensor fusion. The integration of vision-language models will significantly enhance system capability by improving contextual understanding, enabling better decision-making and response in wildfire scenarios. With these advancements, UAVs will become more autonomous, scalable, and reliable tools for wildfire detection, ultimately contributing to safer, more effective fire management systems. Continuous collaboration among interdisciplinary teams will drive these innovations, improving both the technology and its application to real-world fire emergencies.

10 Conclusion

Fire detection is a critical aspect of environmental protection and public safety, as wildfires and structural fires continue to cause widespread ecological damage, economic loss, and human casualties worldwide. Early and accurate detection of fire outbreaks is essential for effective mitigation and timely emergency response. However, conventional fire detection systems face several challenges, including limited spatial coverage, delayed detection, sensitivity to environmental interference, and high false alarm rates. To address these challenges, a variety of approaches have been developed for fire detection, classification, and segmentation. These include sensor-based systems, image processing methods, and more recently, deep learning-based approaches. Among these, the integration of unmanned aerial vehicles (UAVs) with vision-based deep learning models has emerged as a promising solution, due to ease of deployment, cost-effectiveness, coverage capability, and ability to operate in dangerous or inaccessible areas.

This survey presented a comprehensive review of UAV-based fire management systems, with a focus on vision-driven detection, classification, and segmentation techniques. In particular, we examined the application of advanced deep learning techniques, ranging from convolutional and recurrent neural networks, YOLO variants, to transformers and GANs models and highlighted their effectiveness in enhancing system precision and responsiveness for fire recognition tasks. Furthermore, we discussed the various types of UAVs employed for fire detection and compiled detailed information on publicly available fire

datasets to support and advance further research and development in this field. Despite promising advancements, the field still faces significant challenges. These include limited dataset diversity, real-time processing constraints, environmental variability, and data privacy concerns. Addressing these challenges requires future research to focus on dataset diversity, developing lightweight models for real-time processing, and leveraging multi-modal sensor fusion, federated learning, and vision-language models to enhance detection accuracy. Moreover, interdisciplinary collaboration will be key to driving innovation in this domain. This survey aims to serve as a foundational reference for researchers and practitioners seeking to advance intelligent UAV-based fire management systems in both research and real-world applications.

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Data availability No datasets were generated or analysed during the current study.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare no Conflict of interest to report regarding the present study.

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