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 markedly, causing considerable damage to properties and environments. To address this challenge effectively, Unmanned Aerial Vehicles (UAVs) equipped with SOTA artificial intelligence and deep learning techniques are being strategically incorporated into fire management systems to improve intelligent decision-making and operational efficiency and effectiveness. UAVs possess autonomy, rapid deployment and cost-effectiveness while using advanced image interpretation and object recognition techniques. UAVs play an essential role in the detection, classification and segmentation of fire effected regions, significantly contributing to an active vision-based fire management system that improves monitoring and surveillance by leveraging SATA computer vision and deep learning techniques. Existing surveys have primarily focused on conventional machine learning and general artificial intelligence (AI) methodologies. This survey specifically highlights the application of UAVs in vision-based fire management systems. The paper explores fire detection, segmentation, and classification tasks, in order to enhance the fire management system and mitigate impacts on both human and natural environments. It offers comprehensive insights into various UAV-based fire management systems that employ deep learning techniques, along with detailed information on available fire datasets and their corresponding download links. Researchers and professionals can access the GitHub repository at ***https : //github.com/SufyanDanish/Fire_survey***.

Keywords: Fire Management System, Fire Detection , Computer Vision, Artificial Intelligence, UAV , Vision-Based system

1 Introduction

Disaster management has attracted considerable attention from researchers in 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, while natural disasters encompass floods, earthquakes, and fire incidents. Fire is a perilous disaster characterized by its rapid spread and destructive nature, making it challenging to control within a short time frame. Fire is primarily caused by individual activities, such as cooking inside buildings, road construction, and smoking in forested areas, as well as natural factors like thunderstorms and global warming [1]. Uncontrolled fires can have a profound impact on human lives, business, ecology, and the environment at both global and local levels. Recently, climate change has exacerbated the incidence of large-scale wildfires and hazardous fires across diverse landscapes, including forests, urban areas, and industrial sites [2]. 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 the most dangerous disaster and has diverse impacts on 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 CO_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 percent of forest fires are responsible for 80 to 90 percent of the total burned area [4, 5]. In general, fire has a large impact on human life and economics locally and globally. Hence, early fire detection and control are crucial to mitigate the human health, wealth and environmental impacts of fire.

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

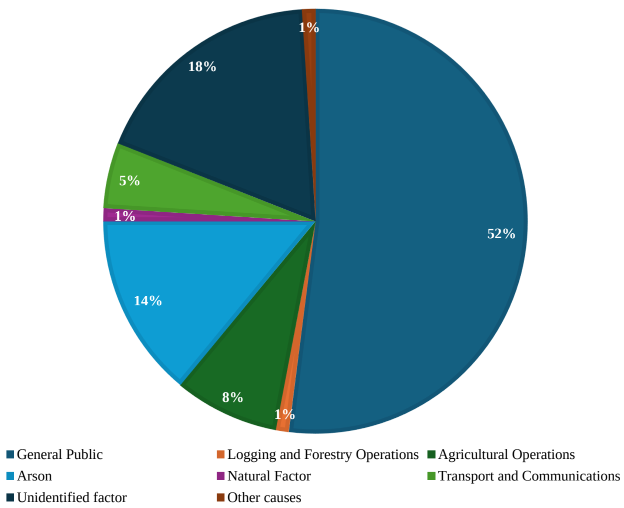

Fig. 1 Statistical information about the causes of fire [3]

smoke sensors [6, 7]. Scalar sensor-based fire detection systems have several advantages, including cost-effective, rapid fire detection, capabilities of early warning, ease in implementation and integration with other fire safety systems [8]. Furthermore, sensor-based systems can provide nonstop environmental monitoring, minimizing the undetected fire risk and allowing for early evacuation. But the sensor-based system has some limitations like generating false alarms due to smoking, steam, dust or cooking [9]. Sensors-based system response time to fire detection increases with time. Moreover, it is challenging to detect fire in the initial stages if the fire is far away 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, an intelligence vision-based fire detection system was proposed which provides wide coverage, no human intervention, prompt response, and ecological robustness. A vision-based fire detection system like closed-circuit television (CCTV) offers broad coverage and real-time fire detection using visual fire indicators including flames and smoke [10, 11]. This type of vision sensor verify fire incidents and make it easier to take action against fire [12]. Nevertheless, it has also reduced the false alarms generated by scalar-based sensor systems [13]. Despite this advantage, CCTV still has some limitations, the most important being limited area coverage and 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

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

proposed as optimal technology for vision-based fire management system due to their enormous potentials [14]. Furthermore, UAVs can fly to high risky spots without the intervention of human beings and give confirmation of fire with real-time updates for accurate planning and monitoring for firefighting, without threatening human lives [6**?**]. UAVs have emerged as effective technologies for fire detection, monitoring, and providing cost-effective solutions for firefighting in high-risk areas and support the development and implementation of novel vision-based fire management systems [15].

UAV-based fire detection has been rising as a new research hot spot due to its various capabilities including clear capturing of fire images from challenging, diverse landscapes and environments and object tracking [16, 17]. Vision-based fire management systems using UAVs can enable different functions such as real-time fire detection, estimating the spreading rate and direction of fire flow utilizing real-world data [18]. **Table 1** represents the overall overview of fire, its factors and challenges, impacts of fire, solutions for safe firefighting using drones and its advantages as compared to human firefighters.

Over the past few years, fire detection and monitoring using artificial intelligence and deep learning techniques have seen significant advancements. Studies show that UAVs are deployed not only for fire detection but also for firefighting [19]. However, further advancements are necessary. Several survey articles have focused on fire detection methods using image processing, machine learning, and deep learning techniques.

Early and vision-based fire detection using UAVs is crucial, as it minimizes the impact on human lives and the economy.

1.1 Types of UAVs

UAV are commonly known as drones, have significantly advanced remote sensing applications in fire detection and fire fighting. Based on the mechanical architecture UAV has four main types as shown in the **Fig. 2**.

Fixed Wing: Models in this category utilize wings with one or more engines for propulsion, requiring a runway for take-off and landing. Course alterations depend on the integration of movable surfaces and thrust. Compared to other UAV types, these models can achieve high speeds and carry heavy payloads. However, their wing design makes them less adaptable to weather conditions.

Flapping Wing: This category includes UAVs with several common features shared with fixed-wing models. The primary difference lies in the wing mechanism, which facilitates direction changes and enhances lift. Their increased maneuverability provides flexibility in strong wind conditions. These models also require a runway for take-off and landing.

Multicopter: Unlike the previous two categories, Multicopter operates solely on rotors without wings. They are capable of vertical fling and landing, eliminating the need for a runway. With rotors mounted horizontally on the main body, these models exhibit increased stability and adaptability to changing flight conditions.

Single Rotor: This type of models consists of single central rotor and a tail rotor, sharing similar features with multicopper but with reduced stability.

The various classifications of UAVs highlight that each category possesses distinct advantages and disadvantages, making platform selection application-dependent. UAVs serve a wide range of applications, delivery supplies, including agriculture, rescue operations and monitoring, inspections, surveying, military applications, filming, cracks in buildings and disaster or hazard identification [20, 21]. **Fig. 2** shows a sample image of various types of drones.

This paper presents an extensive survey of UAV image-based fire detection and localization methods, categorized by basic techniques such as classification, segmentation, and other detection techniques. Research articles on UAV-based fire detection have been reviewed. The main objective is to critically evaluate the existing literature on fire detection, segmentation, and classification using various artificial intelligence and deep learning models, including simple CNNs, Attention-based models, Vision Transformers, YOLO, GANs, and reinforcement learning models. Additionally, the survey explores the diverse types of datasets utilized in the literature, such as RGB, infrared, and thermal images. It also elucidates the advantages, limitations, and challenges faced by researchers using these models. Furthermore, the paper investigates the applications of these models in other fields. Overall, this survey aims to provide comprehensive insights to the research society 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 that covers comprehensive information regarding fire analysis and recognition, variants of AI and deep learning

Figure_2_UAV types.pdf

Fig. 2 The displayed images illustrate various types of Unmanned Aerial Vehicles (UAVs).

models, and datasets. In addition, based on UAV we are also covering varieties of fire scenarios involving commercial buildings, smart cities, residential buildings, and wildlife fires. Furthermore, targeting the limitations of the existing survey followed the research articles, providing valuable insights into the research communities and vision-based fire management system.

- Existing fire survey considered RGB data, while we provided comprehensive details about types of dataset including RGB, Infrared and thermal images in both static (CCTV) and dynamic (drone) vision-based sensors environments. Moreover, to facilitate computer vision researchers, we have given the datasets availability as well.
- Current survey papers individually provide information about fire detection using machine learning approaches and general deep learning models. Not in depth, but

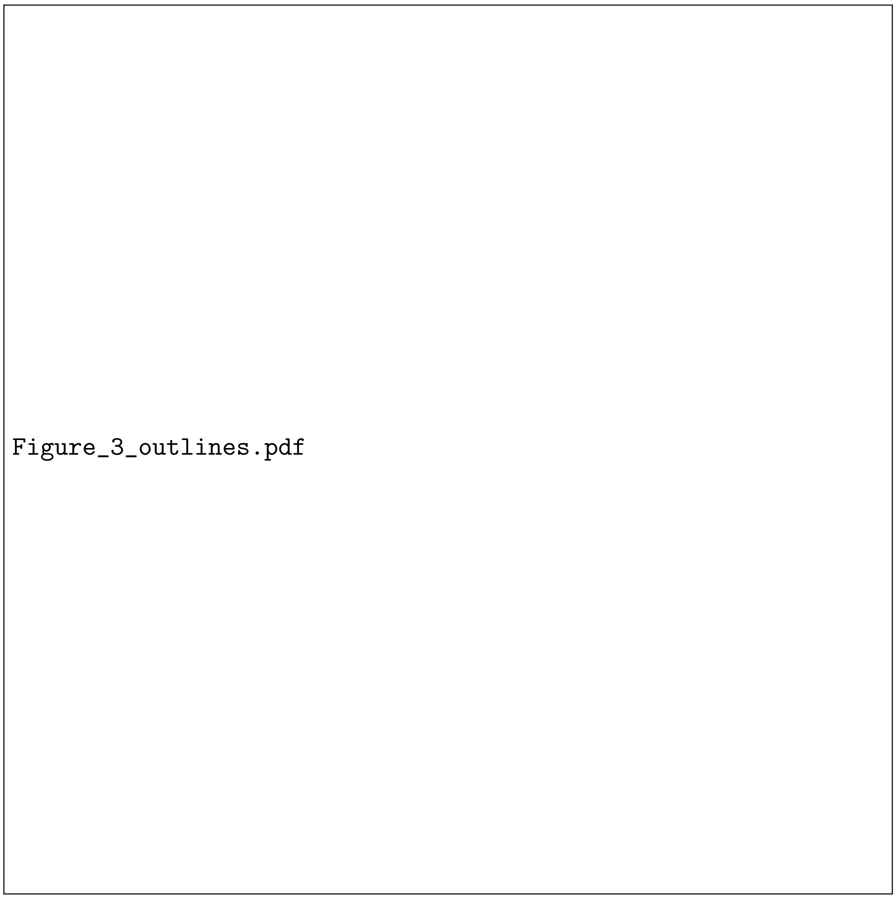

Fig. 3 The structure of a survey Paper: An overview of key components and their organization.

this survey has provided in-depth knowledge of the deep learning and computer vision models followed by their advantages and limitations for UAV technology.

The rest of the paper is arranged as follows: Section 2 presents the research question, Section 3 presents related work, and Section 4 details various deep learning models. Section 5 describes the different datasets used in fire detection research. Section 6 discusses open research limitations and future directions. The paper is concluded in Section 7. **Fig. 3** shows complete content of the survey paper.

2 Research Question

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?

Algorithm 1 Research Paper Selection and Processing Criteria

```
Require: Search in academic databases
Ensure: Relevant research papers from 2018 to 2025
while keywords Fire AND (UAV OR Unmanned Aerial Vehicles OR Drone) do
    while keywords Forest Fire OR Urban Fire OR Rural Fire OR Vehicle Fire OR Wild Fire do
        if paper discusses Deep Learning Models (CNN, RNN, YOLO, Attention Mechanism, or GAN) then
            Include paper for analysis
        else
            Exclude paper from analysis
        end if
    end while
end while
```

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 different fire types.

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

3 Related Work

. In recent years, vision-based fire detection using UAV has gained considerable attention in the research community. Several surveys have explored this field, focusing primarily on forest fires. For our survey, we systematically searched academic databases from 2018 to 2025 to identify relevant papers using keywords such as "forest fire", "urban fire", "rural fire", "vehicle fire", "wildfire", "UAVs", "drones", "computer vision", "deep learning", "remote sensing", "detection", and "monitoring". Papers were selected based on their relevance to UAV-based fire detection, and their titles, abstracts, findings, and overall content were critically analyzed. The **Fig. 4** represents the graphical representation of the research paper collection and analysis while the **Algorithm 1** description pseudocode of the survey paper.

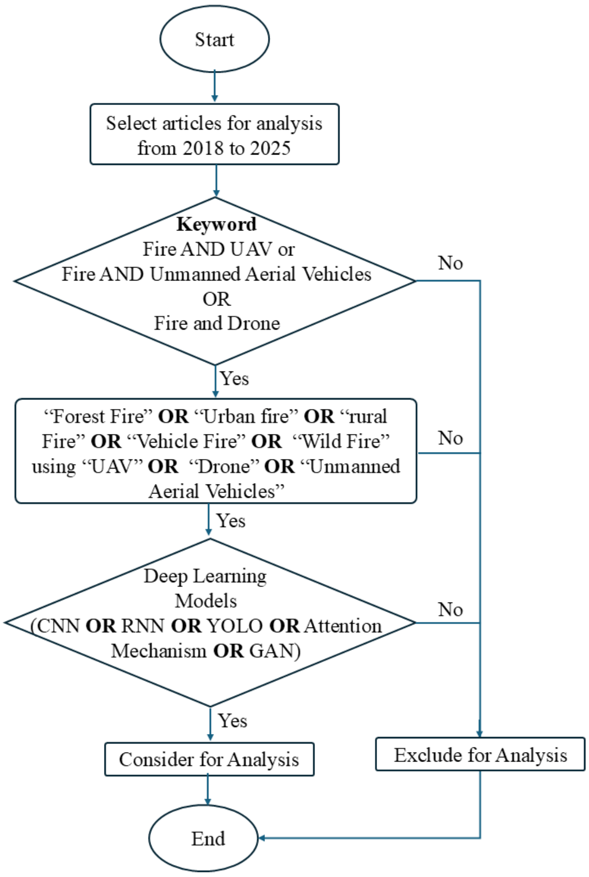

Fig. 4 The graphical representation of the research papers collection and analysis.

Akhloufi et al. [22] conducted a comprehensive study of UAV applications in wildland fire management, focusing on sensor technologies, fire perception algorithms, and operational strategies for both airborne and Unmanned Ground Vehicles (UGVs). They 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 [23] discussed various UAV types, obstacle detection, search and rescue techniques, and machine learning-based fire detection methods [24] but lacked detailed descriptions of DL-based approaches and comprehensive coverage of fire detection techniques.

In a survey [25], optical remote sensing networks for early fire and smoke detection were investigated, emphasizing traditional and deep learning methods across terrestrial, airborne, and satellite platforms. The survey identified strengths and weaknesses of existing fire detection frameworks but primarily focused on detection methods, omitting classification and segmentation techniques and detailed discussions on wildfire datasets. Roldán-Gómez et al. [26] proposed robotic technology-based UAVs for forest firefighting, focusing on detection and prevention with limited coverage of fire segmentation, classification using deep learning, and dataset details.A review [27] of vision-based UAV systems in wildfire detection discussed software algorithms and hardware implementations but lacked comprehensive coverage of UAV technologies, detailed wildfire datasets, and certain detection methods like reinforcement learning and fusion-based frameworks. Similarly, another survey [28] 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 [29] reviewed advancements in UAV-based technologies for wildfire management but did not sufficiently cover fire detection, monitoring, or UAV-based remote sensing systems. It also lacked explanations of DL models and datasets used in this context. In a related study [30] 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 [31] 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. [32] 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 UAV 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 assist the research community. **Tables 3, 2,** and **4** give the short summary of the application, Domains, details of deep learning models mentioned, dataset details, strength and limitation of the existing survey.

4 Deep learning Approaches

In the current era, artificial neural networks have given rise to deep learning and computer vision models. In order to manage massive amounts of tagged analog data, including text, audio, video, and photos, 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 hyper-parameters are critical, such as layer number, activation function types, and node connectivity. 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 output with labeled training data, error metrics are utilized to evaluate the efficiency of the model in supervised environments.

Table 2 Fire behaviors, factors, impacts, and solutions using UAVs.

Reference	Strength	Limitation
[22]	• 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.
[23]	• 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.
[25]	• 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.
[26]	• 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.
[27]	• 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.
[28]	• 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.
[29]	• 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.
[30]	• 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.
[31]	• 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.
[32]	• 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.
Our Paper	• Unmanned Aerial Vehicles, their types, and advantages in fire management. • Updated DL and computer vision-based techniques for fire detection, classification, and segmentation. • Fire datasets, types, and statistical information. • Fire statistical information and their impacts.	

Table 3 Existing survey paper summary of targeted area and application domain.

Ref	Appication			Domain				Deep learning Model							
	Det	Cls	Seg	Forest Fire	Urban Fire	Rural Fire	Vehicle Fire	CNN	Attention	ViT	RNN	GAN	Yolo	G.DL	ML
[22]	✓	-	✓	✓	-	-	-	✓	-	-	-	-	-	✓	-
[23]	✓	✓	-	✓	-	-	-	✓	-	-	-	-	-	✓	✓
[25]	✓	-	-	✓	-	-	-	✓	✓	-	-	✓	✓	-	✓
[26]	✓	-	-	✓	-	-	-	-	-	-	-	-	-	✓	-
[27]	✓	-	-	✓	-	-	-	✓	-	-	-	✓	✓	✓	-
[28]	✓	✓	✓	✓	-	-	-	-	-	-	-	-	-	-	✓
[29]	✓	✓	✓	✓	-	-	-	-	-	-	-	-	-	-	✓
[30]	✓	-	-	✓	-	-	-	✓	-	-	-	-	-	✓	✓
[31]	✓	✓	✓	✓	-	-	-	✓	-	-	-	-	✓	-	✓
[32]	✓	-	-	✓	-	-	-	✓	-	-	✓	-	-	✓	✓
Our paper	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-

Table 4 Existing survey paper summary of dataset types

Reference	RGB	Thermal	IR
[22]	✓	-	✓
[23]	✓	-	✓
[25]	✓	-	✓
[26]	-	-	✓
[27]	✓	-	-
[28]	✓	-	✓
[29]	-	-	-
[30]	-	-	-
[31]	✓	-	-
[32]	✓	-	
Our Paper	✓	✓	✓

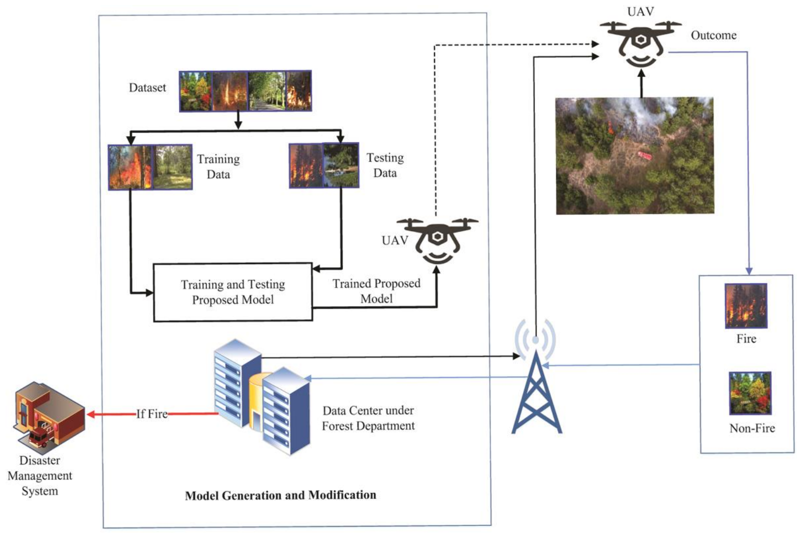

Fig. 5 Forest fire management system using CNN [33].

Deep learning models have significantly advanced UAV-based fire detection, classification, and segmentation [34, 35]. These models leverage sophisticated neural network architectures to process and evaluate large volumes of aerial data, enhancing the capabilities of UAV systems in fire management system. This section explores various deep learning and computer vision approaches tailored for UAV-based fire-related tasks, with references to recent studies in the field. **Table 5** gives the overall summary of the DL model for UAV-based fire classification detection and segmentation.

4.1 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. These models are excellent at recognizing spatial dependencies in images, which makes them perfect for classifying and identifying fire incidents from aerial video. Convolutional layers are used by CNNs to hierarchically extract features, which allows UAVs to identify and classify fires based on their visual properties. For example, Zhang et al. [36] and Liu et al.[37] 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 [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [33], [49], [50], [51], [52], [53], [54] and [55].The **Fig. 5** illustrates the use of CNN for fire management systems.

Challenges in CNN: In fire detection, classification, and segmentation, CNNs show batter performance as compared to traditional machine learning methods but still face some limitations and challenges, including a high rate of false negatives and false positives, high computational cost inhibiting real-time performance, environmental variability, overfitting, and trouble in detecting early-stage fires which is essential for vision-based fire management systems.

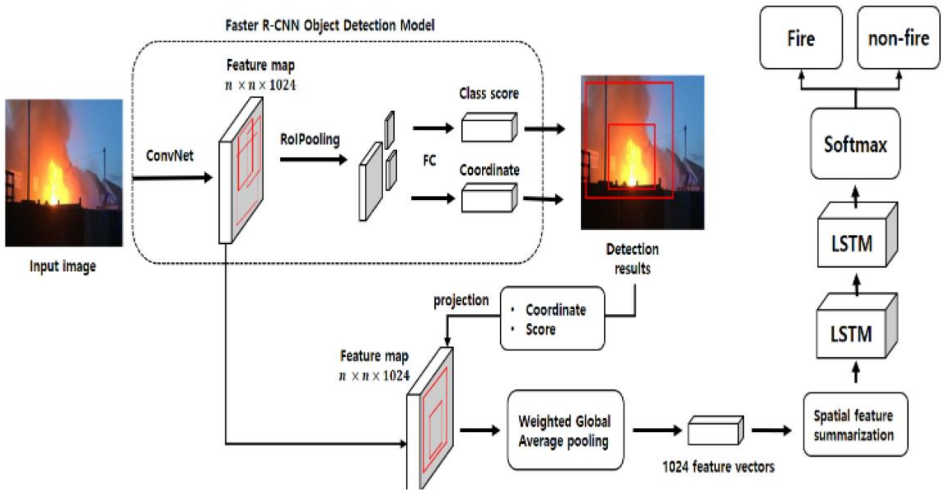

Fig. 6 Application of the LSTM network in fire detection, the RCNN is used to identify the suspected fire region and the LSTM gathers the local features inside the bounding boxes to decide a fire in a short time [56].

4.2 Recurrent Neural Networks (RNNs)

RNNs are useful for handling sequential data, which makes them appropriate for examining the temporal features of flames seen in UAV video streams. RNNs can simulate the evolution of fire behavior over time in UAV-based fire detection, using prior frames to forecast and categorize future states. This capacity is essential for comprehending the mechanics of fire spread and guiding in-the-moment fire management decision-making. Research [57] demonstrates how RNNs can be used to model the dynamics of fire using UAV imagery. Furthermore, other scholars have studied various RNN models for fire detection, classification, and, segmentation contributing to the development of UAV-based fire management [58], [59], [60], [61], [62], [63], [64], [65] [66], [67] and [68]. The **Fig. 6** 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 [56].

Challenges in RNN: RNNs are highly effective in the classification, detection and segmentation of fires 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 encounter challenges including difficulties with long-term dependencies, extensive training requirements, susceptibility to noise, restricted spatial feature extraction, potential for overfitting, and heightened architectural complexity.

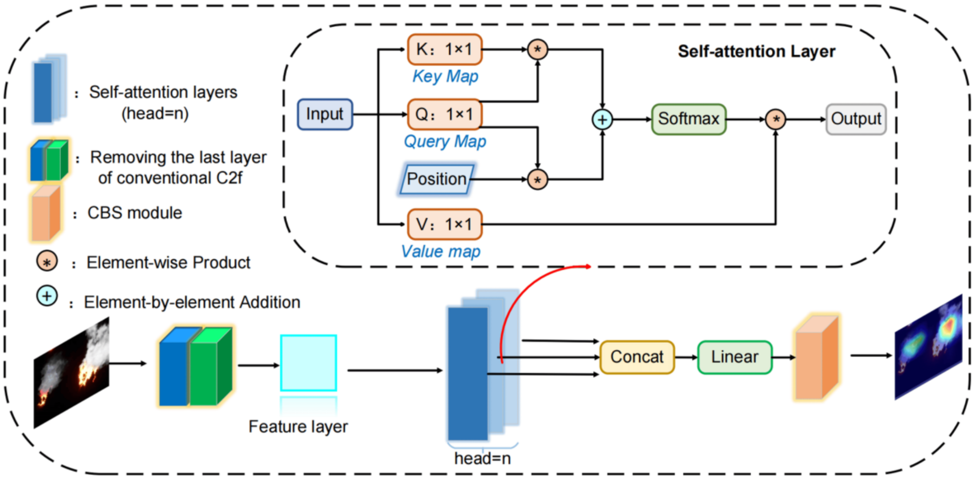

Fig. 7 LUFFD-YOLO model using an attention mechanism and hierarchical feature fusion techniques where GhostNetV2 is used to reduce parameters, an ESDC2f module for small fire detection, and an HFIC2f module to improve feature extraction and fusion [69].

4.3 Attention Mechanisms

Through the emphasis of attention mechanisms on important segments of the input data, CNN performance is improved [70]. Attention mechanisms can selectively concentrate on specific parts of an image or video frame in UAV-based fire detection and classification, which improves the model's capacity to detect important fire-related signals against diverse environmental backgrounds. This method works especially well for drone photos where smoke or foliage may partially hide flames. [**?**] have demonstrated how attention mechanisms with another deep learning model may be employed to 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 [71], [41], [72], [73], [74], [75], [76], [77] [78]. [79], and [80]. [69] present a proposed 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 the **Fig. 7**.

Challenges in Attention mechanism: The overall efficiency of the attention-based model over the CNN in fire classification, detection and segmentation is remarkable. Focused on the relevant feature, integrated contextual information, allowed dynamic feature selection, and reduced the computational costs through targeted processing. However, it has some limitations like high complexity, huge data for training, and reduced interpretability, risk of overfitting.

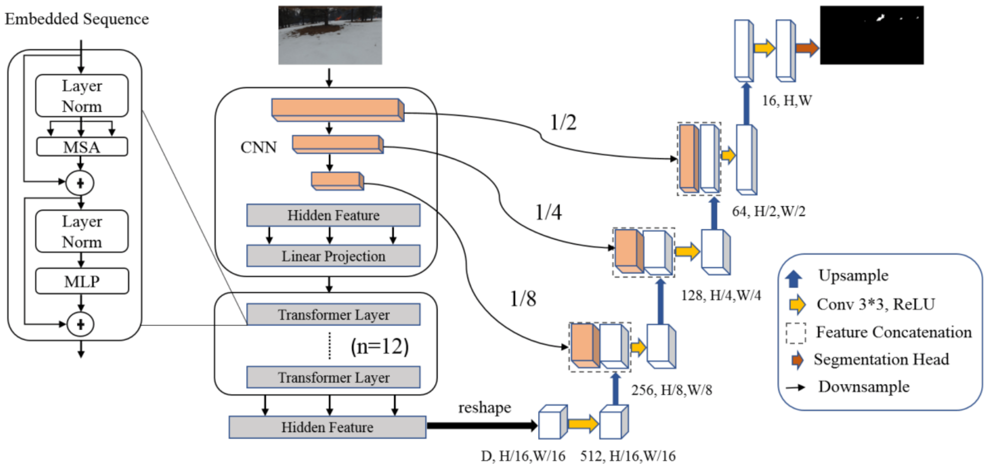

Fig. 8 The proposed TransUNet architecture using ViT [81].

4.4 Vision Transformers

As effective alternatives for CNNs in image analysis applications, vision transformers have gained popularity. These models identify, categorize, and segment flames based on global spatial linkages and contextual information using self-attention techniques to record long-range dependencies in input images. When managing large-scale UAV datasets and obtaining high accuracy in fire-related tasks, vision transformers are especially helpful. Vision transformers have been investigated by Dosovitskiy et al. [82] and Parmar et al.[83] for a different image analysis applications including UAV-based fire classification and detection. Additionally, other researchers have applied vision transfer based DL model for fire detection, classification, and segmentation using drones [84], [85], [86], [87], [88], [89], [90], [91],, [92], [93] [94], [95] [96], [97], [98] and [99]. The author modified and enhanced deep learning techniques for early fire detection by introducing a novel deep ensemble learning methodology that integrates EfficientNet-B5 and DenseNet-201 models 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[81]. The whole process is shown in the **Fig. 8**.

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 is crucial for vision-based fire management system using UAV. However, they have some challenges and limitations, including requiring a large dataset to train.

4.5 You Only Look Once (YOLO) Models

YOLO models are well known for their ability to recognize objects in real-time, which makes them appropriate for segmenting, classifying, and detecting dynamic fire in UAV video feeds [100]. These models enable fast detection and classification of fires with great temporal and spatial precision by processing full pictures or video frames in a single feedforward pass. When responding to fire accidents quickly, YOLO models perform a important role in applications. Saydirasulov et al. [101] and Shamta et al. [102] 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 [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115],[116], [117], [118], [119] and [120]. FSDF improves fire detection by combining YOLOv8 and VQ-VAE (Vector Quantized Variational Autoencoders) for image segmentation and fire detection [121]. The **Fig. 9** show the proposed framework of the FSDF. ***Challenges in YOLO:*** The YOLO shows the best performance in a vision

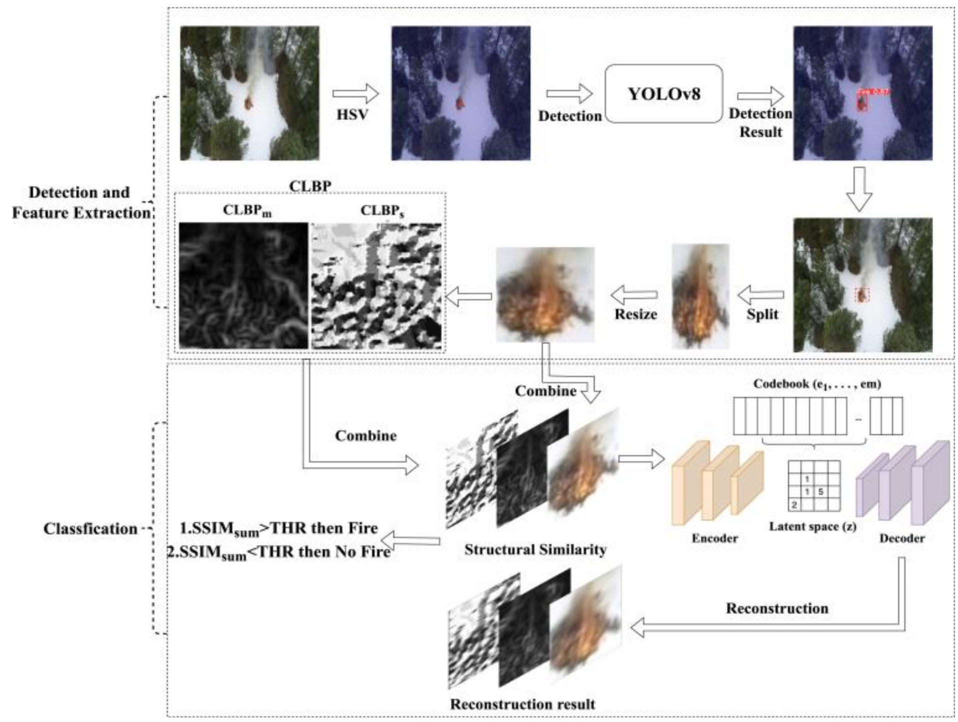

Fig. 9 The overall flowchart of the FSNet model using YOLOv8 [121].

based fire management system using UAV for fire detection, end-to-end training, ease of implementation and single-stage architecture. However, they have some limitations and challenges like handling class imbalances, differentiating overlapping objects, and effectively utilizing contextual information required large datasets for training.

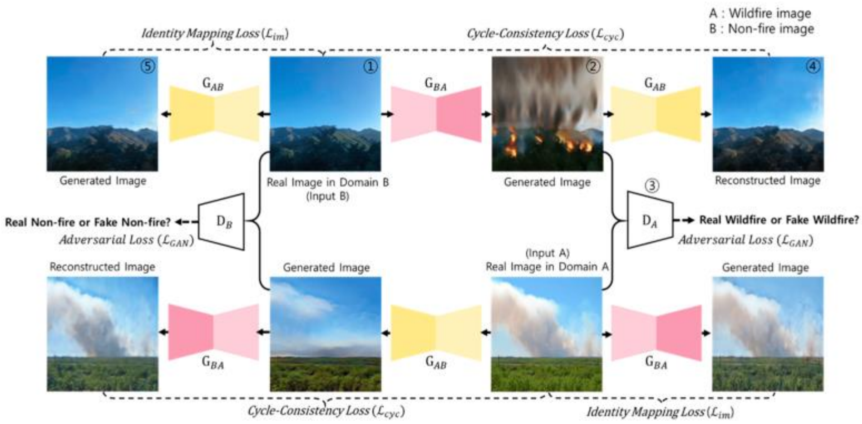

Fig. 10 The proposed DenseNet-based model addresses data imbalance by utilizing fire data generated by CycleGAN-generated [122].

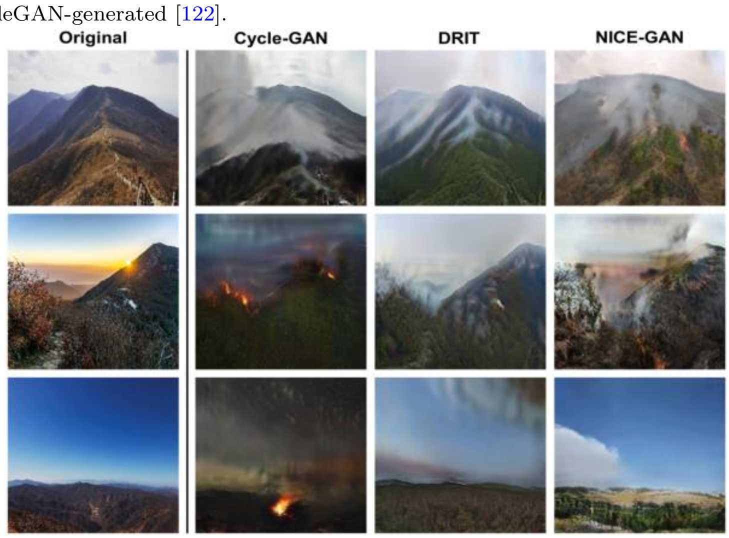

Fig. 11 Synthetic fire image generated by GAN [123].

4.6 Generative Adversarial Networks (GANs)

GANs are employed in UAV-based fire classification detection and segmentation for data augmentation and synthetic data generation. Training a generator network to generate realistic fire-related images and a discriminator network to differentiate between real and generated images, GANs can improve the robustness and generalization capabilities of fire detection and segmentation models. This approach mitigates issues related to limited and imbalanced datasets. The study by Kim et al. [124] 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 [125], [126], [127], [128], [123], [129], [130], [131], [132], [133], [134] [80] and [135]. In this study, the issue of dataset imbalance was addressed using CycleGAN and DenseNet-based models, demonstrating enhanced performance relative to pre-trained models [122] as illustrated in **Fig. 10** while **Fig. 11** shows a sample of the generated image of fire using GAN.

Challenges in GAN: 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.

Table 5: Overview of Deep Learning Models for UAV-Based Fire Detection, Classification, and Segmentation

Ref	Method	Categories		Ref	Method	Categories
[38]	VGG16, VGG19, InceptionV3	CNN		[49]	Intermediate Fusion VGG16 ECP-LEACH	CNN
[39]	FFireNet	CNN		[41]	EfficientNetB7-ACNet	CNN
[40]	Reduce-VGGNet	CNN		[42]	DCNN FireNet	CNN
[43]	X-MobileNet	CNN		[55]	UAV-Net	CNN
[44]	LwF-Inception-V3	CNN		[33]	CNN	CNN
[45]	BCN-MobileNet-V2	CNN		[46]	FireXnet	CNN
[47]	RBFN-AISR	CNN		[48]	SegNet	CNN
[59]	FNU-LSTM	RNN		[60]	RLSTM-NN	RNN
[61]	RNN	RNN		[62]	CNN-RCNN	RNN
[68]	CNN, RNN	RNN		[63]	ABi-LSTM	RNN
[64]	SA-EX-LSTM	RNN		[136]	RNN-WO	RNN
[58] [71]	DIFFDC-MDL ADE-Net	RNN Attention		[137] [41]	FSA ACNet	RNN Attention
[72]	DMFA-Fire	Attention		[73]	Lightweight Model Attention Base CNN	Attention
[74]	UAV-FDN	Attention		[75]	P-DenseNet-A-TL	Attention
[77]	FuF-Det	Attention		[78]	BranTNet	Attention
[76]	YOLOV5, Spatial attention, GTP	Attention YOLO		[69]	LUFFD-YOLO	Attention, YOLO
[81]	TransUNet-R50-ViT	ViT		[85]	FWSRNet	ViT
[87]	ViTM	ViT		[88]	TransUNet, MedT	ViT
[89]	FireViTNet	ViT, CNN		[90]	CT-Fire	ViT, CNN
[94]	FireFormer	ViT, CNN		[96]	Swin Transformer	ViT
[91]	STPMSAHI	ViT,CNN		[95]	Deeplabv3	ViT,CNN
[86]	FFS-UNet	ViT		[92]	Lightweight ViT, CNN	ViT,CNN

Ref	Method	Categories		Ref	Method	Categories
[94]	FireFormer	ViT,CNN		[93]	Modified VIT	ViT
[116]	FL-YOLOv7	YOLO		[117]	YOLO	YOLO
[138]	YOLO-CSQ	YOLO		[103]	YOLOv8, CNN-RCNN	YOLO
[115]	YOLOv5	YOLO		[121]	FSDF	YOLO
[105]	YOLOV8, LSTM	YOLO, RNN		[106]	YOLO3	YOLO
[107]	YOLOV8	YOLO		[108]	FFYOLO	YOLO
[109]	YOLOv8s	YOLO		[110]	Mask R-CNN and YOLO V5,7,8	YOLO
[111]	Yolov5	YOLO		[114]	YOLOV4, YOLOV5, YOLOV7, YOLOV8, and Faster RCNN	YOLO
[118]	YOLO	YOLO		[112]	Yolo-Edge	YOLO
[113]	YOLOv3	YOLO		[125]	FireDM	GAN
[126]	Generative AI	GAN		[127]	FIRe-GAN	GAN
[132]	GAN	GAN		[122]	CycleGAN	GAN
[135]	MGANs	GAN		[128]	ACGAN	GAN
[123]	GAN	GAN		[129]	IC-GAN	GAN
[130]	FGL-GAN	GAN		[131]	GAN	GAN
[133]	AttentionGAN	GAN		[139]	NDGANs	GAN

5 Datasets

Deep learning and computer vision techniques heavily depend on the quantity and quality of training data. Many SOTA datasets have been released as open access to help scientists develop more precise fire detection and classification models. These developments improve early fire incident detection, significantly contributing to protecting life and property. We will review various commonly used datasets for classification, detection, and segmentation. The table below summarizes their distinguishing characteristics, including data type and the number of samples. These datasets are crucial for the significant development in the field of fire detection. They provide a standard basis for evaluating and comparing the performance of different methods, driving the field toward solving more complex, practical, and challenging problems. A comprehensive overview of the commonly employed fire detection datasets is provided in the **Table** 6 along with its download links.

6 Research Trends, Challenges and Future Directions

6.1 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 system fire 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 from aerial imagery and video streams, offering greater accuracy and efficiency than traditional sensor-based systems.

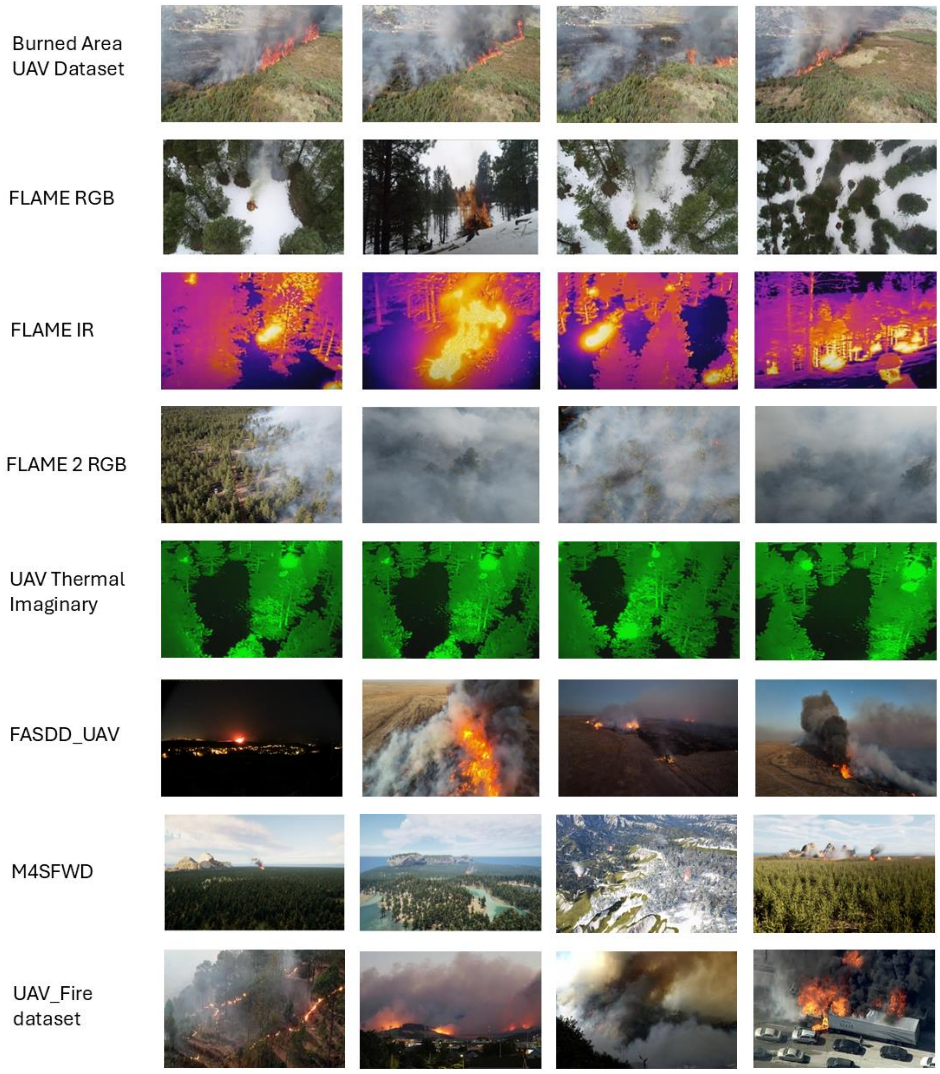

Fig. 12 Sample images collected from various UAV fire datasets

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 (GANs) have become increasingly 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

Table 6 Detection, Classification and Segmentation Datasets

Ref	Dataset name	Dataset Types	Total
[140]	Burned Area UAV dataset	RGB	22500
[141]	FLAME	RGB & IR	47992
[142]	FLAME2	RGB & IR	59451
[143]	FLAME3	RGB & IR	739
[144]	AIDER	RGB	1000
[145]	DC Lab fire dataset	RGB	10210
[146]	Wildfire dataset	RGB	1900
[147]	FireNet	RGB	502
[148]	Fire dataset	RGB	3225
[149]	Fire detection dataset	RGB	864
[150]	Furg fire	RGB	36702
[151]	Mivia's fire dataset	RGB	62690
[152]	Firefly	RGB	19273
[153]	Domestic fire dataset	RGB	5000
[154]	Fire dataset	RGB	999
[155]	DFire dataset	RGB	21000
[156]	Fire Smoke and Human Detector Dataset	RGB	9749
[157]	Fire-Detection- Polygon	RGB	3010
[158]	Activate Fire	Thermal	146,214
[159]	UAV Thermal Imaginary	Thermal	3980
[160]	UAVs-FFDB	RGB	15560
[161]	UAVs-Fire dataset	RGB	2096
[162]	D-Fire	RGB	21,000
[115]	FASDD UAV	RGB	53530
[163]	Corsican dataset	RGB	-
[69]	M4SFWD	RGB , GAN	35,526

models are particularly effective in capturing long-range dependencies within aerial images, which leads 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.

6.2 Challenges

Despite considerable advancements in technology, several challenges persist in the advancement of reliable deep learning and computer vision based fire detection systems: The primary challenge in drone-based fire detection is the lack and imbalance of datasets. Limited fire related imagery is available and existing datasets mostly consist of large fires resulting in insufficient representation of small or early-stage fires. Due to this imbalance, the deep learning models find it significantly difficult to detect smaller fires in real-time situations and limit their ability of generalization. Furthermore, environmental variability presents another considerable obstacle. Fire behavior can change dramatically depending on factors such as wind, fuel type, and atmospheric conditions. These fluctuations affect the appearance of fire, complicating the detection systems ability to maintain accuracy across different environments, particularly in the presence of smoke or complex backgrounds.

The real-time processing limitation imposed by UAVs limited computer power is another significant challenge. Models for fire detection, classification, and segmentation must function with the least amount of latency possible, however onboard systems are frequently unable to interpret high-resolution data in real-time. This calls for lightweight designs and model compression, both of which can occasionally reduce accuracy. Furthermore, minor fires or fires in the early stages of ignition are particularly challenging to detect since they are frequently low in intensity and may be hidden by surrounding conditions. It's still very difficult to get great sensitivity while reducing false alarms.

Enhancing detection accuracy, particularly under difficult circumstances requires the integration of multi-modal data such as RGB, thermal and LiDAR. It is still challenging to accomplish sensor fusion and the effective real-time processing of multi-modal data. It is necessary to integrate and synchronize disparate sensor outputs without incurring a large computing cost. The interpretability of the model is still an issue as well. Despite their effectiveness, deep learning models are frequently opaque, making it challenging to comprehend the reasoning behind their fire detection judgments. This lack of openness can make people less trusting of the system, especially in situations where fire detection is crucial.

Lastly, fire management systems still struggle with false positives and false negatives. While false negatives, in which real fires are overlooked, can cause delays in responses and worsen the effects of wildfires, false positives can result in needless measures like evacuations. Maintaining the dependability and efficiency of UAV-based fire detection systems requires finding the ideal balance between these two.

6.3 Future Directions

Future studies should concentrate on a few crucial areas to address the challenges in vision-based fire management systems using UAV. First, to increase the resilience of the model, improved fire datasets are essential. In order to train models that can manage the complexity and diversity of the actual world, it will be necessary to create large-scale, diversified, and well-annotated datasets that include a range of fire intensities, habitats, and weather conditions. Investigating effective deep learning architectures for UAV deployment is also necessary. Real-time processing on UAVs with limited resources is now possible thanks to advancements in techniques like quantization and pruning, as well as lightweight and energy-efficient models like MobileNet, EfficientNet, and NAS-based architectures.

In terms of improving detection accuracy, adaptive and context-aware models should be developed. These models should dynamically adjust to changing fire conditions, such as shifts in fire intensity or wind patterns, to ensure the highest level of detection performance across diverse environments. Furthermore, interdisciplinary collaboration between experts in environmental science, computer vision, and aerospace engineering is essential to develop a more effective vision-based fire management system. By fostering collaboration among researchers, government agencies, and industry stakeholders, advancements in UAV-based fire monitoring can be accelerated.

Finally, the integration of Vision-Language Models (VLMs) could revolutionize UAV-based fire detection. VLMs, which combine visual understanding with natural language processing, can enhance the system's ability to interpret contextual information. For instance, VLMs could analyze real-time captions or voice commands from fire-fighting teams and integrate textual descriptions of fire behavior (e.g., "fast-spreading fire near the forest edge"). This synergy between visual and textual data would enable UAV systems to better understand and respond to complex fire scenarios, ultimately improving vision-based fire management.

7 Conclusion

In recent years, the increased intensity and frequency of fires have emphasized the need for effective vision-based fire management systems. This survey has shown that advancements in UAV technology, combined with artificial intelligence and computer vision algorithms, offer significant improvements in vision-based fire detection systems for fire detection, classification and segmentation. The autonomy, ease of deployment, and cost-effectiveness of UAVs make them ideal for integrating into fire management strategies. By reviewing various UAV-based fire management systems and emphasizing the application of deep learning approaches, this paper highlights the significant progress made in applying CNNs, RNNs, transformers, and hybrid architectures for fire-related tasks. However, challenges such as dataset limitations, real-time processing constraints, and environmental variability still hinder widespread adoption. Addressing these challenges requires continued research into efficient model architectures, self-supervised learning techniques, and edge AI deployment for UAV-based fire management systems.

Additionally, we have compiled detailed information on publicly available fire datasets, which will facilitate further research and development in this field. Future work should focus on improving dataset diversity, developing lightweight models for real-time processing, and leveraging multi-modal sensor fusion to enhance detection accuracy. Moreover, interdisciplinary collaboration will be key to driving innovation in this domain. In general, artificial intelligence-powered UAV-based fire detection holds immense potential to revolutionize vision-based fire management and disaster mitigation. Continued advancements in AI-driven fire detection will pave the way for smarter, more resilient fire surveillance systems, ultimately safeguarding lives and natural resources from the growing threat of fires.

8 Acknowledgments

This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2020R1A6A1A03038540) and by the institute of Information & communications Technology Planning & Evaluation (IITP) under the Metaverse support program to nurture the best talents (IITP-2023-RS-2023-00254529) grant funded by the Korea government(MSIT).

Declarations

- **Funding:** This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2020R1A6A1A03038540) and by the institute of Information & communications Technology Planning & Evaluation (IITP) under the Metaverse support program to nurture the best talents (IITP-2023-RS-2023-00254529) grant funded by the Korea government(MSIT)

Table 7 List of Abbreviation

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	ou 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

- **Conflicts of Interest:**The authors declare no conflicts of interest to report regarding the present study.
- **Data availability**:$https://github.com/SufyanDanish/Fire_survey$
- **Code availabitity:** Not applicable.
- **Author contribution:** Conceptualization, methodology, statistical analysis, data analysis: S.D, S.U, and J.P ; literature review, discussion, writing-original draft preparation, data downloading: S.D., H.K.S, M.A.K and Y.Z; writing-review and editing: L.M.D, Y.Z, M.A.K, J.P, and H.K.S ; visualization: S.D and S.U; supervision: H.M , J.P All authors read and approved the final manuscript.
- Ethics declarations

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