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A review on early wildfire detection from unmanned aerial vehicles using deep learning-based computer vision algorithms

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ABSTRACT

Wildfire is one of the most critical natural disasters that threaten wildlands and forest resources. Traditional firefighting systems, which are based on ground crew inspection, have several limits and can expose firefighters' lives to danger. Thus, remote sensing technologies have become one of the most demanded strategies to fight against wildfires, especially UAV-based remote sensing technologies. They have been adopted to detect forest fires at their early stages, before becoming uncontrollable. Autonomous wildfire early detection from UAV-based visual data using different deep learning algorithms has attracted significant interest in the last few years. To this end, in this paper, we focused on wildfires detection at their early stages in forest and wildland areas, using deep learning-based computer vision algorithms to prevent and then reduce disastrous losses in terms of human lives and forest resources.

1. Introduction

Forests play several crucial roles in our lives providing various resources. They are considered as the lungs of the planet, where they purify the air by providing Oxygen (O_2) and reducing the amount of Carbon Dioxide (CO_2). Also, they provide habitats for a large number of animals and can be used as a wind-blocking wall to protect agricultural crops. Besides, they purify water by cleaning it from most pollution contributors [7,85]. Forests provide a significant number of jobs and increase the incomes of the countries, thus, improving their economy.

In recent years, a lot of forests and wildlands have been burned and destroyed. Wildfires are considered as a natural uncontrolled disaster that represents a serious threat to countries economy destroying, almost every year, millions of acres of land causing enormous losses in humans lives, vegetation canopy, and forests resources [18,61]. Moreover, they have a bad impact on agriculture activities and crop productivity due to the dryness of the soil and the burning of agricultural crops near the inflamed areas. Several countries have a long history with strong and destructive wildfires, especially United States, Australia, Brazil, and Canada [30,31,38,63,93]. The recent Australian wildfire is the most devastating fire in 2020 causing a lot of losses, including more than 1500 houses destroyed, around half-million animals and 23 people died, and more than 14 million acres burnt [17,62]. Other destructive wildfires were occurred leaving huge losses, such as the 2018s' California fire and Amazon rainforest fire in 2019, which burnt millions of acres of lands [47,93]. According to Vardoulakis et al. [81] and Bo et al. [14], climate change is the fundamental cause behind the aforementioned wildfires.

We could have avoided a lot of damages and losses just by our consciousness. Because human activities are considered as the main reason for wildfires occurrence, where around 85% of occurred fires between 1992 and 2015, in the United States of America, were caused by human beings, and only 15% were occurred due to natural phenomena like lightning and climate change [54]. This could explain the reduction of occurred wildfires since the emergence of the COVID-19 pandemic, where a total lockdown was applied in a large number of countries reducing human activities [69]. Also, early wildfires detection could be a crucial parameter to reduce their risks and losses and can help firefighters to extinguish the fire at its early stages.

In order to minimize the loss of our forests and their resources, we should come up with new techniques to monitor wildfires, and change our fire management systems. The time spend between fire detection and alarming the concerned authorities is the most important factor that could reduce wildfires risks. Therefore, early

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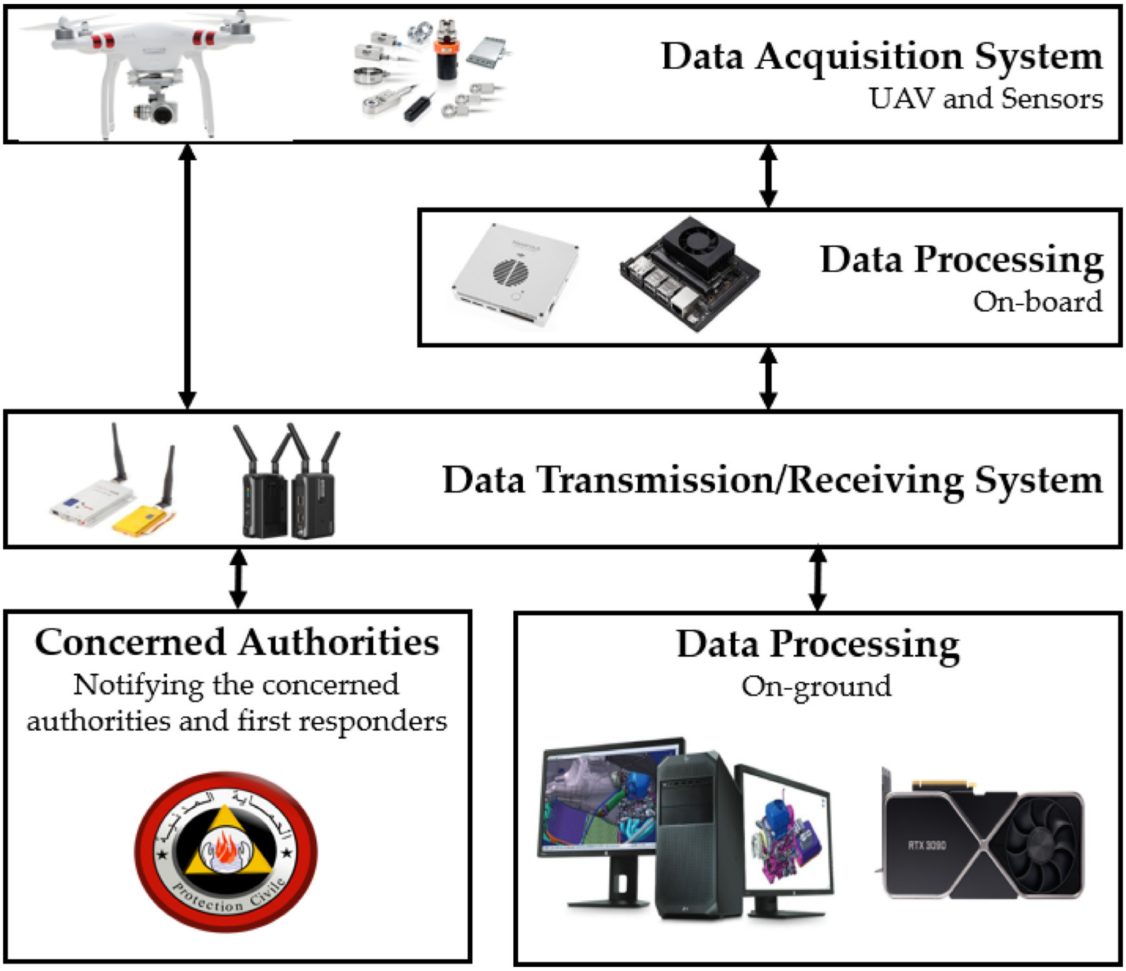


Fig. 1. UAV-based remote sensing system flowchart for forest fire detection and concerned authorities' notifications.

detection of wildfires is fundamental to ensure that fire remains manageable [42]. Several advanced techniques were proposed over the years to help official authorities and first responders in identifying wildfires at their early stages and allocate the right resources to extinguish them. Most of them are based on terrestrial and spatial technologies, including watchtowers equipped with various sensors and satellite platforms. However, these methods are facing several limitations that could reduce fire detection performance. Watchtowers suffer from several limitations such as their limited range of view, and high construction cost. Also, they are very exposed to destruction by the fire causing additional costs. Similarly, satellites provide a very large field of view. However, they have some limitations in terms of cost, flexibility, and spatial/temporal image resolution making fire spot detection at the right time very difficult [3,89].

Recently, UAV-based early wildfire detection and warning systems that integrate various remote sensing technologies and deep learning-based computer vision techniques have emerged as promising technologies for wildfire monitoring [47,64,89] (Fig. 1). Instead of sending ground crews to dangerous environments or using different classical techniques that have many limitations in terms of cost and efficiency, UAVs equipped with visual remote sensing technologies were proposed as new and promising technologies that could help for wildfires monitoring and fighting. Combining UAVs and deep learning architectures could be very useful to detect fires at their early stages and send valuable information to the concerned authorities using efficient communication technologies, including LoraWAN and 5G [43,49]. In the last few years, several deep learning-based fire and smoke detection algorithms were proposed achieving impressive results. Most of the developed detection algorithms are based on Convolutional Neural Networks (CNNs), including different versions of YOLO [15,65–67], R-CNN and its variants [33,34,68], SSD [59], U-Net [70], and DeepLab [25]. Other deep learning architectures also can be used for fire detection, such as Long Short-Term Memory (LSTM) [41], Deep Belief Network [40], and Generative Adversarial Network (GAN) [35]. However, these algorithms demand powerful hardware to be executed in real-time. Therefore, the recent technological advances in terms of processing power, sensing devices, and development software are making wildfire detection using powerful deep learning-based computer vision algorithms on UAVs platforms possible. Nowadays, UAVs can detect, localize and notify the concerned authorities in just a small amount of time.

In this study, we aim to provide the most reliable techniques, based on deep learning techniques and UAV technologies, that could help in fighting wildfires at their early stages and before they become uncontrollable. The contributions of this paper are as follow:

- Presenting the influence of the recent UAV-based visual remote sensing technologies and Deep Learning-based computer vision algorithms to improve firefighting by detecting fires in forests and wildlands at their early stages.
- Helping researchers and firefighters to decide what remote sensing and what algorithms they should use according to the

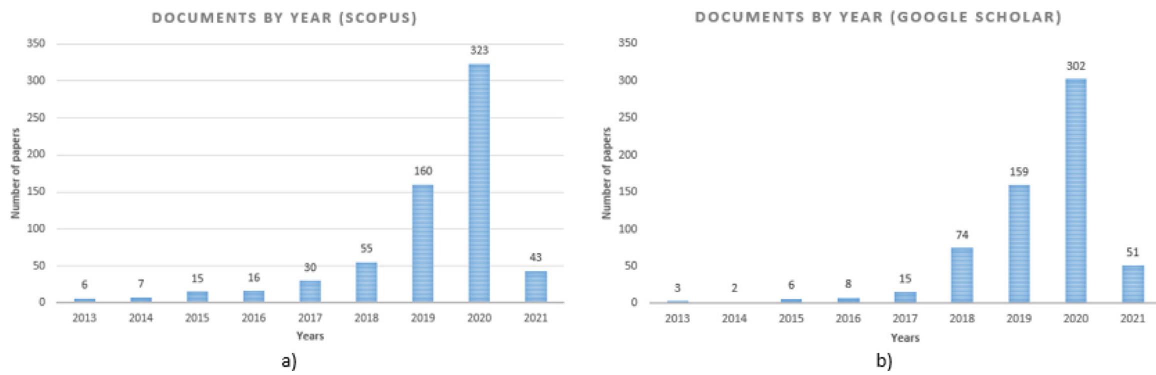


Fig. 2. Number of published documents by year from 2013 to early 2021 on the topics related to early wildfire detection, UAV imagery, and deep learning algorithms (a) from SCOPUS database, (b) from Google Scholar database.

structure of the covered areas and the mission they aim to achieve.

- Discussing different UAV-based fire/smoke detection difficulties, including the variations of smoke/fire appearance, the chosen architecture, among others.

In the literature review process, we performed a systematic search on Scopus and Google Scholar databases with the keywords "deep learning", "wildfire", "forest fire", "smoke", "drone" and "UAV". We obtained a total of 670 papers on Scopus and 620 papers on Google Scholar that are relevant to the topic of early wildfire detection from UAV imagery using deep learning algorithms. Next, we manually selected the most relevant papers to our topic and exclude unrelated ones by applying an inclusion/exclusion criterion, where we get a total number of around 40 strongly related articles. Fig. 2 shows the number of published papers by year in this field from 2013 to early 2021, which are dramatically increased since 2018. The statistics in Fig. 2 represent the number of papers that target wildfire detection using UAV technologies whether using deep learning algorithms or other techniques. However, in this paper, we reviewed only the papers that use both UAVs and Deep Learning algorithms.

Fig. 3 shows the number of published papers for 10 countries (from the Scopus database), where the United States takes the lead with more than 194 scientific papers from 2013 to early 2021 followed by China with 146 papers.

The rest of the paper is organized as follows. In Section 2, we present different visual remote sensing technologies used for wildfire detection in the review methodology. In Section 3, we present different deep learning algorithms used to detect wildfires from images/videos collected through cameras mounted on UAV platforms. We have dedicated Sections 4 and 5 to discussions and conclusions.

2. Vision-based remote sensing technologies

Visual data from UAV-based remote sensing technologies provide valuable information to those fighting destructive wildfires. This information could be employed to save human lives and forest resources. Thus, it could be used to control fire spreading by identifying the most vulnerable regions. Moreover, search and rescue operations could be achieved to help trapped persons in the middle of the forests and save animals while keeping firefighters safe. To this end, several studies have targeted early fire detection in wildlands and forests from visual data collected through different platforms equipped with different types of cameras and visual sensors.

There are three main remote sensing-based methods to detect fire/smoke in forest and wildland areas. Satellites are considered the most used remote sensing technology for many forestry applications. Several studies have adopted satellite imagery to detect wildfires and fire smoke in forest regions, which could help to reduce their risks [1,22,32,50]. However, satellite-based images are not the best solution for early forest fire detection due to the low spatial resolution making small fire spot detection very difficult or impossible in most cases [56]. The satellites' temporal resolution is another major limitation that restricts forest monitoring efficacity, where they are not always available to provide continuous information about the forest state [56,61]. Moreover, cloudy and bad weather conditions prevent satellites to collect clear data of the forests [11,27,80].

Advanced high-resolution fixed cameras mounted on-ground are other available solutions to monitor forest fires. Terrestrial early wildfire detection systems are mainly based on optical/thermal cameras that are mostly mounted on watchtowers. These methods were adopted by many researchers and authorities to detect forest fires, such as in Govil et al. [36]. Most of the time, terrestrial techniques combine visual sensors with other types of sensors, like humidity, smoke, and temperature sensors, to improve the fire/smoke detection performance. These sensors may work very well in a close environment, like buildings, but they suffer in open spaces like forests because they require to be in proximity to the fire or smoke. Moreover, they are not able to provide some valuable information, such as the fire size and location. Similarly, on-ground cameras, including those mounted on watchtowers, can cover only limited areas and need to be placed carefully to ensure adequate visibility. Therefore, we need to install a very large number of sensors to cover the whole forest area making it very expensive.

Unmanned Aerial Vehicle (UAV) platforms have emerged as new efficient technologies that combine satellites and on-ground systems advantages. They can cover larger areas than terrestrial techniques and can provide images with higher spatial and temporal resolutions than satellites. Moreover, their operational cost is much lower than satellite and terrestrial technologies. Thus, UAVs equipped with adequate remote sensing technologies are considered the best choice for wildfire disaster monitoring. UAVs use different types of sensors to collect valuable information about the forest state. Using the right information in the right way could help UAVs to identify fire areas and inform the concerned authorities at the right time allowing a reduction in wildfires losses and risks. In this section, we aim to present the most used cameras for forest fire detection, monitoring, and fighting.

2.1. Optical cameras

The majority of remote sensing cameras mounted on UAV platforms can acquire only the visible bands that range from around 400 nm to about 700 nm, we call them optical (or RGB) cameras.

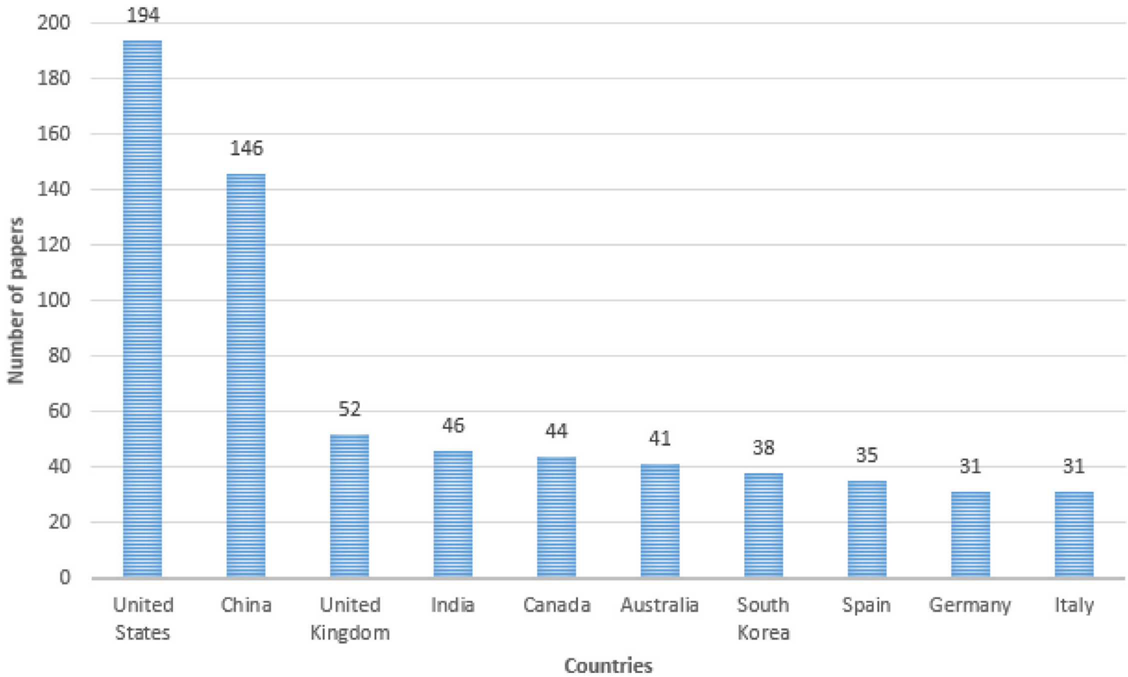


Fig. 3. Number of published documents by country from 2013 to early 2021 on the topic of early wildfire detection from UAV imagery using deep learning algorithms (from SCOPUS database).

Their large use is due to many factors such as low cost, high spatial resolution, ease to use, and lightweight [27]. These pros making optical cameras very suitable for small-size UAVs, especially for low-cost forestry applications. They could be helpful for object detection from UAV imagery achieving various ecological tasks, including fire/smoke identification. UAVs equipped with optical cameras are capable of capturing high-resolution images that could be used to detect wildfires smoke and flame in their early stages easily, especially when we have cameras with good visibility characteristics [11,29,36]. However, most of these cameras have a limited field of view, which obliges us to use more than one camera or take many photos to cover a larger field of view [11].

Recently, other optical cameras were developed to overcome some limitations of conventional optical cameras. The authors in Barmpoutis and Stathaki [10], Barmpoutis et al. [11] adopted a newly introduced CMOS 360° optical camera mounted on a UAV platform to capture unlimited field of view images for early forest fire detection. Converting the equirectangular projections, acquired with the 360° cameras, to stereographic projections could reduce the false detection of wildfires, where the region of interest location is always at the center of the image [11]. In 2009, Microsoft released another special type of optical sensor, called RGB-D cameras [86], to solve the problem of depth information from 2D images [83]. This type of camera combines an RGB camera with a depth sensor to capture 2D images and calculate the distance between the targeted object and the UAV. RGB-D camera was adopted in Novac et al. [64] to identify the forest fire properties, such as its height and exact size. However, optical cameras still facing several issues, where it is impossible to detect wildfire smoke at night time and very hard to detect wildfire flames in dense forests that could be hidden by high trees. Moreover, visible camera sensors are very sensitive to environmental conditions, such as sunlight angle, clouds, and shadows.

2.2. Thermal infrared cameras

Recent advances in camera sensors technologies helped to develop robust lightweight thermal cameras with competitive prices, which give us the possibility to install such impressive cameras on UAV platforms easily. They are capable of capturing different levels of temperature. Nowadays, thermal camera technologies have been widely used as a new solution for wildfire monitoring to overcome some limitations of optical cameras. They are able to measure the thermal radiation emitted by the object making them more suitable than optical cameras for early fire detection. Optical cameras can confuse fire with other similar objects that have the same color and cannot detect hidden fire flames in dense forests. However, thermal cameras turn UAVs into an impressive tool that is independent of light and able of detecting covered wildfire flames through the thermal radiation emitted by the fire within Middle Wavelength InfraRed (MWIR) and Long Wavelength InfraRed (LWIR) spectral ranges (Fig. 4) [9,75]. Sousa et al. [75] explore the effectiveness of thermal images, acquired from static and UAV platforms, in detecting fire outbreaks. The authors in Shamsoshoara et al. [72] used a DJI Matrice 200 equipped with an infrared camera to collect thermal heatmap providing a valuable heat distribution dataset. Thus, it could be helpful to train a deep learning model to detect hidden flames and to improve early forest fire detection due to the thermal images' characteristics. Thermal cameras mounted on UAV platforms could solve several limitations of optical cameras, but they come with their challenges and limitations, including thermal distance problems and low spatial resolution [89,94].

Combining data gathered from thermal and optical, or other types of sensors, is another solution for accurate early wildfire detection. Recently, sensor fusion has emerged as one of the most important topics that are widely used in different fields, including autonomous vehicles, agriculture applications, and even wildfire detection from UAV platforms. This discipline can improve the early wildfire detection accuracy by combining the information collected through multiple types of sensors. Benzekri et al. [13] adopted a sensor fusion method using a network of wireless sensors to measure different parameters, including temperature and the carbon monoxide amount. The collected data were processed using deep learning algorithms to decide whether a for-

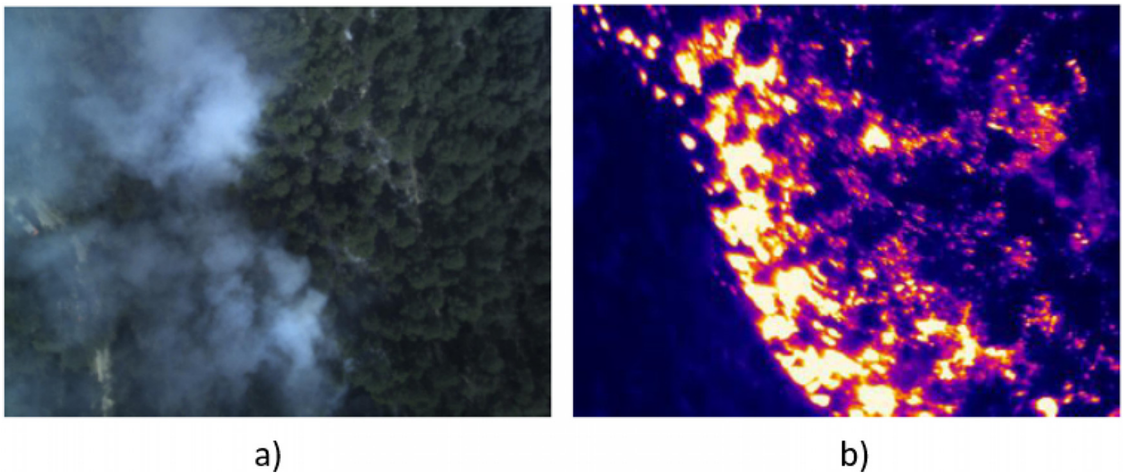


Fig. 4. (a) Optical camera-based image, (b) Thermal camera-based image [82].

est fire was identified or not. To reduce the false detection rate, they used a UAV platform to survey the wanted regions. Also, in Kanand et al. [49], the authors used a VTOL platform hovering on top of the forest, which is equipped with optical and thermal cameras for wildfire detection. The RGB camera was used for smoke detection in the daytime while the thermal camera was adopted to identify hotspots at night-time.

3. UAV and deep learning-based computer vision algorithms for early wildfire detection

Computer vision is the science that gives machines, including UAVs, the ability to perceive their environment visually and respond to it according to the targeted mission. It is inspired by the biological visual system, where the eyes are replaced by camera sensors and the brain by computer vision algorithms, which allow UAVs to extract meaningful information from digital images/videos acquired through cameras. There are two main types of computer vision techniques adopted for wildfire detection. The first one is traditional machine learning-based methods, which are based on handcrafted feature extraction and color transformations [9,44]. However, manual feature selection and engineering take a very long time and need domain experts to select the valuable features that can make machine learning algorithms more efficient. Also, these techniques suffer when we target complex problems, such as fire detection in dense forests with a cluttered background. The second techniques are based on deep learning algorithms, which can extract relevant and strong features automatically. Computer vision is not a new topic, and it has been researched for many decades. However, it achieved state-of-the-art results just recently with the advance of Convolutional Neural Network (CNN) architectures and new hardware (GPUs) and software (Tensorflow, PyTorch, Keras) technologies. Today, deep learning architectures are revolutionizing the world enabling machines to accomplish difficult and complex tasks that were impossible a few years ago. Thanks to the recent advances in computing speed and sensing technologies, these architectures achieve state-of-the-art results in the most complex problems of image processing and computer vision applications, especially CNN architectures. However, computer vision techniques are facing various difficulties and challenges that could affect their performances. Among these challenges, we find viewpoint variation, changing light conditions, flame/smoke appearance variations, scale issues, occlusion, clutter and dense environments, object class variations, to name a few. Even with all of these difficulties, recently, deep learning-based computer vision techniques have achieved impressive results in many fields, including vehicle detection [12], facial recognition [39], self-driving cars [79], plant disease identification [71], among others.

Recently, Unmanned Aerial Vehicles (UAVs) are being increasingly used in various forestry applications, including forest scouting, search and rescue operations, forest resources surveying, and forest fire fighting. They could be one of the most powerful innovative tools to solve such problems. Therefore, the choice of UAVs platforms over other available technologies is due to several properties like low cost, high flexibility, flying at different altitudes, and ease to use. Moreover, thanks to recent advances in hardware and software technologies, it is possible to process heavy and complex visual data on the UAV itself. In recent years, fire and smoke detection, in wildlands and forests, using deep learning-based computer vision techniques have attracted a lot of interest. Two main visual features can help UAVs to identify wildfire sources autonomously using deep learning algorithms, which are flame and smoke. Flame and smoke are the most important visual features for early and precise wildfire detection. Some studies have focused on fire detection through flame [37,64]. Other studies have targeted fire detection by smoke [2,87], which seems more suitable for early detection, because the fire in its early stage could be hidden, especially in dense forests [42]. Recently, many studies have focused on detecting both, flame and smoke, at the same time to overcome some limitations when we target only one object (flame or smoke). Early wildfire detection using UAV and deep learning algorithms could be achieved through three main ways: wildfire image classification, wildfires detection based on object detection algorithms, and semantic segmentation-based wildfires detection. However, these techniques need a very large amount of data and high processing power in the training process. Also, we need to choose the right architecture carefully and how we can train it with the right data. Therefore, in this section, we aim to present the state-of-the-art deep learning algorithms adopted for the early identification of wildfires.

3.1. Image classification-based methods

Image classification-based methods rely on classifying input images into different categories, including images that contain fire instances or not (Fig. 5). Deep CNN architectures are the best choice for image classification task [92] due to their ability to extract high representative features from 2D images. Over the years, different CNN architectures were developed that achieved an accuracy higher than human level. Recently, several studies have adopted CNN to classify UAV-based forest fire images. The authors in Srinivas and Dua [76] proposed applying a basic CNN

Fig. 5. Example of wildfire identification using image classification task [76].

Table 1
Studies targeting early wildfire detection using deep learning-based image classification.

Ref	Method	Flame/Smoke	Camera type	Hardware	Accuracy (%)	FPS	Processing speed (s)
Lee et al. [56]	AlexNet	Flame/Smoke	RGB images	GTX Titan X	94.8	/	7.7
	GoogLeNet				99		11.6
	VGG-13				86.2		10.2
	Modified GoogLeNet				96.9		10
	Modified VGG-13				96.2		7.9
Zhang et al. [87]	SVM-RAW (Train set 1)	Flame	RGB images	/	92.2	/	0.16
	SVM-RAW (Train set 2)				74		
	SVM-Pool5 (Train set 1)				95.6		/
	SVM-Pool5 (Train set 2)				89		
	CNN-RAW (Train set 1)				93.1		2.1
	CNN-RAW (Train set 2)				88.6		
	CNN-Pool5 (Train set 1)				97.3		1.4
	CNN-Pool5 (Train set 2)				90.1		
Srinivas and Dua [76]	AlexNet-like CNN	Flame	RGB images	Tesla K80	95	/	
Chen et al. [26]	CNN-9	Flame/Smoke	RGB images	/	53	/	/
	CNN-9 (hm + na)				61		
	CNN-17 (hm + na)				86		
Novac et al. [64]	VGG-16	Flame	RGB-D	/	99.74	1	/
	ResNet-50				99.38	16.4	
	Inception v3				99.29	13.7	
	DenseNet				99.65	14	
	NASNetMobile				98.94	12	
	MobileNet v2				99.47	19.2	

architecture to classify forest fire images. They stacked convolutional and pooling layers in an AlexNet-like architecture followed by flattening and two dense layers, where they used a sigmoid activation function in the last one for binary classification. Applying such architecture, they achieved an acceptable accuracy of 95% (Table 1). Similarly, the authors in Lee et al. [56] adopted five different CNN architectures to classify images captured by UAVs into fire and non-fire classes. The used architectures are AlexNet [55], GoogLeNet [78], VGG-Net [73], and modified versions of GoogLeNet and VGG-Net, where they achieved an accuracy of 94.8%, 99%, 86.2%, 96.9%, and 96.2%, respectively (Table 1). Chen et al. [27] proposed a CNN-based wildfire detection at its early stage using a hexa-copter equipped with Sony A7 optical camera. Before feeding the images to the developed CNN model, these images passed through some preprocessing techniques like histogram equalization and non-linear filters to enhance the data quality and reduce noises. The proposed model is capable of classifying fire and non-fire scenes using a nine layers CNN achieving good results. However, they trained and tested the developed model on a simulated dataset, which could not fit with real scenarios. Chen et al. improved their work in Chen et al. [26] by adopting two 17 layers CNN architectures, one for smoke images classification and the second for flame images classification. Also, Zhang et al. [87] proposed a vision-based method to classify and give the exact localization of forest fires. This method can be mounted on UAV platforms to perform forest fire detection. They adopted two CNN architectures where the first CNN tends to classify the whole input image as fire or not while the second tends to localize the fire. However, image classification-based methods are the most basic applications that could suffer to classify images that contain only small spots of fires, making them not suitable for wildfire early detection.

3.2. Object detection-based methods

Unlike image classification, object detection algorithms are capable of identifying and localizing the object of interest in an input image/video by drawing a rectangular bounding box around the targeted object [74], which is in our case fires' flames and smokes (Fig. 6). However, compared to image classification task, object detection algorithms require more computational resources for both training and inferencing. Several object detection algorithms were proposed over the past few years achieving very good performances. These algorithms can be divided into two principal groups, which are two-stages and single-stage detectors. The two-stages, or region-based, algorithms consist of two main parts. Regions of interest that may contain fire instances are generated in the first stage, using the selective search or RPN, while the second part is responsible to classify each of these regions depending

a) b)

Fig. 6. Example of object detection operation; (a) Flame and smoke detection, (b) Flame detection [42].

on the occurrence or not of the targeted object. The R-CNN family are the most known and efficient two-stages detection algorithms. On the other hand, single-stage detectors skip the region proposal generation step and process the input image in one single pass providing higher detection speed while keeping remarkable accuracy. Among the most efficient one-stage detectors, we cite different YOLO variants, SSD, and RetinaNet [58]. Other object detection algorithms that could achieve good results can be used to detect forest fires were recently proposed. Zhifan Zhu and Zechao Li proposed a Local and Mid-range feature Propagation (LMP) object detection algorithm to detect objects from videos [91]. Zhou et al. [90] proposed a CAD framework for real-time object detection. Also, a Facebook research team developed an object detection algorithm called DETR (DEtection TRansformer) [21], which is based on a transformer network providing impressive results. These algorithms are very effective to achieve object detection tasks, including fire detection. However, in this paper, we only reviewed the object detection algorithms that are used in the literature to detect wildfires.

The authors in Kinaneva et al. [52] and Barmpoutis et al. [11] showed the great results achieved using Faster R-CNN algorithms to detect both smoke and flames in UAV imagery. As shown in Table 2, the Faster R-CNN used in Barmpoutis et al. [11] provides the second-best results among the tested object detection algorithms achieving an F1-Score rate of 72.7%, 70.6%, and 71.5% for flame, smoke, and both flame and smoke, respectively. SSD algorithm was adopted in many studies providing acceptable results for identifying forest fires, but it is considered as the least effective detector for wildfire detection application as shown in the works of [2,11,84] as presented in Table 2. From 2016 to 2018, Redmond developed three versions of the most effective and used object detection algorithms that provide the best tradeoff between accuracy and speed. YOLO was adopted in several wildfire-related studies. Alexandrov et al. [2] adopted five different techniques to detect forest fire smoke from UAV-based RGB imagery, where three of them are based on deep learning techniques, including Faster R-CNN, SSD, and YOLOv2. Among these detectors, the YOLOv2 detector achieved impressive results providing the best inference speed (FPS = 6), precision (100%), recall (98.3%), F1-score (99.14%), and accuracy (98.3%) (Table 2). YOLOv3, YOLOv3-Tiny, YOLOv3-SPP, YOLOv4, CSResNext50-Panet-SPP, and SSD-ResNet were adopted in Yadav [84] for wildfire detection. YOLOv3 provides the best mean Average Precision (mAP) of 89.5% on the emergency fire dataset while YOLOv3-SPP achieved slightly better mAP of 97.81% than YOLOv3 (97.6%) on the single flame dataset. However, YOLOv3-Tiny achieved the lowest inference speed of around 0.2 s making it more suitable for real-time operations. Similarly, to identify wildfires at their early stages, the authors in Jiao et al. [46], 47] proposed a modified version of YOLOv3-tiny and YOLOv3, respectively. They are used to detect flame and smoke instances from UAV imagery in real-time. To improve small spots detection, Jiao et al. [47] added four DBL layers (DBL = Darknet convolutional layer, Batch Normalization layer, and Leaky ReLU layer) achieving a precision rate of 82% while providing an inference speed of 6.5 FPS on the DJI MANIFOLD onboard computer. Also, Goyal et al. [37] adopted YOLOv3 as the main architecture to identify wildfires and notify the concerned authorities as fast as possible achieving an F1-Score of around 91%, which is a good result. The methods based on object detection techniques are more effective than the classification-based ones ether in terms of processing speed or precision. They perform the wildfire detection task as an end-to-end operation to improve the inference speed making them more suitable to achieve real-time applications.

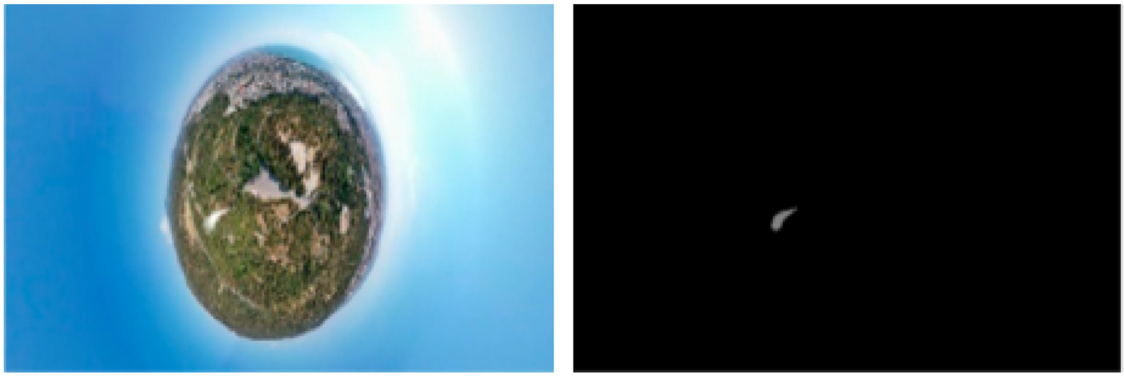
3.3. Semantic segmentation-based methods

The application of deep learning-based computer vision algorithms is not restricted to image classification and object detection, but it can be used for semantic and instance segmentation. Semantic segmentation algorithms are considered among the most effective deep learning techniques for forest fire identification, which tend to classify each pixel in the image according to the objects' class it belongs to (flame, smoke, forest) (Fig. 7). Therefore, semantic segmentation algorithms are more powerful than bounding box-based object detection techniques. However, they are more complex and demand higher computation performances and longer time for annotating training images. Several semantic segmentation techniques were proposed over the years to identify wildfires in digital images and videos captured through UAV platforms with higher precision, including DeepLab [25], U-Net [70], SegNet [8], CTNet [57], among others.

The famous Googles' DeepLabV3+ architecture was adopted by Barmpoutis et al. [11], where they applied two Inception-ResNet v2-based [77] DeepLabV3+ for smoke and fire detection and localization in forest regions. The raw images acquired with an RGB 360° camera mounted on a UAV were converted from equirectangular format to stereographic format before feeding them the semantic segmentation algorithm. The proposed system achieved remarkable results with a reduced number of sensors, which may reduce the complexity of the system. Zhao et al. [89] developed a saliency detection algorithm that is based on Deep CNN architecture to localize and segment fire areas from UAV imagery achieving an accuracy of 98%. They used color and texture information to identify areas that were more likely represent fire spots.

Table 2
Studies targeting early wildfire detection using deep learning-based object detection.

Ref	Method	Flame/Smoke	Camera type	Hardware	Precision (%)	Recall (%)	F1-Score (%)	mAP (%)	Accuracy (%)	FPS	Processing speed (s)
Jiao et al. [47]	YOLOv3-tiny	Flame/Smoke	Optical/Infrared	DJI MANIFOLD	82	79	81	79.84		3.2 - 6.5	
Jiao et al. [46]	YOLOv3	Flame/Smoke	Optical/Infrared	NVIDIA RTX 2080	84	78	81	78.92		30 - 82.4	
Barmpoutis et al. [11]	SSD	Flame	360° Optical				69.7				
		Smoke					67.3				
		Flame/Smoke					67.6				
	YOLOv3	Flame					80.6				
		Smoke					78.3				
		Flame/Smoke					78.8				
	Faster R-CNN	Flame					72.7				
		Smoke					72.7				
		Flame/Smoke					70.6				
Goyal et al. [37]	YOLOv3	Flame	Optical		90	92	91				
Hossain et al. [42]	Proposed method (color + multi-space LBP + ANN)	Flame	Optical	Intel Core i7-9750H	89	80	84				
		Smoke			93	88	90				
	Color + multi-space LBP + SVM	Flame			89	72	80				
		Smoke			90	86	88				
	Color + multi-space LBP + random forest classifier	Flame			92	57	71				
		Smoke			92	78	84				
	Color + multi-space LBP + Bayes classifier	Flame			37	67	48				
		Smoke			68	92	79				
	YOLOv3	Flame		Google Collaboratory	93	47	62				
		Smoke			98	64	77				
Yadav [84]	YOLOv3-Tiny (Emergency fire dataset)	Flame	Optical	Intel i5-6200U CPU				/			~0.2
	YOLOv3-Tiny (Single flame dataset)							/			
	YOLOv3 (Emergency fire dataset)							89.5			~0.8
	YOLOv3 (Single flame dataset)							97.6			
	YOLOv3-SSP (Emergency fire dataset)							88.3			1
	YOLOv3-SSP (Single flame dataset)							97.81			
	YOLOv4 (Emergency fire dataset)							~88.4			~1.3
	YOLOv4 (Single flame dataset)							~97			
	CS-ResNext50-Panet-SPP (Emergency fire dataset)							~82			1.5
	CS-ResNext50-Panet-SPP (Single flame dataset)							~96			
	SSD-ResNet (Emergency fire dataset)							85			~1.9
	SSD-ResNet (Single flame dataset)							~92			
Alexandrov et al. [2]	LBP	Smoke	RGB images		81.3	100	89.7		81.3	22.4	
	Haar				87.4	100	93.3		87.4	14.62	
	YOLOv2				100	98.3	99.14		98.3	6	
	Faster R-CNN				100	95.9	97.9		95.9	4	
	SSD				88.4	90.7	89.53		81.1	1	



a) b)

Fig. 7. Example of semantic segmentation operation; a) Input image, b) Flame/Smoke detection [11].

Table 3
Studies targeting early wildfire detection using deep learning-based semantic segmentation.

Ref	Method	Flame/Smoke	Camera type	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)	Processing speed (s)
Barmpoutis et al. [11]	DeepLabV3+ (proposed)	Flame	360° Optical	/	/	94.8	/	*/
		Smoke				93.9		
		Flame/Smoke		90.3	99.3	94.6		
	DeepLabV3+	Flame		/	*/	81.3		
		Smoke				80.1		
		Flame/Smoke		68.9	99.3	81.4		
	FireNet	Flame		/	/	72.2		
		Smoke				70.5		
		Flame/Smoke				71.7		
	U-Net	Flame				74.4		
		Smoke				71.3		
		Flame/Smoke				71.9		
Zhao et al. [89]	Model 1 - Original image dataset	Flame/Smoke	/	/	/	/	95.2	0.032
	Model 1 - Saliency-base augmented dataset	/	/	/	/	/	97.1	
	Model 2 (Fire_Net) - Original image dataset						97.4	0.041
	Model 2 (Fire_Net) - Saliency-base augmented dataset						98	
	Model 3 - Original image dataset						97.2	0.039
	Model 3 - Saliency-base augmented dataset						97.8	
	Model 4 - Original image dataset						97.7	0.068
	Model 4 - Saliency-base augmented dataset						98	
Shamsoshoara et al. [72]	U-Net	Flame	Optical	92	84	88		

According to Tables 2 and 3, the authors in Barmpoutis et al. [11] show that semantic segmentation provides better results to achieve flame and/or smoke detection from UAV imagery.

3.4. Other deep learning-based methods

There are several different types of deep learning techniques that were adopted in various studies targeting early wildfire detection enhancement. However, to the best of our knowledge, these techniques are not yet used for forest fire detection from visual data acquired from UAV platforms, but it still worth mentioning them. Usually, CNN performs very well on static images achieving impressive results. However, they still facing some limitations in the case of sequential data like videos, because they do not consider the temporal image variations along the time [51]. Recurrent Neural Network (RNN) is another important deep learning architecture that can provide a solution for such a problem giving deep neural networks the concept of memory via the hidden state. Different RNN types (RNN, GRU, and LSTM) was adopted by Benzekri et al. [13] to detect forest fires at their early stages from wireless sensor network mounted on the ground achieving remarkable accuracy of 99.89% 99.82%, and 99.77% for GRU, LSTM, and RNN respectively. To confirm the wildfire occurrence, they used a UAV to hover on top of the region of interest. Also, Cao et al. [20] proposed the Attention enhanced Bidirectional LSTM (ABi-LSTM) algorithm for early forest fire smoke identification from videos achieving impressive accuracy of 97.8% and provide lower false detection rates. In [45], the authors combine a CNN-based detector and a lightweight version of LSTM for wildfire smoke detection in real-time from videos acquired through cameras mounted on watchtowers. To improve the detection speed of LSTM architecture, they reduced the number of layers and cells constituting the original LSTM architecture. The YOLOv3 architecture is used to detect wildfire smoke while the lightweight student LSTM is used for fire verification by analyzing smoke motion. Luo et al. [60] developed Slight Smoke Perceptual Network (SSPN) for smoke detection from videos. The proposed architecture is divided into two parts where they used CNN architecture to extract static features and an LSTM architecture for dynamic feature extraction. However, it is not an end-to-end fire detection technique, which could affect the detection speed.

An evolved CNN architecture, called Generative Adversarial Network (GAN), was invented in 2014 by Ian Goodfellow [35], which is considered a great advancement in the deep learning field. Mostly, GANs are used for data augmentation generating new unseen instances of a targeted object. Therefore, they could be very helpful to overcome the lack of wildfire dataset problem. Recently, GANs were used even for wildfire smoke and flame detection. Aslan et al. [6] proposed a two-stage training approach adopting Convolutional Generative Adversarial Neural Networks (DCGANs) to detect wildfire smoke. They trained regularly the DCGAN with real images and noise vectors while the discriminator was trained separately, without the generator, using images that contain smoke. Similarly, in Aslan et al. [5], DCGAN architecture with temporal slices was used for flame detection in video achieving good results with negligible false alarm rate. Another deep learning algorithm, called Deep Belief Network (DBN), was adopted in Kaabi et al. [48] for early smoke identification of forest fires in video scenes achieving a detection rate of 95%. Although most of these techniques have not yet been used to detect forest fires from UAV-based images/videos, they may provide results that could achieve even better results than the ones obtained through the use of CNN-based methods.

3.5. Datasets and evaluation metrics

Data collection is one of the most important steps to build an effective deep learning-based wildfire detection model, where the data type, size, and quality have a significant impact on the performance of the deep learning-based approaches. In any research field, standard datasets are critical for fairly evaluating the performance of any deep learning-based model. However, there is a lack in wildfire images/videos accessible datasets, especially those collected from UAV platforms. Therefore, in this section, we aim to present some commonly used datasets in the literature, as well as the most important evaluation metrics used to evaluate deep learning-based wildfire detection models.

3.5.1. Datasets for wildfire detection

FLAME dataset The FLAME dataset [72] is a publicly available dataset that consists of fire images and videos acquired through UAV platforms equipped with RGB and thermal camera sensors. It contains RGB/FLIR videos and RGB images acquired through DJI Phantom 3 Professional and DJI Matrice 200 drones equipped with Zenmuse X4S, FLIR Vue Pro thermal camera, and DJI Phantom 3 camera. The first video is a 16 min raw video recorded at 29 Frames Per Second (FPS) using the Zenmuse X4S camera. Similarly, the second video is another 16 min raw video recorded at 29 FPS through the Zenmuse X4S camera, where it shows the behavior of one pile from the beginning of the burning process. Both the first and second videos were of a resolution of 1280 × 720. The third, fourth, and fifth videos are 89 s, 5 min, and 25 min WhiteHot, GreentHot, and fusion heatmap videos, respectively. These videos were recorded using the FLIR Vue Pro R thermal camera with a resolution of 640 × 512 at 30 FPS. The sixth one is 17 min of high-quality RGB video acquired from the DJI Phantom 3 camera at 30 FPS with a resolution of 3840 × 2160. The seventh and eighth repositories contain 39,375 and 8617 images resized to 254 × 254 pixels that could be used to perform the image classification task. The ninth and tenth repositories have more than 2000 high-resolution fire images and masks to achieve the fire segmentation task. This dataset was mainly created to achieve fire/not fire images classification and fire images segmentation. Also, they could be used to perform fire detection from RGB and thermal UAV imagery.

Fire detection 360-degree dataset The fire detection 360-degree dataset [11] is another dataset that consists of 150 360° equirectangular images that contain synthetic and real fire events in the forest and urban regions. These images were collected using a 360° CMOS optical camera mounted on a UAV platform equipped with GPS technology. This dataset could be used to perform wildfire detection and segmentation tasks.

Other datasets Due to the shortage of UAV-based visual datasets, most of the wildfires datasets used in the literature that contain aerial images were extracted from other datasets that consist of fire images at different environments (including forests) or collected from various news reports and search engines, such as Google, Baidu, YouTube, Yandex, Flickr, Bing, among others. Several studies that targeted wildfire detection from UAV platforms used visual datasets collected from different search engines. For example, the authors in Hossain et al. [42], Lee et al. [56], Novac et al. [64], Zhang et al. [87], Zhao et al. [89] collected datasets that consist of aerial images containing forest fires from different search engines. Other studies [76,87] have extracted some relevant data that contains forest fire aerial images from pre-exited datasets, such as the FireSmoke [28], FireDetectionImage [19], Flickr-FireSmoke [23], and Fire detection dataset [24]. Also, the authors in Zhang et al. [88] inserted real and simulated smoke instances on forest background to overcome the shortage of datasets. However, all of the aforementioned techniques could affect the performance of the deep learning model due to the quality of the data that is acquired using different platforms like satellites and airborne, which do not have the same characteristics as UAV platforms.

3.5.2. Evaluation metrics

Deep learning models' evaluation is the process that allows to determine the effectiveness of the trained model to identify wildfires. After the development of the deep learning model, we need to find out how good it is through different evaluation metrics. Before presenting the evaluation metrics, we need to present some important metrics that are used to calculate the evaluation metrics. These metrics are True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP). These results could be obtained from the confusion matrix. TP is when there is a fire in the input image/video and the model correctly predicted that there is a fire. True Negative (TN) is when the model correctly predicted that there is no fire instance in the input image/video. False Negative (FN) is when we have a negative prediction and the model incorrectly predicted it as a positive one. False Positive (FP) is when the model incorrectly predicted that there is a fire; however, there are no fire instances in the input image/video. Depending on the study's goal, several evaluation metrics could be measured to evaluate the deep learning models, including accuracy, precision, recall, and F1-score. Therefore, in this section, the most important evaluation metrics are presented.

Accuracy The accuracy represents the simplest and the most used evaluation metric to measure the performance of the trained deep learning model. According to Eq. 1, the accuracy metric refers to the number of correct predictions out of the whole number of predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

However, it seems that accuracy is not always the best evaluation metric that we can use, because it can provide misleading results in the case of imbalanced data, which could affect our judgment on the models' performance. Therefore, we need to perform more evaluation measurements, including Precision, Recall, F1-score, and Average Precision.

Precision

The Precision rate (or specificity) is another way to evaluate how good a model is. It shows how many of the non-fire instances our model incorrectly predicted as fire. The following equation is used to determine the Precision rate:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall

The Recall rate (also known as sensitivity) is the opposite of the Precision rate, where it indicates how many of the images that contain fire instances our model incorrectly predicted as no fire. Unlike the Precision rate metric that focuses on false-positive values, the Recall rate allows to focus on the false-negative part. The Recall rate can be determined using the following equation:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1-score

The F1-score is another evaluation metric that considers both Precision and Recall rates. The F1-score metric represents a weighted harmonic mean of Precision and Recall rates, where it can be calculated using the following equation:

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Average precision (AP) and mean average precision (mAP)

The AP and mAP are other popular evaluation metrics that are widely adopted for measuring the performance of deep learning-based object detection algorithms. The AP metric is calculated from the area under the precision-recall curve across all the Recall values that vary between “0” and “1”, where a higher score means a better model and vise versa. Furthermore, mAP is the average value of the AP across all classes, where we need to calculate the AP for each class and averages them. In the literature, these two terms (AP and mAP) are frequently used interchangeably. The AP and mAP metrics can be calculated according to the following equations:

$$AP = \int_0^1 P(R)d(R) \tag{5}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{6}$$

where P, R, and N denote Precision rate, Recall rate, and the number of classes, respectively.

Frame rate The frame rate, also called frame per second (FPS) is a very important metric that provides the information about the detection speed. Higher frame rates mean a faster model that could perform wildfire detection in real-time. The frame rate depends on the complexity of the selected deep learning model architecture and the used hardware.

4. Discussions

4.1. Wildfire characteristics and camera sensors

Flame and smoke are the main visual features that could be used to identify wildfires at their early stages. Several studies targeted fire flame detection from UAV imagery using deep learning-based techniques, such as object detection and semantic segmentation. However, it is very challenging to detect wildfires from flame features, especially at their beginning due to several reasons. Detecting wildfire flames visually still very hard in dense forests and cluttered images with objects that have similar features as fire flames. Moreover, most of the fires do not even have a flame at their start, where they could be covered by their smoke. To overcome such a problem, some researchers have adopted thermal cameras to measure the thermal radiation emitted by the fire [37], where they have achieved acceptable results. Also, instead of flame detection, other studies are based on smoke detection achieving impressive results in wildfires detection at their early stage [2,42]. Smoke detection is more suitable to detect wildfires at their beginning because smoke appears earlier than fire flame and can be seen from farther distances while covering larger areas making it easier to be detected. However, these systems suffer in detecting smoke during nighttime and, also, can confuse smoke with other similar objects like fog, clouds, and chimney smoke. To this end, several researchers have proposed to use algorithms that can detect both, flame and smoke, at the same time [11,26,52,56,89]. As shown in Table 2, fusing thermal and optical sensors to detect wildfire smoke and flame, as done in Jiao et al. [47] and Jiao et al. [46], is a very useful solution that could improve the detection performance in both day and night times.

4.2. UAV imagery data considerations

The lack of available UAV-based forest fire datasets is one of the biggest problems facing deep learning developers and researchers. Many solutions have been proposed to overcome such a limitation. Lee et al. [56] gathered their training dataset of wildfires by extracting frames from aerial videos available on the internet. The authors in Hossain et al. [42], created a dataset by collecting images available on the web from different image search engines and press reports. The created dataset in Hossain et al. [42] consists of aerial images with different resolutions of recent wildfires, including California and Australia wildfires. Data augmentation is another effective solution that is adopted by many researchers [42,56]. The authors in Hossain et al. [42], Lee et al. [56] used data augmentation techniques based on random cropping, resizing, and horizontal and vertical flipping. Moreover, the impact of data augmentation on the performance of wildfire detection was investigated in Yadav [84], where they achieved the best average precision by augmenting 50% of the RAW data. Similarly, as shown in Table 3, the authors in Zhao et al. [89] showed the impact of data augmentation on the detection accuracy. Collecting and labeling more data could be a very good solution to improve detection accuracy, but it might be very costly and it is not always a feasible solution. Thus, other studies are based on tuning some hyperparameters and transferring pre-trained model’s knowledge to achieve acceptable results with just a few data [84,87]. The transfer learning technique is about transferring the knowledge from a pre-trained model in a specific dataset targeting one domain to another model that targets another related domain. Thus, the authors of [87] fine-tuned a pre-trained AlexNet model to overcome the lack of dataset. Similarly, in Allauddin et al. [4] and Kinaneva et al. [53], the authors used one of the state-of-the-art one-stage detectors, called SSD_MobileNet-V1, for wildfire detection from UAV imagery.

4.3. Solutions for real-time applications

Detecting and notifying concerned authorities in real-time can prevent disastrous losses, but it still one of the biggest challenges facing researchers. Some studies have adopted lightweight models deployed on the UAV itself to perform wildfire detection as fast as possible like the work done in Jiao et al. [47]. However, this will come at the cost of reducing the detection accuracy leading to a false alarm rate increasement [16]. In [37], the authors used an accelerator neural stick to improve YOLOv3 inference speed on Raspberry Pi 3 achieving an F1-Score of 91% (Table 2). Other studies have adopted complex and deep architectures to improve the accuracy. Lee et al. [56] developed a system based on deep CNN architecture and a UAV platform for wildfire detection. Thus, AlexNet, GoogLeNet, VGG-13, and modified versions of GoogLeNet and VGG-13 CNN architectures were evaluated, where GoogLeNet achieves the best accuracy of 99%. The used architectures provide high accuracy but it takes a considerable amount of time to classify each image due to the large number of trainable parameters, where they achieved a classification time of 7.743 s/image at the best cases when they applied AlexNet architecture. However, these algorithms are not suitable to be implemented on UAV platforms due to the limitation of computational resources. These systems collect data using UAV platforms and transmit them to powerful on-ground computational systems or doing the processing task on the cloud. The adopted UAV in Jiao et al. [47] embed a lightweight DJI MANIFOLD on-board computer, to perform flame/smoke detection through a modified YOLOv3-tiny. They achieved acceptable results on forest flame/smoke detection achieving a precision rate of 82%. However, the limited processing power of the on-board computer still cannot perform the detection operation in real-time achieving only 3.2 frames per second (FPS). Hence, they proposed to perform the detection task on the ground station using YOLOv3 architecture [46]. They achieved similar results in terms of precision, recall, and F1-Score, but with a higher processing speed of around 80 FPS due to the good processing power of the adopted hardware (NVIDIA RTX 2080). Similarly, YOLOv3 was adopted in Goyal et al. [37] to detect wildfires as fast as possible and notify the concerned authorities in real-time. According to Table 2, they achieved an F1-Score of around 91%, which is a good result. However, the proposed system takes a relatively long time to detect forest fires, which is done in the first 12 h of its initialization. Srinivas and Dua [76] proposed a whole IoT system that can detect forest fires with an accuracy of 95% while notifying the concerned authorities in real-time. The proposed detection method was based on an AlexNet-like CNN architecture, where the processing is done on the cloud to improve detection speed. Moreover, the UAV flying time should be increased by performing the heavy computation on the on-ground station. However, we need strong algorithms to secure such a system against attackers and hackers, which could be very challenging and complex.

4.4. The deep learning models architectures selection and accuracies

The architecture of the selected network plays a crucial key in the whole performance of the wildfire detection system. As shown in Table 1, the authors in Chen et al. [26] investigated the impact of the selected CNN architecture and image preprocessing operations. They achieved an accuracy rate of 86% by applying a 17 layers CNN with some image preprocessing techniques while they achieved an accuracy of 53% and 61% by applying CNN-9 and CNN-9 (hm + na), respectively. Also, the proposed model in Barmpoutis et al. [11], which is based on DeepLabV3+ architecture, provided the best results achieving an F1-Score of 94.6% against other tested architectures, such as SSD (67.6%), FireNet (71.7%), YOLOv3 (78.8%), Faster R-CNN (71.5%), and U-Net (71.9%). Also, it is worthy to mention that fire detection through flame achieved slightly better results than through smoke detection, which could be due to the presence of objects with smoke-like features resulting in higher false alarm rates. Moreover, as shown in Tables 1 and 2, the proposed system has a very low missed detection rate achieving a recall of 99.3%. However, the proposed system still faces some limitations making it not able to detect forest fire at night time. In [89], the authors showed the impact of batch size and dropout ratio on the accuracy of the model. Also, they compared four different model architectures. Fire_Net architecture provides the best trade-off between speed and accuracy achieving a validation accuracy of 98% and a processing speed of 41.5 ms. According to the results presented in Table 2, the proposed ANN-based approach in Hossain et al. [42] achieved the best results against the other presented methods including a state-of-the-art deep learning-based detector (YOLOv3), where they achieved an F1-Score of 84% for flame detection and 90% for smoke detection, against 62% and 77% achieved by YOLOv3 while providing a near-real-time processing speed of 19 fps. The proposed approach is based on resizing the input images before feeding them to the ANN, which could affect the quality of the image resulting in bad classification. Also, it has some limitations to identify smoke blocks with a smooth texture. As shown in Table 2, YOLOv3 provides the highest precision rate with the lowest false alarm, but it provides the worst recall rate that means a higher missed detection rate, especially for fire flame and smoke represented with a small number of pixels. However, recent deep learning advancements could improve the YOLOv3 algorithm and solve some of its limitations. Also, Alexandrov et al. [2] compared different classical and deep learning-based approaches to detect wildfire smoke. As shown in Table 2, YOLOv2 and Faster R-CNN achieved an F1-Score of 99.14% and 97.9%; respectively, with very low false alarm and missed detection rates where they achieved precision rates of 100% both and recall rates of 98.3% and 95.9%, respectively. However, compared to classical approaches, deep learning models are very slow achieving 6 fps as the best detection speed for YOLOv2.

5. Conclusions

UAV-based remote sensing technologies play a very important role in vision-based forest monitoring systems. Therefore, combining them with recent deep learning-based computer vision algorithms and powerful computational hardware may provide smart UAVs that are able to navigate, detect forest fires, and notify the concerned authorities autonomously without any human intervention. UAVs are capable of providing high-resolution images in real-time from very hard and complex forest and wildlands locations with ease making them the most suitable platforms for wildfire identification and monitoring. Thus, in this study, we investigated several deep learning methods and approaches for wildfire early detection from UAV imagery. According to the reported works in the literature, deep learning techniques showed impressive results both in speed and accuracy, which should help firefighters to intervene as fast as possible to reduce wildfire risks.

Different deep learning-based methods for early wildfires' smoke and flame detection, namely image classification, object detection, and semantic segmentation. In general, techniques based on object detection algorithms are the most adopted among all of them due to their high accuracy and ease compared to image classification and semantic segmentation, respectively. Other deep learning algorithms are presented in this review, which can improve wildfire detection, especially in the case of fire detection from video scenes. However, these algorithms are not tested yet on UAV-based images. Thus, LSTM algorithms will be investigated in future works to improve wildfire early detection from streaming videos acquired through UAV platforms. Also, GANs will be investigated to solve the problem of dataset lack, which could help to generate new instances of fire scenes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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