Review

Computer Vision for Fire Detection on UAVs—From Software to Hardware

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Abstract: Fire hazard is a condition that has potentially catastrophic consequences. Artificial intelligence, through Computer Vision, in combination with UAVs has assisted dramatically to identify this risk and avoid it in a timely manner. This work is a literature review on UAVs using Computer Vision in order to detect fire. The research was conducted for the last decade in order to record the types of UAVs, the hardware and software used and the proposed datasets. The scientific research was executed through the Scopus database. The research showed that multi-copters were the most common type of vehicle and that the combination of RGB with a thermal camera was part of most applications. In addition, the trend in the use of Convolutional Neural Networks (CNNs) is increasing. In the last decade, many applications and a wide variety of hardware and methods have been implemented and studied. Many efforts have been made to effectively avoid the risk of fire. The fact that state-of-the-art methodologies continue to be researched, leads to the conclusion that the need for a more effective solution continues to arouse interest.

Keywords: UAV; Computer Vision; fire detection; wildfire; smoke

1. Introduction

Unmanned Aerial Vehicles (UAVs) in recent years have been the center of many studies. They are aerial robotic vehicles that are capable of high speeds and carrying heavy loads. Due to their maneuverability which makes them capable of avoiding easier obstacles and flying above them, unlike ground-based robots, they are ideal for many applications. Some of these applications are: infrastructure monitoring and inspection, earth science, defense and security, agricultural and in applications of environmental interest [1]. Research on UAVs has led to the development and design of different types of vehicles that differ in a variety of characteristics, such as weight, size, mode of operation and flight, engine type and mechanisms involved in the vehicle.

Two main categorizations that have been made in UAVs concern their weight and flight mode based on their aerodynamic design. Based on their weight [2], UAVs can be distinguished according to the characteristics of Table 1 in Super Heavy, Heavy, Medium, Light and Micro. This categorization has an impact on further categorizations of UAVs, such as the variation in the volume or type of engine that powers their system.

Table 1. Classification based on weight.

Type	Weight
Super Heavy	W > 2000 kg
Heavy	200 kg < W ≤ 2000 kg
Medium	50 kg < W ≤ 200 kg
Light	5 kg < W ≤ 50 kg
Micro	W ≤ 5 kg

Another classification can be done regarding their mechanical design. Based on this, there are four main categories. These are Fixed wing, Flapping wing, Multicopter and Single rotor [3–5].

Fixed wing: Models in this category use wings that have one or more propellers to move in the environment and a runway is mandatory for takeoff and landing procedures. The change in their course depends on a combination of movable surfaces and thrust. These models compared to the other types of UAVs can travel with high speed carrying heavy payloads [6] and, due to the design of their wings, they cannot be easily adapted to wind conditions.

Flapping wing: This category includes vehicles that have many common features with the UAVs of the previous category. The difference is inside the mechanism that exists in the wings which facilitates the change of direction of the vehicle and helps increase the lift. Their increased maneuverability makes them more flexible than fixed wing models, in cases where there are strong winds. Models in this category require also a runway for taking off and landing.

Multicopter: This category of UAVs differs in many aspects from the previous two. The operation of the multicopter is based only on the rotors it has, as it has no wings at all. They are capable of vertical taking off and landing and do not require any kind of runway. Its rotors are mounted horizontally on the main body of the vehicle and the models have increased stability and are able to adapt to flight conditions and constantly change their speed.

Single rotor: This category includes models with a single central rotor and a tail rotor. They share the same features as multicopters except that they are more unstable models.

The various classifications in UAV show that every category has its own pros and cons. As a result, the suitable platform selection varies and depends on the application. The applications using UAV capabilities are many and differ in their structure and purpose. More specifically, different types of UAVs have been used in applications, such as agriculture, inspections, delivery supplies, rescue operations, surveying, filming, military applications and disaster or hazards identifications.

One application that belongs to the group of implementations related to hazard monitoring and prevention is fire detection. With the help of UAVs, fires can be detected early or even before they start. Due to the fact of their movement in the air above obstacles, they have a larger optical range that covers a large area. However, as the height increases, the resolution of the sensors decreases. UAVs flying at low heights are able to detect easier fires over areas such as forests or residential areas. Based on the above and a proposed communication system or network, it is possible to detect a fire early by UAVs before it becomes hazardous to the environment. UAVs are very effective because they are suitable for supervision and monitoring applications and due to their flexibility and free movement in the aerial environment.

In addition, in many cases, Synthetic Vision Systems (SVSs) are used. SVSs provide a computer-generated visualization of the environment, through the sensors, according to the path that the UAV follows or its position. These types of systems are very useful in cases where the operation of vehicles is done remotely through an operator. However, the use of these systems in autonomous navigation missions is also important and feasible. SVS systems provide an augmented visualization of non-physical constraints and exo/ego centered views [7,8].

The camera with which the UAV will be equipped plays a very important role in the successful achievement of early fire detection. Without the necessary sensor equipment, such an application becomes impossible. Of course, it is not only the sensor that is very important but also the way in which the risk will be identified, the type of classification and all those procedures related to the data transfer to a server.

The goal of this research was to examine the use of UAVs and the state-of-the-art Computer Vision techniques to improve efforts to detect and prevent fires. Fire is a very dangerous situation for humans and animals as well as for the environment itself. Therefore,

the research in this field has to keep evolving in order to prevent any kind of unplanned or uncontrolled fires. The study presents the Computer Vision models, the corresponding UAVs and the mission processes and materials for detecting fires. This literature review presents the stages and equipment that can be included in a fire detection and classification plan. The main contribution of the review is the screening of the most-used types of UAVs, cameras, Computer Vision models and AI algorithms. Furthermore, the key components and techniques which improve the quality of the mission are presented. In addition, frameworks, software and the main datasets are also presented. It is noted here that the above emerged after a study of published scientific works of the last decade.

The present work is organized as follows: Section 1 consists of the introduction which presents core meanings of UAVs. Section 2 describes fire detection using Computer Vision on UAVs and, more specifically, the related work and the fire detection framework. Section 3 describes the research methods used to construct this review, the way the research was executed, and the early statistics of the research. Section 4 presents the taxonomy of the hardware and software/methods of the research and the dataset subsection includes the literature used datasets. Section 5 contains the discussion on the results of the literature review. Finally, Section 6 summarizes the final conclusion of the literature review.

2. Fire Detection Using Computer Vision on UAVs

This section describes the big picture of applied Computer Vision methods to UAVs in order to detect a fire. More specifically, the related work of the field is described and also the framework of UAV fire detection workflow is laid out.

2.1. Related Work

In the recent years, there are significant research projects for fire detection algorithms on a UAV platform, using Computer Vision methods. Firstly, fire detection is a standalone research field. There are a lot of proposed applications and algorithms, to obtain the best accuracy of the early detection of a fire. Images and videos are used for data acquisition. It is proven that when the data are forwarded through a Machine Learning Algorithm, prediction is more accurate than using a bare sensor [9]. These results are getting better using more advanced Artificial Intelligence algorithms. When the proposed fire detection models went deeper, using Convolutional Neural Networks, then the accuracy increased and showed a lot of potential [10]. There are great Computer Vision models, such as Visual Geometry Group (VGG) or GoogleNet with tremendous accuracy in image classification [11,12]. The various models are continuously improving and obtain better scores on various benchmarks such as the ImageNet Large Scale Visual Recognition Challenge [13]. Moreover, there are literature reviews, focusing on UAV and Computer Vision in different fields, foremost in navigation [14].

2.2. Fire Detection Framework

Prior to beginning the mission, the navigation plan, the identification of appropriate algorithms and models must be selected and implemented in the system. The procedures that will be done through the camera, consist of taking photos or videos and preprocessing them, including image segmentation. Then, the fire detection and features extraction are due:

Preprocessing: The purpose of Computer Vision is to analyze the information coming from the image in order to perform the appropriate processes to locate the fire. After the image acquisition procedures, preprocessing consists of procedures related to image enhancement or verification of its suitability for the respective method. Procedures related to image optimization through preprocessing are noise reduction, in order to reduce or remove the image's noise, normalization processes for changing the range of pixel intensity values and scaling for image's resizing.

Segmentation: Once the image has been obtained and the appropriate optimization procedures have been performed through the preprocessing, the pixels must be separated

into those that describe the object of interest from other image information. In the case of fire, the segmentation consists of pixels associate with fire. The way in which segmentation will be done differs between the methods. More specifically, these methods can be based on colors, motion or even intensities.

Fire Detection and Features Extractions: Through the feature extraction, the appropriate actions are taking place on the image in order to analyze the segmented image and to identify the key points of interest. The image then is passed to a trained model in order to find the patterns that will confirm or reject the presence of fire.

In the next step, in case of a positive result of the artificial intelligence model processes, the system sends an alarm via the UAV or ground support station to the fire protection personnel for further actions. Figure 1 shows the aforementioned flowchart.

At this point, it is worth noting that the methodology described above is the basic way of fire detection. Deep learning techniques involved in this process have greatly simplified the processes of segmentation and feature extractions by replacing classical algorithms [15].
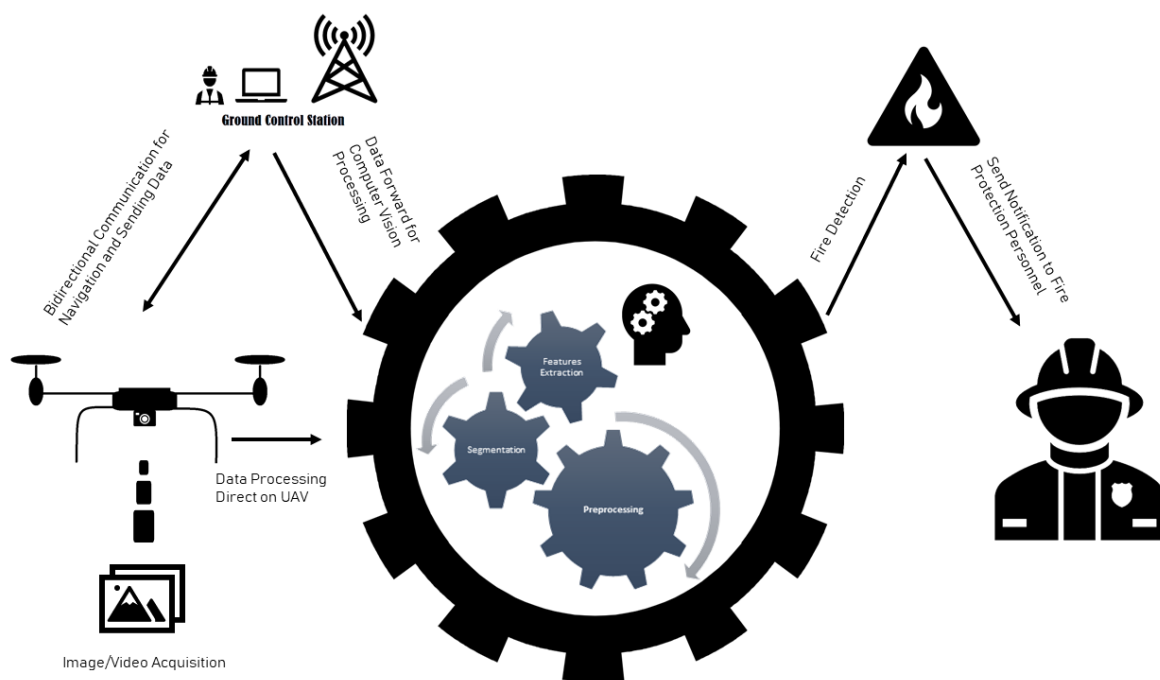

Figure 1. Fire Detection with UAV using Computer Vision Framework.

3. Literature Review

This section consists of two parts. The scope and the research criteria are presented first. The second part contains the taxonomy of the results about the Hardware and Software used in UAV for fire detection purposes. Figure 2 shows the flow diagram followed using the PRISMA (http://prisma-statement.org/ (accessed on 31 July 2021)) methodology.

3.1. Research Execution

The paper is a systematic literature review (SLR), which is a secondary research. The first step of this review method is to address the research questions.

3.1.1. Research Questions

Q1. What is the suitable hardware for fire detection with UAV?

Q2. What methods are used for image processing to detect the fire after the images/video acquisition?

Q3. What is the current framework for fire detection using UAV?

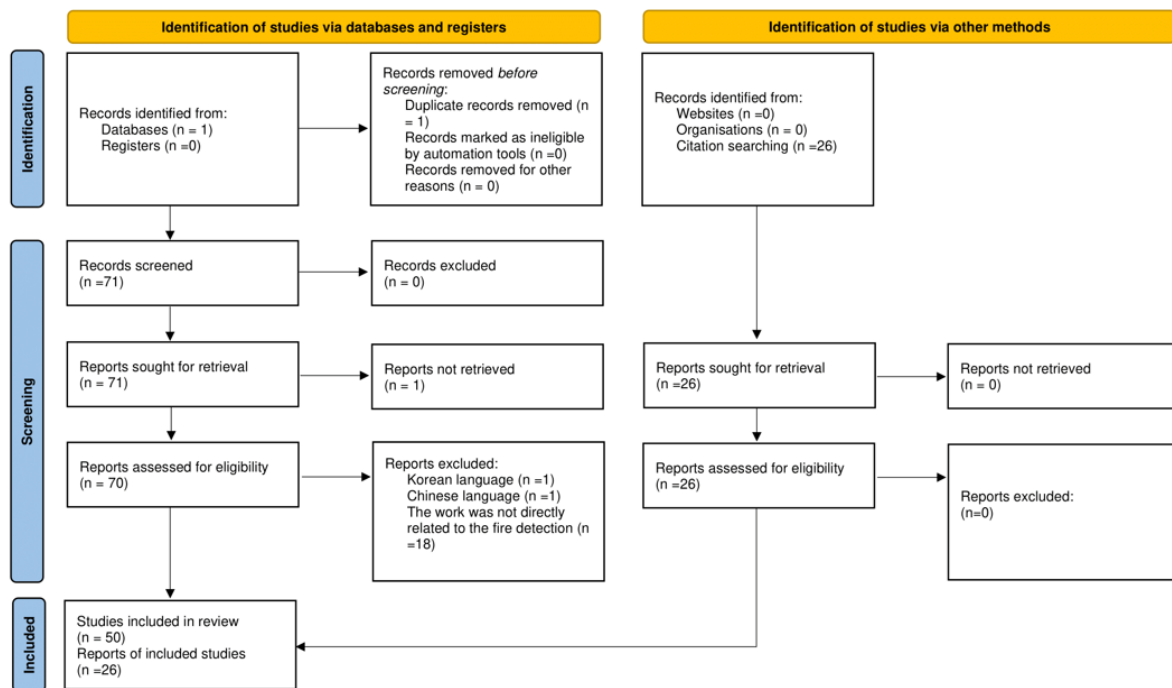Q4. What datasets are used to evaluate the models' accuracy?

Figure 2. Adopted PRISMA flow diagram 2020.

3.1.2. Research Database

The database used was Scopus (https://www.scopus.com/ (accessed on 31 July 2021)), which is a very reliable database [16]. In order to answer the above questions, the following search query was designed:

"Computer Vision" OR "video tracking" OR "image restoration" OR "image analysis" OR "image processing" OR "object detection"

AND

"UAV" OR "unmanned aircraft system" OR "UAS" OR "aerial robotics" OR "autonomous aerial vehicle" OR "unmanned aerial vehicles" OR "unmanned combat aerial vehicle" OR "UCAV"

AND

"Wildfire" OR "firefighting" OR "fire fight" OR "firefight" OR "conflagration" OR "fire" OR "smoke"

AND

Publication Year > 2010

3.2. Research Early Statistics

The query was executed on 25 March 2021 and 72 documents emerged. All the papers were reviewed in order to obtain the necessary information and early statistics came in place. First of all, the usage of the VOSviewer (https://www.vosviewer.com/ (accessed on 31 July 2021)) software tool was proposed. It is a tool for constructing and visualizing bibliographic couplings. These couplings are presented in Figure 3, according to the country of origin. The 7th most referred countries filter was applied and eight of them are visible. This clustering technique shows the country impact for publications related to fire detection using UAV's [17].

More specifically, the cluster connections shows Canada has a huge impact. According to Figure 4, whose data were taken from the platform Statista (https://www.statista.com/

(accessed on 31 July 2021)), this great impact on Canada is due to the great forest fires issue Canada is facing for decades. The average number of wildfires in Canada is 6704 fires per year, bringing the total number of wildfires in the last two decades to 134,082. Figure 5, whose data were also taken from Statista, shows the number of burned areas by forest fires. It is clear that Canada has been facing a major fire problem for many years and its contribution to solving this problem through the UAVs and Computer Vision is huge. In addition, Greece, Cyprus and Spain are suffering from deforestation through wildfires.

Moreover, based on Figure 3, Canada, France, China, Greece and Australia are bibliographically neighboring. This fact shows that between these countries, there is a strong citation relationship by referencing common papers from countries that participate in the same cluster. Conversely, USA and Austria are showing two different approaches to UAV fire detection, setting the papers apart from what is published in the other countries [18].
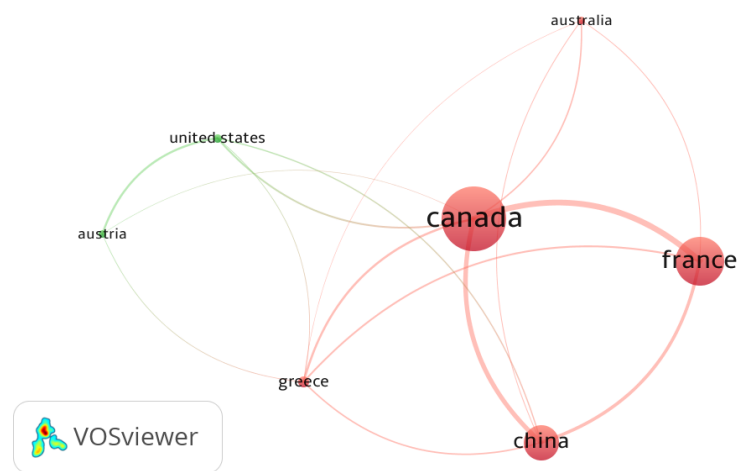

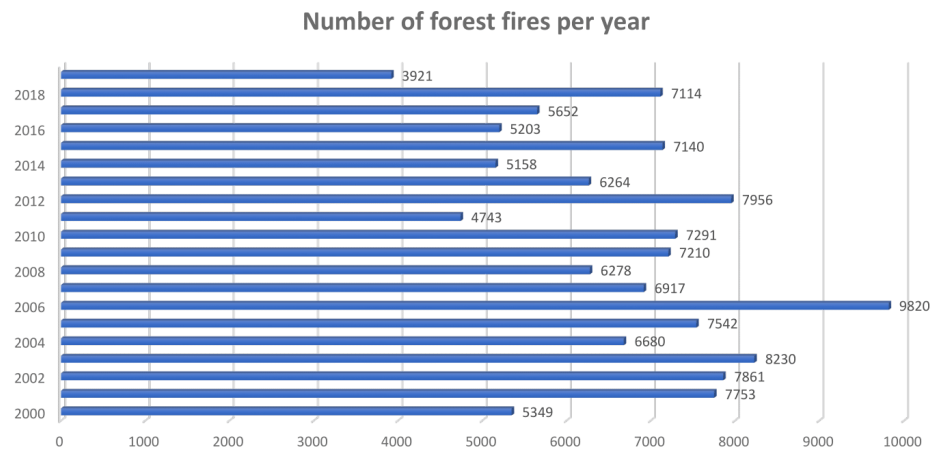**Figure 3.** Top-7 bibliographic couplings between countries.

Figure 4. Number of forest fires in Canada from 2000 to 2019.

Finally, the number of publications was analyzed via Scopus, in order to reveal any trend in the last decade. Figure 6 shows an exponential increase from 2016 until year 2019. This increase is due to the integration of deep learning through CNN models in the field of Computer Vision and, when compared to classical algorithms, it is observed that their implementation is an easier process. In 2020, there was a slight decrease which continues to decrease further in 2021. The exponential growth until the year 2019 is due to the development of Computer Vision and more specifically Machine Learning methods. The years 2020 and 2021 are pandemic years due to the COVID-19 disease. Moreover, the research was done in the first trimester of 2021, so there were fewer publications.
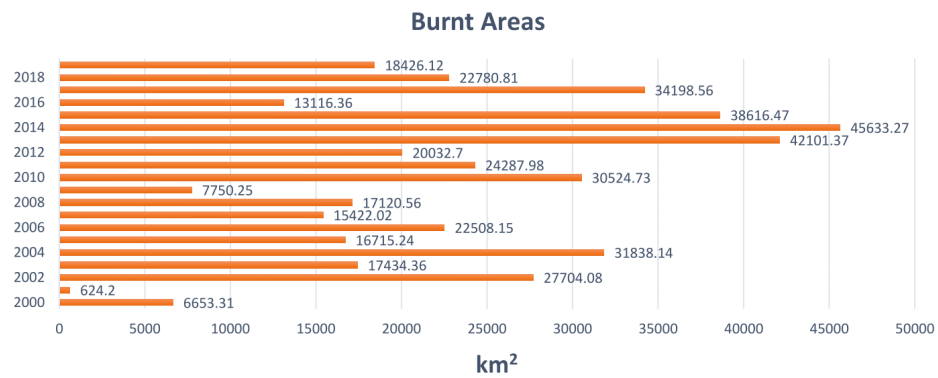
Burnt Areas

Figure 5. Burnt areas by forest fires in Canada from 2000 to 2019.
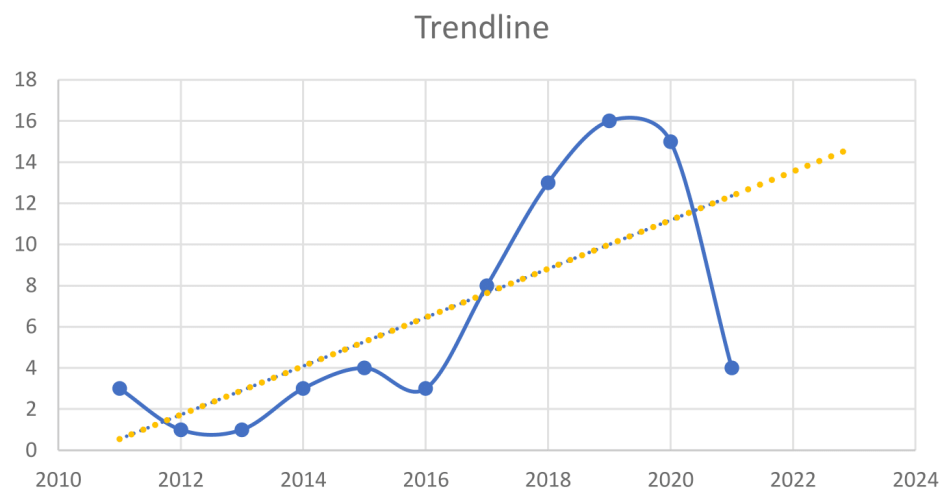
Trendline

Figure 6. Fire Detection using UAV trendline.

4. Taxonomy

4.1. Hardware

4.1.1. UAVs

Initially, in terms of vehicle type, 17 types of UAVs were mentioned specifically. The types of UAVs were three: drones, fixed-wing and single-rotor. It should be noted here that the drones category includes all vehicles that have more than one propeller mounted horizontally to the main body of the vehicle. More specifically, there were ten applications with drones: seven with quadcopters [19–25], three applications with hexacopter [15,26,27] and one with octacopter [28]. In addition, there were four applications with fixed-wing UAVs [29–32], while with single-rotor, it was limited to one application [33]. Finally, one application [34] was implemented with 2 UAVs, one fixed wing and one quadcopter.

The application implemented via single-rotor UAV (Helicopter) is one of the oldest applications of the review (2011). In addition, two applications with fixed-wing UAVs are also two of the oldest implementations (2011, 2012). The two newer applications with fixed-wing UAVs (2019, 2020) were implemented through these vehicles, as their mission was to supervise a large area that required great autonomy of vehicles. The applications with octacopter and hexacopter were part of a stereovision system. The rest of the applications were implemented via quadcopters.

The results of the research lead to the conclusion that the implementations of the last decade regarding UAVs and Computer Vision in the field of fire detection are implemented in the largest percentage (70.58%) with drones. In Figure 7, the tree-map for UAVs types used in the reviewed applications is shown.

Compared to other types of UAVs, multicopters are capable of being firmly above a point in hover mode. This capability provides a 360° visual contact from the camera. Other

than that, they do not require a runway to take off and land. A disadvantage of this type of UAVs is their reduced autonomy, compared to fixed wing that have a long duration time [4].
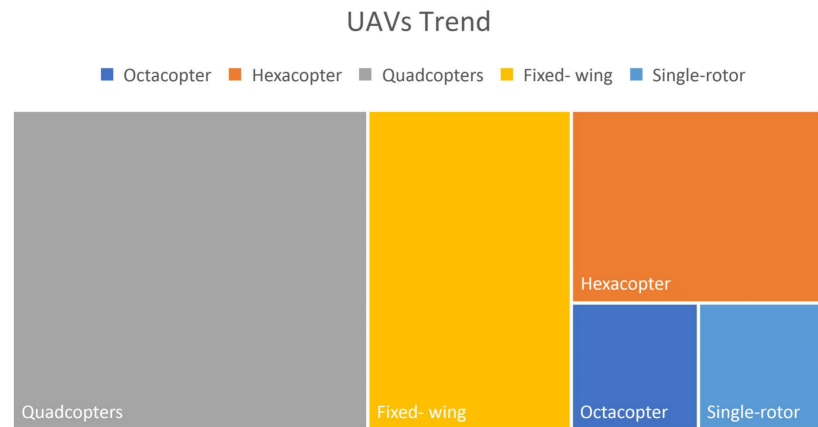
UAVs Trend

■ Octacopter　■ Hexacopter　■ Quadcopters　■ Fixed- wing　■ Single-rotor

| Quadcopters | Fixed- wing | Hexacopter |
| | | Octacopter · Single-rotor |

Figure 7. UAV type tree-map based on number of applications.

4.1.2. Cameras

Computer Vision in most applications and studies is based on the use of cameras. In some applications, more than one camera or even sensors were used to help capture images from the UAV. During the review of scientific studies, some categories of cameras emerged:

Visible Spectrum: This category includes all those devices that have input images that are visible to the human eye. In the present review, this category includes RGB 4K, HD, monocular, 3D devices, CCD technology devices, panorama, stereo depth devices, webcams, mirrorless digital and optical cameras. Of course, all these cameras have different principles of operation and different results in terms of quality, but they all work in the visible light.

IR Systems: The infrared waves can be displayed through the IR sensors. These systems can be categorized into three types: short-wave (SWIR), middle-wave (MWIR) and long-wave Infrared (LWIR). MWIR and LWIR sensors have the ability to integrate a passive temperature sensor which is able to detect the temperature difference in an environment and then displays the difference in an image (thermal cameras). Many devices of this type, including SWIR, can also present a black and white image. This makes it harder to detect temperature changes in the image but easier to recognize image features. As a result, in many cases, the image is not completely clear in terms of the morphology of its content compared to an RGB camera. Its operation is not limited only during the day, but it can also offer night vision capabilities. Most of the time, such a sensor is combined with a simple camera, so that the images that are taken are not limited only to thermal infrared radiation but also to visible light [35]. Additionally, the SWIR sensors do not need the use of an IR light source, unlike the MWIR and LWIR sensors which require such a light source.

Multispectral/Hyperspectral: These types of cameras capture the information they receive using multiple wavelengths of light. They are devices for obtaining millions of spectral information for each pixel of the image [36,37]. More specifically, multispectral cameras use 3–10 extended bands, while hyperspectral cameras use hundreds of narrow bands in wavelengths of light. Hyperspectral cameras consist of detailed spectral information and are used for image acquisition with high spatial and spectral resolutions [38]. In contrast, multispectral cameras, although not as detailed as their display due to their smaller pixel spectral distribution, are used in applications where real-time information exchange is required. This is achieved due to the smaller size of the information being processed [39], compared to the size of the hyperspectral camera information [38].

Additional to the types of the previous cameras described, regarding Computer Vision, some detectors were included in some applications. More specifically, an ultraviolet (UV) detector was used to detect flames through smoke. Through this detector, the danger is identified from the ultraviolet radiation that is created during the fire [19]. Obviously, there are applications and equipment for ultraviolet, visible and also for short, middle and long infrared wavelengths.

Figure 8 shows the total percentages of cameras per type used in the applications included in the review. Out of the total number of applications, 38 mentioned what type of camera was used.
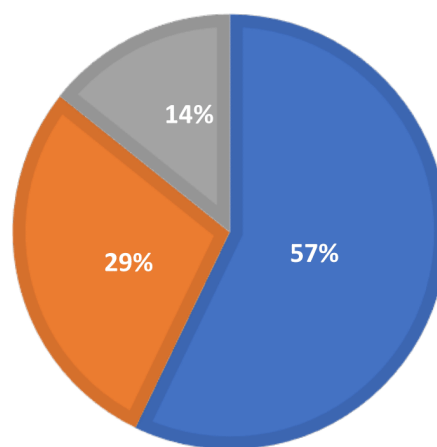
PERCETANGES OF CAMERAS PER TYPE

Figure 8. The total percentages of cameras per type used in the applications.

In addition to the above, other types of hardware were used in the applications included in the review. As shown in Table 2, the hardware that was implemented in each application, depended on the purpose of each mission. The most prevalent type of microprocessors was the ARM Cortex, while there were applications based on single- board computers and, more specifically, the Raspberry Pi. In addition, the on-board computers for drones DJI Manifold and Odroid-XU4 system were used. Finally, the type of the implemented integrated circuits (ICs) were Field-Programmable Gate Array (FPGA).

Table 2. Types of hardware.

Hardware	Reference
Raspberry	[23,40]
ARM	[41,42]
FPGA	[43,44]
Smartphones/Tablets	[45,46]
IMU	[19,40]
GPS	[19,26,29,40,41,47]
GNSS	[47]
Bluetooth	[19]
On- board Computers	[20,30,48]

Concerning the communication and monitoring purposes, Bluetooth modules, smartphones and tablets were used. As regards the navigation and positioning systems, the main module was GPS. Furthermore, one application was implemented with a proposed mobile station called D-RTK 2 through the Global Navigation Satellite System (GNSS). Finally, in some applications, it was a combination of GPS and Inertial Measurement Unit (IMU) for the vehicle's maneuvers and positioning.

4.2. Software/Method

Artificial intelligence models for image classification and recognition could not be missing from such applications. Kinaneva D., Hristov G., Raychev J and Zahariev present in their paper an object detector for smoke and fire detection based on Faster R-CNN [34]. The corresponding ROC curve shows great results above 90%. It is noted here that prediction results of the fire detection were slightly better than the smoke detection. As expected, a lot of images were required for training and testing purposes. In order for the training to be more efficient, the images have to be different but similar. Sometimes, the model performance will be reduced if the images failed to match the quality and quantity criteria. The aforementioned object detector was applied by the same scientific team to a UAV platform for Early Forest Fire Detection [29]. Faster R-CNN had also great performance and a threshold of 90% accuracy was applied. The threshold was used as a proposed trigger and when the possibility of fire detection was over 90%, the system recognized an emergency and sent a notification to the authorities. Object detectors in this specific area are the You Only Look Once model (YOLO) and the Single Shot MultiBox Detector (SSD). Three applications used the YOLOv3 [48–50]. YOLOv3 shows great adaptability achieving very high performance. When using the precision as a metric, the model's accuracy was over 90%. However, in the application of Anim Hossain, Youmin M. Zhang, and Masuda Akter Tonima [48], the observation of the recall and F1 metrics reveals a YOLO weakness achieving very low results (50%). They manage to overcome this hurdle by creating a novel model for flame and smoke signatures using a combination of a proposed local binary pattern alongside an Artificial Neural Network (ANN) and a Support Vector Machine (SVM). The SSD [40], in this specific application, was a group of MobilNets. The reason for this architecture was to gain benefits from the MobileNet characteristics achieving great prediction results with low latency. There are also other CNN approaches for the fire detection problem. Kyrkou, C. with Theocharides [51], Qiao L. with Zhang Y. and Qu, Y. [52] and Nguyen A. with Nguyen H., Tran, V., Pham H and Pestana [40] used pre-trained CNN models and, more specifically, the VGG-16, Resnet34, Resnet50, U-Net and MobileNet. The advantages of a pre-trained CNN model is that when it is applied to an experimental problem, it can achieve great prediction results. However, when they are used for real-world problems, their results have problems regarding the number of false negatives or positives. Furthermore, Kyrkou C. and Theocharides T. selected another approach, thus creating new CNN models instead of using pre-trained versions of popular CNN's [20,51]. These are the ERNet and the Emergency Net. Both models were designed for low power consumption and computational needs matching UAV special characteristics. Additionally, they have been trained on the same dataset such as the AIDER and achieved similar results compared to the traditionally powerful CNN such as VGG-16 and ResNet50, but with less computational cost. More specifically, ERNet achieved an average accuracy of 90.1% with 18.7 ms latency compared to VGG-16 and ResNet50 with 91.9% (346 ms) and 90.2% (257 ms), respectively. The Emergency Net F1 score was 95.7% with 57×10^6 FLOPS comparing also with VGG-16 and ResNet50 with 96.4% ($17,620^6$ FLOPS) and 96.1% (4533×10^6 FLOPS). Besides the above, Fuzzy Systems were also used in [41]. Their approach was by fusing the images from two cameras and reducing noise from vibrations. As a result, they obtained improved accuracy of the fire detection. In addition, a proposed Optimal Residual Network-Based Features Extraction algorithm (O-RNBFE) for feature extraction and a Latent Variable Support Vector Machine (LVSVM) for classification can be used for

fire detection. Such a combination of methods was also used for a Generative Adversarial Network (GAN) enhancement with a U-net [52] and achieved also good results.

In addition to artificial intelligence models, some software is used. More specifically, two applications used the well-known MatLab computing environment with appropriate Computer Vision packages [26,53]. In addition, the DroneDeploy [54] and the PIX4D [27] as drone mapping software were used to assist the fire detection procedure. Finally, the open-source Robot Operating System (ROS) [19,49] for drone navigation as well as the Node-Red [29] for programming event-driven applications were also selected.

Moreover, some methods and algorithms were used for feature extraction. The Gray Level Co-occurrence Matrix (GLCM) is able to perform texture analysis and extract the features from images [53]. Furthermore, other methods include the Spatial and Geometric Histograms (SGH) descriptor, which is a feature descriptor for three-dimensional (3D) local surface [54,55], the visual descriptor Local Binary Pattern (LBP) [48], which is a texture operator for image classification [49] or even a novel method the Forest Fire Detection Index (FFDI) [56] which was developed first by Henry Cruz, Martina Eckert, Juan Meneses and José-Fernán Martínez [57].

In terms of APIs, in addition to OpenGL, TensorFlow Object Detection was used in four applications [29,30,34,58] and the OpenCV library in two applications [29,50]. Of particular interest is the THEASIS system which is a stand-alone proposed platform for early detection of big wildfires and was implemented in three applications [22,30,34].

4.3. Datasets

Every machine learning application has a common hurdle to overcome. This is the proper dataset acquisition. A rule of thumb is that when more data are used to train the model, then its accuracy will be better. When the dataset is big, the various Machine Learning Models and, especially, Artificial Neural Networks have a tendency to perform better, achieving better prediction accuracy. In addition, it is desirable that the contents of the various items have diversity ensuring better training results. As a result of the above, the quantity and the quality of the different dataset elements are major concerns for all researchers and, in order to create a prediction model, some ML methods require image data. The fire detection prediction models belong to this category. The images are obtained directly from raw/pre-processed images or from a video frame. In this section, they are presented in form of a table obtained from the datasets used in the reviewed papers so that future researchers have a quick access and can use it as a reference guide.

There are many approaches for fire-detection datasets. In some papers, the images were obtained directly from the experimental customized UAV. The benefit of this approach is that it is easy to obtain the desired content and apply some customized criteria. However, these data are not public and most of the owners do not share them. It is likely that there are a few publicly available databases. Furthermore, some of them are images and others consist of videos capturing a scene involving a fire. Another approach is to obtain images or videos from various websites after a thorough search. The websites http://www.forestryimages.org/ (accessed on 31 July 2021) and http://www.wildlandfire.com (accessed on 31 July 2021) have images from forest and some wildfires. Additionally, the well-known flickr (https://www.flickr.com/ (accessed on 31 July 2021)), is a way to obtain visual data when specific search criteria applied.

A more efficient way for optimal model training is to develop a dataset, especially for fire detection. In some papers, the databases included fire and other categories [20,51,59] and others contain only fire images/videos [40,60]. In some cases, the raw data were an image, a video, or a combination of them. The aforementioned datasets are presented in Table 3. Finally, in another paper [61], the dataset was a combination from web-searched images, with a proposed method of synthesized image datasets [62].

Table 3. Fire Detection Datasets.

Datasets	Corsican Fire	Dyntex	YUPENN	Maryland	Foggia	Aider
Number of Images/Videos	1135	650 video	60	10 videos	31 videos	520 Fire Images
Resolution	1024×768	720×576	original aspect ratio	varies	varies	varies
Year	2017	2010	2015	2010	2015	2019 2020
Reference	[60]	[63]	[64]	[65]	[66]	[20,51]

5. Discussion

Fires are catastrophic events that are constantly being studied and researched. As a result, more effective ways are being discovered to prevent them. The present review, which was carried out in order to record all the above used methods, techniques, software and hardware, presents a complete set of possible solutions for future researchers. Initially, the most used UAV models were drones. Such vehicles, in addition to their mechanical advantages, such as weight, vertical takeoff and landing have also the tremendous ability for fast maneuvers and high integration of the various components and materials. Furthermore, drones can also hover. Through this state of flight, the vehicle can be stationary at one point and monitor a specific area. This increases its flying and taking-images capabilities. Of course, for such a case, due to their structure, these vehicles can easily integrate more than one camera with a more evenly distributed weight, compared to other types of vehicles.

In terms of cameras, the RGB, with various resolutions and architecture, alongside thermal cameras have key positions in this type of applications. Through thermal cameras, a sharp change in temperature can be detected, even if there are visual obstructions, which makes it easier to detect fires [67].

A very important role, of course, is the ability of the vehicle to send information about the location via GPS. Many implementations have used this module as well as various others such as the use of GNSS or IMUs. Without this kind of technique, it would not be possible to identify the vehicle's location and position. In this case, a real-world fire detection application will be useless and such an implementation would be only for research purposes.

The fire detection is done through AI models. The development of new artificial intelligence models leads to applications with high accuracy. More specifically, the Convolutional Neural Networks (CNNs) have been applied to more and more Computer Vision applications. Convolutional Neural Networks gradually replace the classic Computer Vision algorithms, due to their great accuracy results and their ease of implementation. For this reason, CNNs, such as Faster CNN, YOLO v3 and VGG-16, have the largest number of applications compared to classical Computer Vision algorithms or even other artificial intelligence models, such as neural networks or fuzzy systems and Support Vector Machines (SVM).

In addition, the increased interest in UAVs and Computer Vision leads to constantly improved versions of platforms and software which are used more and more in applications related to this type of implementation. Some of them aim at the construction, the mapping of the environment of the UAV or its path planning. Furthermore, others have been developed to achieve higher accuracy of the models or algorithms as well as to improve the quality of the images and the data transmission capabilities. The constant development in terms of hardware and software, shows that the interest of researchers and engineers remains unwavering and the need to achieve greater accuracy in applications where UAVs and Computer Vision are used.

The used datasets are always one of the most important elements of the training process of an AI model. It has been observed that there are datasets consisting of a large number of diverse photographs, which concerns the fires themselves as well as the image filters and their environment. As already mentioned, CNNs are constantly evolving and being implemented in more and more implementations. This leads to the construction and

the usage of large datasets because CNN's seems to perform better with large datasets. The more successful the training of a model is, the better its performance in practical applications. When this application concerns a dangerous situation, then the effectiveness of each model acquires an ethical framework with respect to humans, fauna and flora of the planet.

Finally, after researching the applications, it was observed that the models achieve a high degree of accuracy in detecting fire in general, regardless of the ways of transmitting various information such as location or information about the fire or the vehicle which have reached a satisfactory level but continue to evolve. However, one problem that continues to exist in this area is vehicle autonomy. Drones have many advantages that help in the early and effective detection of fire but lack autonomy even when in hovering mode. In addition, CNN models have high computational costs and, in the case that the calculations are done on-board, then the power consumption is even more important. This fact in combination with a battery-powered UAV results in the reduction in the autonomy of these vehicles.

Interesting future research might be to compare CNN models, as they are now the most accurate and used in most implementations, in terms of computational cost. Such research would provide interesting information in order to make a careful comparison of the models in the computational part in order to combine the power consumption and the processing power. In this way, the best models can emerge based on the relationship between computational cost, performance and autonomy.

6. Conclusions

The present work is a product of a literature review, consisting of 72 scientific publications. These publications were Computer Vision implementations with UAVs in the field of fire detection. The time frame of these implementations concerned the last decade. From the beginning of 2016 until the end of 2019, there is a sharp increase in fire detection applications. It should be noted that the time period in which the downward trend of publications begins coincides with the beginning of the COVID-19 pandemic situation.

In this literature review, different types of UAVs, Computer Vision AI models, sensor types as well as integrated hardware are presented. After a thorough study of the papers, a comparison was made between the various vehicles, models and methods and the proposal for the most efficient solution in fire detection applications were presented. In terms of vehicles, multicopters seem to be the most suitable for such applications. Their vertical take-off/landing and hovering capabilities in combination with their stability and their ability to remain in a constant position allows a 360°-view of the operational area. In the field of sensors, the combination between visible light and IR sensors increases the effectiveness of early detection of fire or smoke. Additionally, very important auxiliary systems, which are integrated in the vehicle, are the GPS and IMUs, providing information about the location of the vehicle. Furthermore, with regard to the Computer Vision applied methods, when the calculations are made on-board, ERNet provides high accuracy and low power consumption compared to the other high-accuracy models. In case when the calculations are done in a ground-based station, VGG-16 constitutes an effective solution, because alongside its high performance, it implies big computational costs. In any case, CNN models achieve higher performance. Finally, ROS is ideal for path planning and autonomous navigation and Pix4D for photogrammetry and mapping. Both of them are software applications that automate the essential processes of each mission and provide a larger amount of necessary information.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CDD	Charge-Coupled Device
CNN	Convolutional Neural Network
FFDI	Forest Fire314Detection Index
FPGA	Field-Programmable Gate Array
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HD	High Definition
LBP	Local Binary Pattern
RGB	Red-Green-Blue
ROS	Robot Operating System
SVM	Support Vector Machine
SVS	Synthetic Vision System
UAS	Unmanned Aerial Systems
UAV	Unmanned Aerial Vehicle
UCAV	Unmanned Combat Aerial Vehicle
UV	Ultra Violet
YOLO	You Only Look Once

References

1. Mitka, E.; Mouroutsos, S.G. Classification of Drones. *Am. J. Eng. Res. (AJER)* **2017**, *6*, 36–41.
2. Arjomandi, M.; Agostino, S.; Mammone, M.; Nelson, M.; Zhou, T. Classification of Unmanned Aerial Vehicles. Available online: https://www.e-education.psu.edu/geog892/node/5 (accessed on 31 July 2021).
3. Mueller, T.J. *Fixed and Flapping Wing Aerodynamics for Micro Air Vehicle Applications*; American Institute of Aeronautics and Astronautics: Reston, VA, USA, 2001.
4. Boon, M.; Drijfhout, A.; Tesfamichael, S. Comparison of a Fixed-Wing and Multi-Rotor Uav for Environmental Mapping Applications: A Case Study. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2017**, *42*, 47. [CrossRef]
5. Fennelly, L.J.; Perry, M.A. Unmanned Aerial Vehicle (Drone) Usage in the 21st Century. In *The Professional Protection Officer*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 183–189.
6. Alladi, T.; Chamola, V.; Sahu, N.; Guizani, M. Applications of blockchain in unmanned aerial vehicles: A review. *Veh. Commun.* **2020**, *23*, 100249. [CrossRef]
7. McCarley, J.S.; Wickens, C.D. Human Factors Concerns in UAV Flight. Available online: https://ininet.org/human-factors-concerns-in-uav-flight.html (accessed on 31 July 2021).
8. Torres, O.; Ramirez, J.; Barrado, C.; Tristancho, J. Synthetic vision for Remotely Piloted Aircraft in non-segregated airspace. In Proceedings of the 2011 IEEE/AIAA 30th Digital Avionics Systems Conference, Seattle, WA, USA, 16–20 October 2011; p. 5C4-1.
9. Çetin, A.E.; Dimitropoulos, K.; Gouverneur, B.; Grammalidis, N.; Günay, O.; Habibo?lu, Y.H.; Töreyin, B.U.; Verstockt, S. Video Fire Detection—Review. *Digit. Signal Process.* **2013**, *23*, 1827–1843. [CrossRef]
10. Frizzi, S.; Kaabi, R.; Bouchouicha, M.; Ginoux, J.M.; Moreau, E.; Fnaiech, F. Convolutional Neural Network for Video Fire and Smoke Detection. In Proceedings of the IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 23–26 October 2016; pp. 877–882.
11. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.
12. Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going Deeper with Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12 June 2015; pp. 1–9.
13. Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.; Bernstein, M.; et al. Imagenet Large Scale Visual Recognition Challenge. *Int. J. Comput. Vis.* **2015**, *115*, 211–252. [CrossRef]
14. Kanellakis, C.; Nikolakopoulos, G. Survey on Computer Vision for UAVs: Current Developments and Trends. *J. Intell. Robot. Syst.* **2017**, *87*, 141–168. [CrossRef]
15. Chen, Y.; Zhang, Y.; Xin, J.; Yi, Y.; Liu, D.; Liu, H. A UAV-Based Forest Fire Detection Algorithm Using Convolutional Neural Network. In Proceedings of the 2018 37th Chinese Control Conference (CCC), Wuhan, China, 25–27 July 2018; pp. 10305–10310.
16. Martín-Martín, A.; Orduna-Malea, E.; Thelwall, M.; López-Cózar, E.D. Google Scholar, Web of Science, and Scopus: A Systematic Comparison of Citations in 252 Subject Categories. *J. Inf.* **2018**, *12*, 1160–1177. [CrossRef]
17. Zhao, D.; Strotmann, A. Analysis and Visualization of Citation Networks. *Synth. Lect. Inf. Concepts Retr. Serv.* **2015**, *7*, 1–207. [CrossRef]

18. Van Eck, N.J.; Waltman, L. Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef]

19. Esfahlani, S.S. Mixed Reality and Remote Sensing Application of Unmanned Aerial Vehicle in Fire and Smoke Detection. *J. Ind. Inf. Integr.* **2019**, *15*, 42–49. [CrossRef]

20. Kyrkou, C.; Theocharides, T. Deep-Learning-Based Aerial Image Classification for Emergency Response Applications Using Unmanned Aerial Vehicles. *arXiv* **2019**, arXiv:1906.08716.

21. Bilgilioglu, B.B.; Ozturk, O.; Sariturk, B.; Seker, D.Z. Object Based Classification of Unmanned Aerial Vehicle (UAV) Imagery for Forest Fires Monitoring. *Fresenius Environ. Bull.* **2019**, *28*, 1011.

22. Aspragathos, N.; Dogkas, E.; Koutmos, P.; Paterakis, G.; Souflas, K.; Thanellas, G.; Xanthopoulos, N.; Lamprinou, N.; Psarakis, E.Z.; Sartinas, E. THEASIS System for Early Detection of Wildfires in Greece: Preliminary Results from Its Laboratory and Small Scale Tests. In Proceedings of the 2019 29th Annual Conference of the European Association for Education in Electrical and Information Engineering (EAEEIE), Ruse, Bulgaria, 4–6 September 2019; pp. 1–6.

23. Chamoso, P.; González-Briones, A.; De La Prieta, F.; Corchado, J.M. Computer Vision System for Fire Detection and Report Using UAVs. Available online: http://ceur-ws.org/Vol-2146/paper95.pdf (accessed on 31 July 2021).

24. Saadat, M.N.; Husen, M.N. An Application Framework for Forest Fire and Haze Detection with Data Acquisition Using Unmanned Aerial Vehicle. In Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication, Langkawi, Malaysia, 5–7 January 2018; pp. 1–7.

25. Almeida, M.; Azinheira, J.R.; Barata, J.; Bousson, K.; Ervilha, R.; Martins, M.; Moutinho, A.; Pereira, J.C.; Pinto, J.C.; Ribeiro, L.M. Analysis of Fire Hazard in Campsite Areas. *Fire Technol.* **2017**, *53*, 553–575. [CrossRef]

26. Ciullo, V.; Rossi, L.; Pieri, A. Experimental Fire Measurement with UAV Multimodal Stereovision. *Remote Sens.* **2020**, *12*, 3546. [CrossRef]

27. Shin, J.I.; Seo, W.W.; Kim, T.; Park, J.; Woo, C.S. Using UAV Multispectral Images for Classification of Forest Burn Severity—A Case Study of the 2019 Gangneung Forest Fire. *Forests* **2019**, *10*, 1025. [CrossRef]

28. Ciullo, V.; Rossi, L.; Toulouse, T.; Pieri, A. Fire Geometrical Characteristics Estimation Using a Visible Stereovision System Carried by Unmanned Aerial Vehicle. In Proceedings of the 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), Singapore, 18–21 November 2018; pp. 1216–1221.

29. Georgiev, G.D.; Hristov, G.; Zahariev, P.; Kinaneva, D. Forest Monitoring System for Early Fire Detection Based on Convolutional Neural Network and UAV Imagery. In Proceedings of the 2020 28th National Conference with International Participation (TELECOM), Sofia, Bulgaria, 29–30 October 2020; pp. 57–60.

30. Kinaneva, D.; Hristov, G.; Raychev, J.; Zahariev, P. Early Forest Fire Detection Using Drones and Artificial Intelligence. In Proceedings of the 2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 20–24 May 2019; pp. 1060–1065.

31. Nebiker, S.; Eugster, H.; Flückiger, K.; Christen, M. Planning and Management of Real-Time Geospatial UAS Missions within a Virtual Globe Environment. Available online: https://pdfs.semanticscholar.org/e165/7605fa9ef451e2152ba012688ed47b992ac4.pdf (accessed on 31 July 2021).

32. He, Q.; Chu, C.H.H.; Camargo, A. Architectural Building Detection and Tracking under Rural Environment in Video Sequences Taken by Unmanned Aircraft System (UAS). In Proceedings of the International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV), Las Vegas, NV, USA, 16–19 July 2012; p. 1.

33. Royo Chic, P.; Pastor Llorens, E.; Solé, M.; Lema Rosas, J.M.; López Rubio, J.; Barrado Muxí, C. UAS Architecture for Forest Fire Remote Sensing. Available online: https://upcommons.upc.edu/handle/2117/16549 (accessed on 31 July 2021).

34. Kinaneva, D.; Hristov, G.; Raychev, J.; Zahariev, P. Application of Artificial Intelligence in UAV Platforms for Early Forest Fire Detection. In Proceedings of the 2019 27th National Conference with International Participation (TELECOM), Sofia, Bulgaria, 30–31 October 2019; pp. 50–53.

35. Giordan, D.; Adams, M.S.; Aicardi, I.; Alicandro, M.; Allasia, P.; Baldo, M.; De Berardinis, P.; Dominici, D.; Godone, D.; Hobbs, P.; et al. The Use of Unmanned Aerial Vehicles (UAVs) for Engineering Geology Applications. *Bull. Eng. Geol. Environ.* **2020**, *79*, 3437–3481. [CrossRef]

36. Liang, H. Advances in Multispectral and Hyperspectral Imaging for Archaeology and Art Conservation. *Appl. Phys. A* **2012**, *106*, 309–323. [CrossRef]

37. White, R.A.; Bomber, M.; Hupy, J.P.; Shortridge, A. UAS-GEOBIA Approach to Sapling Identification in Jack Pine Barrens after Fire. *Drones* **2018**, *2*, 40. [CrossRef]

38. Qin, J.; Chao, K.; Kim, M.S.; Lu, R.; Burks, T.F. Hyperspectral and Multispectral Imaging for Evaluating Food Safety and Quality. *J. Food Eng.* **2013**, *118*, 157–171. [CrossRef]

39. Akhloufi, M.A.; Toulouse, T.; Rossi, L.; Maldague, X. Multimodal Three-Dimensional Vision for Wildland Fires Detection and Analysis. In Proceedings of the 2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA), Montreal, QC, Canada, 28 November–1 December 2017; pp. 1–6.

40. Nguyen, A.; Nguyen, H.; Tran, V.; Pham, H.X.; Pestana, J. A Visual Real-Time Fire Detection Using Single Shot MultiBox Detector for UAV-Based Fire Surveillance. In Proceedings of the 2020 IEEE Eighth International Conference on Communications and Electronics (ICCE), Phu Quoc Island, Vietnam, 13–15 January 2021; pp. 338–343.

41. Sherstjuk, V.; Zharikova, M.; Dorovskaja, I.; Sheketa, V. Assessing Forest Fire Dynamicsin UAV-Based Tactical Monitoring System. In *International Scientific Conference—Intellectual Systems of Decision Making and Problem of Computational Intelligence*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 285–301.

42. Khachumov, V.M.; Portnov, E.M.; Fedorov, P.A.; Kasimov, R.A.; Linn, A.N. Development of an Accelerated Method for Calculating Streaming Video Data Obtained from UAVs. In Proceedings of the 2020 8th International Conference on Control, Mechatronics and Automation (ICCMA), Moscow, Russia, 6–8 November 2020; pp. 212–216.

43. Giitsidis, T.; Karakasis, E.G.; Gasteratos, A.; Sirakoulis, G.C. Human and Fire Detection from High Altitude Uav Images. In Proceedings of the 2015 23rd Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, Turku, Finland, 4–6 March 2015; pp. 309–315.

44. Amanatiadis, A.; Bampis, L.; Karakasis, E.G.; Gasteratos, A.; Sirakoulis, G. Real-Time Surveillance Detection System for Medium-Altitude Long-Endurance Unmanned Aerial Vehicles. *Concurr. Comput. Pract. Exp.* **2018**, *30*, e4145. [CrossRef]

45. Fuentes, S.; Tongson, E.J.; De Bei, R.; Gonzalez Viejo, C.; Ristic, R.; Tyerman, S.; Wilkinson, K. Non-Invasive Tools to Detect Smoke Contamination in Grapevine Canopies, Berries and Wine: A Remote Sensing and Machine Learning Modeling Approach. *Sensors* **2019**, *19*, 3335. [CrossRef]

46. Athanasis, N.; Themistocleous, M.; Kalabokidis, K.; Chatzitheodorou, C. Big Data Analysis in UAV Surveillance for Wildfire Prevention and Management. In *European, Mediterranean, and Middle Eastern Conference on Information Systems*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 47–58.

47. Shao, Z.; Li, Y.; Deng, R.; Wang, D.; Zhong, X. Three-Dimensional-Imaging Thermal Surfaces of Coal Fires Based on UAV Thermal Infrared Data. *Int. J. Remote Sens.* **2021**, *42*, 672–692. [CrossRef]

48. Hossain, F.A.; Zhang, Y.M.; Tonima, M.A. Forest Fire Flame and Smoke Detection from UAV-Captured Images Using Fire-Specific Color Features and Multi-Color Space Local Binary Pattern. *J. Unmanned Veh. Syst.* **2020**, *8*, 285–309. [CrossRef]

49. Raveendran, R.; Ariram, S.; Tikanmäki, A.; Röning, J. Development of Task-Oriented ROS-Based Autonomous UGV with 3D Object Detection. In Proceedings of the 2020 IEEE International Conference on Real-Time Computing and Robotics (RCAR), Asahikawa, Japan, 28–29 September 2020; pp. 427–432.

50. Meng, L.; Peng, Z.; Zhou, J.; Zhang, J.; Lu, Z.; Baumann, A.; Du, Y. Real-Time Detection of Ground Objects Based on Unmanned Aerial Vehicle Remote Sensing with Deep Learning: Application in Excavator Detection for Pipeline Safety. *Remote Sens.* **2020**, *12*, 182. [CrossRef]

51. Kyrkou, C.; Theocharides, T. Emergencynet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutional Feature Fusion. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 1687–1699. [CrossRef]

52. Qiao, L.; Zhang, Y.; Qu, Y. Pre-Processing for UAV Based Wildfire Detection: A Loss u-Net Enhanced GAN for Image Restoration. In Proceedings of the 2020 2nd International Conference on Industrial Artificial Intelligence (IAI), Shenyang, China, 23–25 October 2020; pp. 1–6.

53. Hossain, F.A.; Zhang, Y.; Yuan, C.; Su, C.Y. Wildfire Flame and Smoke Detection Using Static Image Features and Artificial Neural Network. In Proceedings of the 2019 1st International Conference on Industrial Artificial Intelligence (Iai), Shenyang, China, 22–26 July 2019; pp. 1–6.

54. Garcia Millan, V.E.; Rankine, C.; Sanchez-Azofeifa, G.A. Crop Loss Evaluation Using Digital Surface Models from Unmanned Aerial Vehicles Data. *Remote Sens.* **2020**, *12*, 981. [CrossRef]

55. Rajagopal, A.; Ramachandran, A.; Shankar, K.; Khari, M.; Jha, S.; Lee, Y.; Joshi, G.P. Fine-Tuned Residual Network-Based Features with Latent Variable Support Vector Machine-Based Optimal Scene Classification Model for Unmanned Aerial Vehicles. *IEEE Access* **2020**, *8*, 118396–118404. [CrossRef]

56. Jiao, Z.; Zhang, Y.; Xin, J.; Yi, Y.; Liu, D.; Liu, H. Forest Fire Detection with Color Features and Wavelet Analysis Based on Aerial Imagery. In Proceedings of the 2018 Chinese Automation Congress (CAC), Xi'an, China, 30 November–2 December 2018; pp. 2206–2211.

57. Cruz, H.; Eckert, M.; Meneses, J.; Martínez, J.F. Efficient Forest Fire Detection Index for Application in Unmanned Aerial Systems (UASs). *Sensors* **2016**, *16*, 893. [CrossRef] [PubMed]

58. Nagaraj, K.; Sadashiva, T.G.; Ramani, S.K.; Iyengar, S.S. Image Feature Based Smoke Recognition in Mines Using Monocular Camera Mounted on Aerial Vehicles. In Proceedings of the 2017 2nd International Conference On Emerging Computation and Information Technologies (ICECIT), Tumakuru, India, 15–16 December 2017; pp. 1–6.

59. Zheng, J.; Cao, X.; Zhang, B.; Huang, Y.; Hu, Y. Bi-Heterogeneous Convolutional Neural Network for UAV-Based Dynamic Scene Classification. In Proceedings of the 2017 Integrated Communications, Navigation and Surveillance Conference (ICNS), Herndon, VA, USA, 18–20 April 2017; pp. 5B4-1–5B4-12.

60. Toulouse, T.; Rossi, L.; Campana, A.; Celik, T.; Akhloufi, M.A. Computer Vision for Wildfire Research: An Evolving Image Dataset for Processing and Analysis. *Fire Saf. J.* **2017**, *92*, 188–194. [CrossRef]

61. Kamilaris, A.; van den Brink, C.; Karatsiolis, S. Training Deep Learning Models via Synthetic Data: Application in Unmanned Aerial Vehicles. In *International Conference on Computer Analysis of Images and Patterns*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 81–90.

62. Kar, A.; Prakash, A.; Liu, M.Y.; Cameracci, E.; Yuan, J.; Rusiniak, M.; Acuna, D.; Torralba, A.; Fidler, S. Meta-Sim: Learning to Generate Synthetic Datasets. In Proceedings of the IEEE/CVF International Conference on Computer Vision, Seoul, Korea, 27–28 October 2019; pp. 4551–4560.

63. Péteri, R.; Fazekas, S.; Huiskes, M.J. DynTex: A Comprehensive Database of Dynamic Textures. *Pattern Recognit. Lett.* **2010**, *31*, 1627–1632. [CrossRef]

64. Derpanis, K.G.; Lecce, M.; Daniilidis, K.; Wildes, R.P. Dynamic Scene Understanding: The Role of Orientation Features in Space and Time in Scene Classification. In Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition, Providence, RI, USA, 16–21 June 2012; pp. 1306–1313.

65. Shroff, N.; Turaga, P.; Chellappa, R. Moving Vistas: Exploiting Motion for Describing Scenes. In Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Francisco, CA, USA, 13–18 June 2010; pp. 1911–1918.

66. Foggia, P.; Saggese, A.; Vento, M. Real-Time Fire Detection for Video-Surveillance Applications Using a Combination of Experts Based on Color, Shape, and Motion. *IEEE Trans. Circuits Syst. Video Technol.* **2015**, *25*, 1545–1556. [CrossRef]

67. Gade, R.; Moeslund, T.B. Thermal cameras and applications: A survey. *Mach. Vis. Appl.* **2014**, *25*, 245–262. [CrossRef]