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REVIEW ON FOREST FIRES DETECTION AND PREDICTION USING DEEP LEARNING AND DRONES

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ABSTRACT

Forests everywhere in the world are essential components for protecting the biosphere. They strongly contribute to the global carbon cycle and sustain a wide variety of plant and animal life forms. In many areas of the globe, forest fires are one of the major threats to living beings; it leads the ecosystem in jeopardy, including animals, plants, and even people. Last year, the Mediterranean and North African regions were devastated by wildfires. The earlier discovery of forest fires is strongly required to save lives and properties. Forest fires detection or prediction are difficult tasks because wildfires start small and are difficult to see from a distance, and then can quickly spread to become large and dangerous fires. The combination of drones and deep learning can be used to detect wildfires using images with high accuracy. The use of drones can help to identify the location of the fire and its spreading area, while deep learning can be used to identify the characteristics of the fire. This combination is a key foundation to create a system capable to detect wildfires more accurately. This paper examines current state-of-the-art published research papers on detecting forest fires using deep learning and drones.

Keywords: *Forest Fires, Wildfire, Deep Learning, Drone, UAV*

1. INTRODUCTION

Forests are one of the most vital ecosystems on the planet. They are vital to the global carbon cycle and home to a diverse range of plant and animal species. Humans benefit from forests in a variety of ways, including timber products, water resources, and recreation [1]. Wildfires, deforestation, or clear-cutting of forests, can have serious environmental consequences, including biodiversity loss, soil degradation, and increased greenhouse gas emissions.

Forest fires are a significant issue in many parts of the world. They can cause significant environmental and wildlife damage, as well as endanger human lives. In fact, in recent years, forest fires have emerged as one of the world's leading causes of natural disasters. This year's forest fires have ravaged much of the Mediterranean and North Africa, thousands of fires had been reported as of 2021, consuming nearly hundreds of thousands of hectares of land [2], from Turkey to Italy to Greece to Algeria and Morocco [3], the biggest wildfires in decades have ravaged these nations, claiming the lives of dozens and causing significant economic damage. The fires have resulted in numerous fatalities and injuries, as well as extensive property and ecosystem damage [4].

Forest fires are common in many parts of the world and can cause significant environmental damage. The hot, dry conditions required for a fire to start can also cause it to spread quickly, destroying trees, homes, and other structures. A fire's smoke and heat can also be harmful to humans and animals. Forest fires can be started by a variety of factors such as lightning, careless campers, or arsonists. Fighting a forest fire often involves a large number of people and agencies, including firefighters, police, and forestry workers.

Detecting forest fires is an important task for protecting forests and preventing loss of property and human life. Deep learning and drones have the potential to significantly increase the speed and accuracy of forest fire detection. The deep learning algorithm can be trained to recognize forest fire characteristics in aerial imagery. Drones can provide more frequent and accurate images of the forest canopy than ground-based imagery can. There are several reasons why using drones to detect forest fires is preferable to satellite imagery (the most known and used aerial imagery approach). For starters, satellites are not always capable of detecting smaller fires, and drones can because they can fly lower and collect more accurate data. Second, the cost of employing drones is less than that of employing satellites, and drones can be used for a variety of tasks, including fire detection, crop monitoring, infrastructure inspection, and many others. Finally, drones are more versatile than satellites, and they can send images out every day, whereas satellites may only be able to send images out every few days or weeks. This combination of deep learning and drones has the potential to significantly improve forest fire detection. The purpose of this paper is to review current state-of-the-art methods for detecting forest fires using deep learning and drones.

2. BACKGROUNDS

2.1 Computer Vision (CV)

Computer vision [5] is the ability of a computer system to interpret and understand digital images. The ability to interpret and understand digital images has many practical applications, such as in the field of automatic inspection and machine vision. In the field of automatic inspection, computer vision can be used to inspect the quality of products as they are being manufactured. In machine vision, computer vision can be used to "see" the world and to guide robots or other machines. There are many other applications of computer vision, including medical diagnosis, video surveillance, and 3D reconstruction. In each of these applications, computer vision can be used to interpret and understand digital images in order to achieve some desired goal. In recent years, the application of deep learning in computer vision has achieved great success. Compared with traditional machine learning methods, deep learning has the advantage of learning multiple layers of representations for data, which can better capture the complex structure of data and improve the performance of pattern recognition. Computer vision has many fields of study, including but not limited to: classification, segmentation, and object detection.

2.1.1 Classification (CLA)

Traditionally, image classification was performed by human experts who examined images and determined which category they belonged to. Image classification is now performed by machines, which can learn to recognize patterns in images more accurately than humans can [6].

Deep learning networks can be trained to recognize the features of various objects in images when it comes to image classification. A deep learning network, for example, could be trained to recognize the features of a dog, such as its fur, eyes, and ears. Once trained, a deep learning network can be used to classify images into various categories. A deep learning network, for example, could be used to determine whether an image is of a dog or a cat [7].

Deep learning for image classification has the advantage of learning to recognize patterns that are too complex for humans to detect. This means that deep learning networks can frequently outperform traditional image classification methods [8].

2.1.2 Segmentation (SEG)

Deep learning methods have been applied to the task of image segmentation, which involves dividing an image into a set of regions that correspond to different objects or classes of objects. A deep neural network for image segmentation will typically have several layers, each of which is responsible for gradually refining the image segmentation [9].

The first layer of a deep neural network (using CNN in particular) for image segmentation is typically a convolutional layer that learns to detect image features. These characteristics can be simple, such as edges or corners, or complex, such as object shapes [10]. The convolutional layer produces a set of feature maps, which is then passed on to the next layer. The following layer is typically a pooling layer, which reduces the dimensionality of the input by averaging the values within a small patch of the input feature maps. This is followed by fully connected layers (one layer or more) that learn to recognize the objects in the image. The network's final layer will generate a set of labels indicating the type of object or objects present in the image [11].

Although there are several picture segmentation methods, the most may well be divided into three categories: semantic, instance, and panoptic:

a) Semantic segmentation: is a technique for distinguishing items in a picture from the background. This is normally accomplished by recognizing and categorizing each object in the image using a pre-determined set of labels. A segmentation algorithm, for example, maybe trained to recognize different sorts of vehicles, such as automobiles, trucks, and buses [9], [12].

b) Instance segmentation: is a technique for identifying and isolating specific objects in an image. This is frequently accomplished by identifying the pixels that comprise an object and then grouping them together. A segmentation algorithm, for example, could be trained to recognize different parts of the human body, such as the head, torso, and legs [13].

c) Panoptic segmentation: is a technique for generating a three-dimensional representation of an object from a single image. This is accomplished by mapping the surface of the object onto a 3D grid and then reconstructing the object by interpolating the data from the grid cells. This method is frequently used to detect objects that are too small or difficult to detect using other methods [14].

2.1.3 Object Detection (OD)

Object detection in computer vision is the task of locating a specific object in an image or video sequence. Object detection can be used to locate a single object or a group of objects [15]. Many object detection algorithms, most notably deep learning-based object detectors, have been developed in recent years [16]. Deep learning-based object detectors have achieved cutting-edge performance on a variety of object detection benchmarks. The YOLO algorithm, the SSD algorithm, and the Faster R-CNN algorithm are three of the most popular deep learning-based object detectors [17].

The YOLO algorithm is a fast and efficient object detector that detects objects at different scales [18]. The SSD algorithm is a fast and accurate object detector capable of detecting objects in real-time [19]. The Faster R-CNN algorithm is a deep learning-based object detector that outperforms the competition on a variety of object detection benchmarks [20].

To summarize, classification is the most basic type of object categorization. Each object in the image is assigned a category by the algorithm, such as animal, plant, or person. The categories are fixed and will not change. Classification is a static process that does not take into account the object's location or size in the image. Classification is simpler than segmentation, where an image is divided into regions by the algorithm, such as the sky, clouds, and ground. Segmentation is a dynamic process that takes the location and size of the object in the image into account. And the most difficult type of object categorization is object detection. The algorithm detects objects in an image, such as people or cars. Object detection is a dynamic process that takes into account the object's location and size in the image.

2.2 Deep Learning (DL)

Deep learning is a class of machine learning that focuses on algorithms that enable computer systems to learn from data in the same way that humans do. Deep learning aims to develop computer systems that can learn to recognize patterns and insights in data, with the goal of allowing these systems to make predictions or decisions in ways similar to humans. Deep learning algorithms differ from traditional machine learning algorithms in that they use multiple layers of processing, where each layer is a model that is trained on data, and the output of one layer is used as the input for the next. This approach allows deep learning algorithms to learn more complex patterns and insights in data than traditional machine learning algorithms [21].

Deep learning has been demonstrated to be extremely effective in a variety of applications, including speech recognition [22], image recognition [23], cybersecurity [24], and natural language processing [25]. Some of the most successful deep learning applications have been in the field of computer vision, where deep learning algorithms have achieved cutting-edge results in tasks such as facial recognition and object recognition [26]. Deep learning algorithms have also been shown to be effective in the field of machine translation, with results comparable to human translators [27]. There are numerous deep learning algorithms, some of the most popular are convolutional neural networks (CNNs) [28], recurrent neural networks (RNNs) [25], and generative adversarial networks (GANs) [29].

2.2.1 Convolutional Neural Networks (CNN)

CNNs [30] are a type of deep learning algorithm that mimics the operations of the human brain. They are made up of a series of interconnected layers, each of which serves a specific purpose. A convolutional neural network's first layer is typically a "kernel" layer that performs a series of mathematical operations on the input data. This layer is followed by a series of "feature" layers that extract specific data features. The final layer is a "classifier" layer that labels the input data [31].

Each layer of neurons in a convolutional neural network is "connected" to a certain number of neighboring layers, and each connection has a weight. When a neuron in one layer fires, it sends a series of input signals to the neurons in the layer below it. Neighboring neurons then combine those input signals with their own to generate new signals, which are then passed on to the next layer of neurons [27]. This process is repeated until the signals reach the output layer and are interpreted. The weight of each connection determines its strength. When a neuron fires, it sends a signal to its neighbors, and the neighbor with the strongest input signal "fires"

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the most. This is referred to as "spiking," and it allows the network to learn which connections are important and which can be ignored. Convolutional neural networks have the advantage of being able to learn complex patterns and recognize objects in images. They can also generalize these patterns, which means they can identify an object not only in a single image but also in a series of images [32].

There are several variants of CNN that can be used for object detection, such as R-CNN (Region-based CNN) and Bi-CNN (Bidirectional CNN);

R-CNN combines a Region Proposal Network (RPN) with a Convolutional Neural Network (CNN) to detect objects in images. The RPN generates a set of region proposals, each of which is a rectangular area in the image that may contain an object. The CNN then classifies each region proposal as containing an object or not [33].

Bi-CNN is similar to R-CNN, but instead of a single CNN, it uses two CNNs, one for the forward pass and one for the backward pass. This allows the Bi-CNN to better learn the relationships between object proposals and the objects they contain [34].

2.2.2 YOLO

In recent years, there has been a growing interest in developing systems for object detection and recognition in videos. One such system is YOLO, or "You Only Look Once" [19]. YOLO is a real-time object detection system that can detect and recognize objects in videos with a high degree of accuracy. It is fast and efficient and can be run on a laptop or mobile device [20].

YOLO works by detecting objects in a video based on their appearance. It uses a deep learning algorithm to learn the features of different objects and then detects objects in the video based on their similarity to the objects that have been learned. YOLO has proven to be very accurate and can detect and recognize a wide range of objects, including cars, people, and animals. It is also able to detect objects in a variety of environments, including outdoors and in closed spaces.

The YOLO algorithm is a variant of the CNN algorithm (Convolutional Neural Network), to detect objects in an image, it employs a single neural network. The detection network and the category prediction network are the two main components of the YOLO algorithm. The detection network detects objects in an image, and the category prediction network predicts the object's category. The YOLO algorithm's detection network is made up of a series of convolutional layers and a pooling layer. The convolutional layers detect features in the image, and the pooling layer combines the features detected by the convolutional layers. A succession of fully connected layers makes up the category prediction network.

2.2.3 Mobilenet

Mobilenet [35] is a deep learning network architecture designed specifically for mobile devices. It is intended to provide efficient and accurate deep learning model execution on mobile devices while consuming minimal resources. The Google Brain team created Mobilenet, which is based on the original MobileNet model.

Mobilenet is suitable for mobile devices due to its small size and low computational complexity. It also has a small number of parameters, which reduces its computational requirements even further. Mobilenet achieves high accuracy while keeping the model size to a minimum by employing a simplified architecture with only five layers.

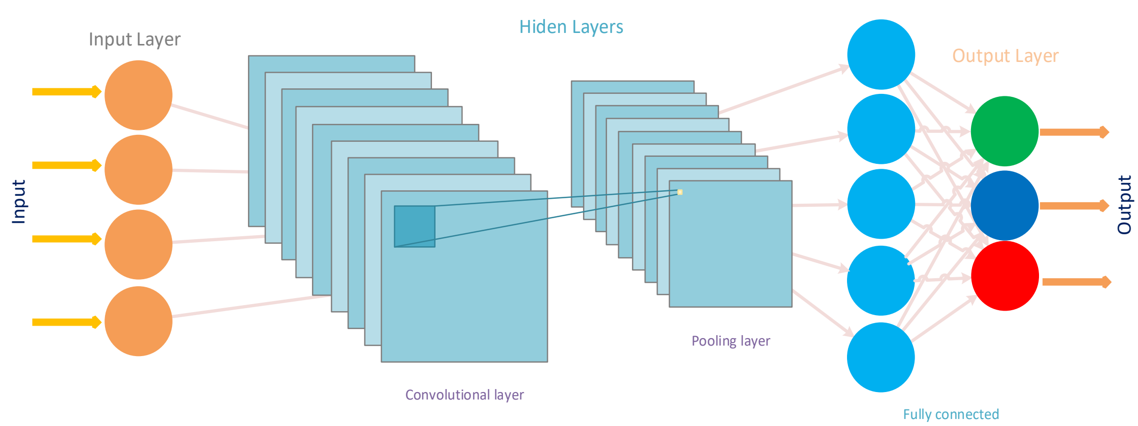

Figure 1: CNN layers architecture

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Mobilenet is effective and simple to use. It works with both CNNs and RNNs.The Mobilenet architecture has been used to successfully train several deep learning models for mobile devices.

2.2.4 U-Net

The U-Net [36] is a neural network designed specifically for image recognition tasks. The U-Net has been found to be especially effective for image classification, semantic segmentation, and object detection. The main advantage of the U-net is its ability to achieve good performance while minimizing the number of hidden layers and parameters. As a result, the U-net is relatively simple to train and efficient in terms of computation. The U-net is made up of convolutional layers and pooling layers. Convolutional layers are used to extract features from the input image, whereas pooling layers are used to reduce the number of parameters and improve the network's efficiency. The U-final net's layer is a fully connected layer that is used to classify the image.

The U-net has been found to be especially effective for image classification, semantic segmentation, and object detection.

2.2.5 DenseNet.

DenseNet [37] is a visualization technique used to improve the accuracy and interpretability of deep neural networks. It was developed in response to the limitations of the convolutional neural network (CNN) approach, which can lead to over-fitting and difficulty in interpreting the results.

The key difference between DenseNet and most other deep learning architectures is that DenseNets connect every layer in a deep network with every other layer, including the input and output layers. This densely connected network topology is claimed to result in improved learning performance and feature reuse [38].

2.2.6 ResNet

Deep residual networks ResNet [39] have achieved great success in image recognition tasks. Several state-of-the-art results on the ImageNet database have been reported by training a deep residual network.

To understand the reason for the superior performance of the deep residual networks, let's first take a look at the structure of a deep residual network. A deep residual network is a deep neural network with a large number of layers and a large number of channels. The structure of a deep residual network is similar to the structure of a deep neural network, but each layer in a deep residual network is connected to a number of residual layers [40].

The residual layers are connected to the input layer, the hidden layer, and the output layer in a deep residual network. The input layer is connected to the first residual layer, the first residual layer is connected to the second residual layer, and so on. The residual layers are also connected to each other. The connection between the first residual layer and the second residual layer is called the first residual connection, the connection between the second residual layer and the third residual layer is called the second residual connection, and so on.

The connections between the residual layers and the input layer, the hidden layer, and the output layer are called the input connections, the hidden connections, and the output connections, respectively.

2.2.7 AlexNet

AlexNet [41] is a convolutional neural network that was designed by Alex Krizhevsky and trained by himself and his colleagues. AlexNet consists of five convolutional layers and three fully-connected layers, it was originally trained to classify images into 1000 object categories, such as “Zebra”, “Horse”, and “Cat”. However, AlexNet has also been applied to other tasks such as recognizing letters, facial recognition, and automatic speech recognition.

2.2.8 FireNET

FireNet [42] is a deep learning real-time fire detection project, it provides a labeled dataset, pre-trained deep learning models, and inference codes are included in the project. FireNet pre-trained deep learning models are a low-weight neural network architecture that is well-suited for mobile and embedded applications and has an excellent performance in real-time fire detection and monitoring. On less powerful, low-cost single-board computers like the Raspberry Pi 3B, the network operates at a very high frame rate of more than 24 frames per second. The proposed neural network is made up of three convolutional layers and four dense layers (including an output softmax layer).

2.3 Drones / Unmanned Aerial Vehicles (UAV)

UAVs [43], or drones, have become commonplace in the military and law enforcement communities all over the world. Drones used for reconnaissance, surveillance, and target acquisition have allowed militaries to operate with greater precision and safety, while also providing troops with greater situational awareness on the battleground. Drones have been used in law enforcement for search and rescue operations, crime scene investigation, and suspect tracking.

In the internet of things (IoT) industry, drones are growing rapidly. IoT drones are remotely controlled devices that can be used to collect data or perform tasks. They are also becoming more sophisticated, with capabilities such as obstacle avoidance and automated landing, which makes them easier to use. Additionally, the development of 5G networks is expected to boost drone use in the IoT industry, as they will provide the necessary bandwidth and speed to support the high-volume data traffic generated by drones [44]. They have a variety of uses, including delivery, surveillance, and agriculture. They are frequently small, light, and agile, which makes them excellent candidates for difficult or dangerous tasks. Numerous drones are equipped with sensors that enable them to collect data about their surroundings and use it to optimize their efficiency or safety.

Drones [45] are now being used in commercial and private sectors, in addition to the military and law enforcement communities. Drones are being used by farmers to survey their crops and identify potential problems such as pests and diseases. Drones are being used by power companies to inspect transmission lines and identify damage. Aerial shots that were previously impossible to obtain are now possible thanks to the use of drones by cinematographers. Drones are being used by private citizens to record weddings, birthday parties, and other special events. Recently, there has been discussion about using drones to assist in the detection of wildfires in forest areas. This would be a significant benefit because firefighters would be alerted to a potential fire much sooner than is currently possible.

Drones have some advantages over traditional wildfire detection methods. For example, can fly over difficult terrain that ground crews cannot access. They can also collect data faster and more efficiently than humans on the ground. Drones can also be used to map the extent of a fire, which is useful for fighting the fire and preventing it from spreading. However, it can have some potential drawbacks; for example, it may not be able to detect all fires because some are too small to detect from the air. Bad weather conditions, such as fog or rain, can also impede drone operations.

Overall, the potential applications of drones in wildfire detection are promising. Drones may become an important tool for firefighters in preventing the spread of wildfires as technology advances.

3. METHODOLOGY

In our study, we used the search criterion wildfire OR “wild fire” OR “forest fire”, and we got around 33811 documents as results, indicating a high level of interest in wildfires and forest fires among academic researchers. Afterward, we narrowed our search results by including other words to the criteria ((wildfire OR "wild fire" OR "forest fire") AND ("deep learning" OR dl) AND (UAV OR drone)) that are relevant to the objective of this review, and we obtained around 30 document results. These resulted papers were published between 2017 and December 2021. As a consequence of the relevance of wildfire, we omitted certain findings because they only represented the first few pages of conference proceedings and not actual articles, and we also excluded several irrelevant papers since they were not related to wildfire, leaving us with 16 papers for this review. All of the information in this table (see Table 1) was obtained from the Scopus database, which is the world's largest abstract and indexing database of peer-reviewed literature, and which contains publications as well as conference proceedings, patent records, and websites in the most important subject fields.

4. FINDINGS

We analyze below the results of Table 1. First, we clarify the comparison criteria employed:

- ✓ Year: the year in which the paper was published;
- ✓ Deep Learning Model: the used Deep Learning models;
- ✓ Dataset: the used data to train and evaluate the proposed deep learning model;
- ✓ Best achieved results: the best results for the proposed model based on the metrics used;
- ✓ Type of detection: the used computer vision techniques; CLA: classification, SEG: segmentation, and OD: object detection;
- ✓ D/P/A: nature of the treated problem; D: fire detection; P: fire prediction; A: after fire;
- ✓ F/S/ALL: the nature of the treated objects; F: flame; S: smoke; ALL: a wide range of objects including, but not limited to, flame and smoke.

The majority of the papers in this review focus on either detecting forest fires [46]–[55] or on detection and curation [56]–[58]. However, papers [59]–[61] integrate both detection and prevention. Fire detection are addressed in three major ways: classification [49], segmentation [46], [47], [53], [58], and object detection [48], [52], [54], [56], [57], [61].

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Table 1: Description of papers studied

Year	Paper	DL Model	Dataset	Best achieved results	Type of detection	D/P/A	F/S/ALL
2021	[52]	MobileNet v3 YOLOv4	MSCOCO+Collected images (1844)	Recall = 99.21% Precision = 99.21% Accuracy = 99.57% Inference time reduction = 75.68%	OD	D	F/S
2021	[53]	CNN UNet	FLAME (Fire Luminosity Airborne-based Machine learning Evaluation)	CLA : Accuracy = 76.23% SEG : Recall =83.88% Precision = 91.99% F1-score = 87.75%	SEG	D	F/S
2021	[56]	DenseNet121 Resnet152 MobileNet v2	COCO Dataset	MobileNet : Accuracy = 87.5%	OD	D-A	ALL
2021	[57]	DenseNet121 Resnet152 MobileNet v2	UAV Dataset Kaggle Image from the drone Open-source photos	DenseNet : Accuracy = 93.1%	OD	D-A	ALL
2021	[59]	Author's own model	Images captured by drone	Accuracy = 81.97%	CLA - SEG	D-P	-
2021	[46]	R-CNN	Data originated from the ConFoBi project	Precision = 43.4% Accuracy = 92.4%	SEG	D	ALL
2020	[58]	UNet++ UNet	Collected from a forest fire in Andong, the Republic of Korea, in April 2020	Specificity = 91.77% , 83.11%	SEG	D-A	-
2020	[47]	DenseNet CycleGAN	Images generated using CycleGAN	Precision = 99,38% F1-Score = 98,16% Accuracy = 98.27%	SEG	D	F/S
2020	[48]	CNN	Images captured by drone	*****	OD	D	F/S
2020	[54]	YOLOv3	Videos from drone	Recall = 78% Precision = 84% F1-score = 81%	OD	D	F
2020	[55]	MobileNet v2 CNN FireNet AlexNet	2096 images collected from the internet	Parameters = 2.5M Accuracy = 99.3%	CLA-SEG	D	F/S
2020	[49]	CNN RNBFE	Two open-access dataset: UCM Dataset WHU-RS Dataset	Accuracy (UCM)= 97.84% Accuracy (WHU)= 97.%	CLA	D	ALL
2019	[60]	YOLOv3	Videos from drone	Precision = 82% Recall = 79% F1-score = 81%	-	D-P	F/S
2019	[61]	CNN	IRIS Dataset	*****	OD	D-P	F/S
2018	[50]	FireNet(DCNN)	Images from Google an Baidu AInML lab Dataset	Accuracy = 98%	CLA - SEG	D	F/S
2017	[51]	Bi-CNN	YUPENN Dataset BUAA Dataset Maryland Dataset	Mean Accuracy = 93%	OD-CLA	D	F/S

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A mixture of classification and segmentation was found in the papers [50], [55], [59]. Only [51] used the classification and object detection approaches. Among the papers working on object detection, [54] seeks to detect simply the flame, whereas [48], [51], [52], [61] intend to detect the fire by the flame or/and the smoke. Reforestation in burnt regions was addressed by [56], [57] in terms of detecting any form of object in these regions.

Table 2 displays the distribution of papers by the Deep Learning model as a solution to the forest fires problem.

The most used technique for forest fire detection is object detection, with various versions of the YOLO and MobileNet models being the most frequently adopted.

The DL CycleGAN model is not mentioned in Table 2 although it is used in the paper [47] for the simple reason that it is only exploited for image generation during the data augmentation phase. It's rare to find a paper that clearly explains how the data used for training, validation, and testing is divided up.

The absence of publicly accessible drone datasets on wildfires is one of the most common obstacles encountered in the evaluated papers. Due to safety, ethical considerations, and governmental regulations, collecting comprehensive datasets on wildfires is challenging. As a consequence, there are no publicly accessible datasets that include fire data, and several of the evaluated papers relied upon images collected from the web [50], [52], [55]–[57]. Papers [48], [54], [59], [60] experimented using either images or videos taken by their own Drones. And others [46], [47], [49], [51], [53], [58], [61] are part of project-based research work.

This review of the literature reveals some difficulties, such as distinguishing fire from other natural phenomena, such as sunlight reflecting off of trees, these papers such as [46], [47], [57], [60], [61], [48]–[53], [55], [56] intended to predict not only flames but a variety of objects such as smoke, clouds, fog and other objects available in the forests.

The results clearly show that object detection is the best way to solve our problem and that the DL YOLOv4 model used in the paper [42] provided the best performance. Although the results for almost all of the works are very encouraging, this is due in most cases to the images chosen, which are globally easily classifiable. Furthermore, the angles of the images used do not correspond to those normally captured by a drone. To account for these constraints as well as the geographical and climatic peculiarities of the Mediterranean region, especially Morocco's Eastern region, we are working on a dataset composed of images obtained from a drone (DJI Tello EDU drone) acquired as part of the project (Low-cost, real-time Forest Fire Detection System based on Wireless Sensor Net-works - SDF-RCSF).

The advantages of deep learning object detection are thus visible in the detection of forest fires. Some of the benefits of using deep learning object detection in the detection of forest fires include:

- ✓ Improved performance: Deep learning object detection algorithms can learn features from data automatically. This leads to improved performance because the features learned by the deep learning algorithm are more relevant to the task at hand.
- ✓ Improved accuracy: Deep learning detection models can generalize better to previously unseen data. This means that deep learning object detection models can detect objects with greater accuracy even when the object is not explicitly present in the training data.

Table 1: Distribution of papers by Deep Learning model

	CNN	R-CNN	Bi-CNN	YOLO	MobileNet	Unet	DanseNet	FireNet	AlexNet	ResNet	Author's own model
SEG		[46]				[58]	[47]				
SEG + CLA	[53] [55]				[55]	[53]		[55] [50]	[55]		[59]
CLA	[49]										
CLA + OD			[51]								
OD	[48] [61]			[52] [54] [60]	[52] [56] [57]		[56] [57]			[56] [57]	

- ✓ Reduced processing time: Deep learning detection models can learn from data automatically. Because there is no need to engineer features specifically for the task at hand, the processing time is reduced.
- ✓ Improved efficiency: Deep learning detection models can detect objects with greater accuracy even when the object is not explicitly present in the training data. This is due to the large deep learning models' ability to encode a large amount of information about the data.

The benefits of deep learning object detection are thus visible in the detection of forest fires. Deep learning object detection algorithms can learn features from data automatically. This leads to improved performance because the features learned by the deep learning algorithm are more relevant to the task at hand. Furthermore, deep learning object detection models generalize better to previously unseen data. This means that deep learning object detection models can detect objects with greater accuracy even when the object is not explicitly present in the training data.

Despite its benefits, using deep learning and drones to detect and predict forest fires has a number of drawbacks. To begin, deep learning algorithms need a big quantity of data to train, and this data is often unavailable during forest fires. Second, deep learning techniques demand a significant amount of computer power, which may be costly and challenging to scale. Thirdly, using drones to gather data on forest fires may be risky and difficult to arrange. Finally, the accuracy of deep learning system predictions may be difficult to verify in the real world, and even minor errors can jeopardize the forest ecosystem.

5. CONCLUSION

Forest fires can be devastating, burning houses, animal habitats, and wood while polluting the air with potentially toxic pollutants. Fire also releases carbon dioxide into the environment. To avoid the uncontrolled broad spreading of forest fires, it is vital to identify wildfires in an earlier stage and control their propagation. It is necessary to mobilize appropriate fire apparatus and qualified operating people as rapidly as possible to the source of the fire.

In conclusion, this literature review has found that deep learning-based classifiers are more accurate than traditional methods, and object detection was the most commonly used technique for forest fire detection. We also found that drones can be used to obtain high-resolution images of the forest, allowing more accurate fire location detection than is possible with satellite imagery.

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