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Advancements in Intelligent Technologies Approaches for Forest Fire Detection: A Comparative Study

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Abstract

Forest fires pose a significant threat to ecosystems, wildlife, and communities worldwide, leading to severe environmental impacts such as soil degradation, reduced air quality, and increased greenhouse gas emissions. Effective forest fire prevention and management are a critical global challenge, with detection and suppression technologies constantly evolving. This paper provides a comparative study of various forest fire detection techniques, including watchtowers, satellites, wireless sensor networks (WSN), cameras, and drone systems. By examining the advantages and limitations of each method, the paper highlights specific examples of recent research using Artificial Intelligence (AI) and Internet of Things (IoT) technologies to illustrate their effectiveness and the problems. A detailed comparison table is included to summarize the performance and applicability of these techniques. The study concludes by evaluating the current state of fire detection technologies and proposing future research directions to enhance early fire detection systems. This comprehensive review aims to inform ongoing efforts in wildfire management and advance the development of more efficient detection strategies.

Keywords: Forest fire, satellites, drones, Wireless Sensor Networks, Internet of Things, Deep Learning, Camera.

1. Introduction

Forests are essential ecosystems for maintaining the planet's ecological balance, and their importance cannot be overestimated. Carbon storage, biodiversity, the water cycle, soil protection, and air quality are among the reasons why forests are important (Wietecha et al., 2019; Bouguettaya et al., 2022). Therefore, their sustainable preservation and management are essential to ensuring the health and well-being of all living beings on Earth. The forest biome covers more than 4.1 billion hectares of the earth's surface globally (Antwi et al., 2022). In addition to producing wood, forests provide nutrition resources, comfort, and recreation, highlighting its importance in many ways. Biodiversity and cultural biodiversity in forest landscapes are becoming increasingly difficult to maintain because of the unabated expansion of the terrestrial human footprint, in addition to adverse effects on forest ecosystem services. As a result, the effects of large and small development or disturbance activities like harvesting or logging, forest fire, climate change, and silvicultural practices on forests must be continuously monitored (Antwi et al., 2022).

Forest fires spread rapidly in areas with extensive forests and agricultural lands (Chowdary et al., 2022). According to federal data cited by the National Park Service, humans are responsible for about 85% of all wildfires in the United States each year (URL-1). Forests are vulnerable to fires, which can be caused by natural events like lightning strikes, volcanic eruptions (Kaur et al., 2020), sparks from falling rocks (Dubey et al., 2019), severe droughts, and hot and dry climates (Sharma et al., 2020). Unplanned burning of sawdust and dry leaves can also lead to fires (Sasmita et al., 2018), as can human activities such as campfires, discarded cigarette, burning debris, and intentional actions (Kaur et al., 2020; Chowdary et al., 2022). Natural fires often take longer to detect and control, resulting in larger burned areas. Unlike human-caused fires, they can be detected early and extinguished quickly (Sharma et al., 2020).

Forest fires can be classified into three main types: Surface Fires: These fires burn through the forest ground, consuming leaves, twigs, and other debris. Crown Fires: These fires spread rapidly through the canopy, often fueled by strong winds and dry conditions. Ground Fires: These fires burn beneath the forest ground, consuming organic matter in the soil. Their fuel source is peat, humus, and dead and flammable plants. Forest fires are hazardous because they are only detected once they spread over a large area, making them difficult to control and extinguish (Chowdary et al., 2022). Accurate location and early notification of firefighting units are crucial, as they can help save lives and reduce damage.

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In the last, forest fire detection was primarily based on human observation from lookout towers and ground patrols. While essential at the time, these methods, were limited in scope and efficiency. Observers relied on visual cues such as smoke plumes and direct sightings of flames, which often resulted in delays in detection and response. Many technologies have subsequently emerged to detect and monitor forest fires, including satellite systems, optical sensors, camera systems, wireless sensor networks (WSNs), and Unmanned Aircraft Systems (UASs).

In recent years, the integration of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) has revolutionized forest fire detection. These advanced technologies utilize data from various sources, including satellites, drones, and ground-based sensors, to provide real-time monitoring and predictive analytics. Advanced algorithms now enable the rapid detection of fires, prediction of fire spread, and optimization of firefighting strategies, reducing the impact on both natural and human environments.

This paper will highlight the main automatic or powerful techniques employed to detect and predict forest fires. We will discuss their advantages and disadvantages. Hence, we did a comparative study based on several factors, including spatial coverage, discovery speed, discovery reliability, cost, false alarm rates, and accuracy, to evaluate them objectively. By comparing these factors to each forest fire detection technique, it is possible to identify the best-performing technique in each case. The rest of the paper is organized as follows: After an introduction in Section 1, forest fire detection techniques are described in Section 2. Section 3 provides a comparison study between the techniques. Finally, Section 4 discusses some future work directions.

2. Forest Fire Detection Systems

In recent years, the increase in the frequency and severity of forest fires have underscored the critical need for advanced and efficient detection techniques. This research paper delves into novel approaches, focusing on three key technological solutions: satellites, cameras, Wireless Sensor Networks (WSNs), and hybrid systems. As we navigate through each subsection dedicated to these technologies, a recapitulation table is added to encapsulate key findings and comparative insights. These tables serve as succinct summaries, aiding readers in comprehending the nuanced strengths and limitations of satellite, WSN, and camera-based forest fire detection methods. This structured recapitulation enhances the clarity of our exploration, allowing for a more accessible understanding of the intricate details associated with each technology.

2.1. Satellite based systems

Forest fires can be detected; in many cases, they are recorded, have been observed and detected using earth-orbiting satellites and even air-floating devices. Many satellites with forest fire detection abilities are currently operational. They provide images that can be used to locate fires. The advanced very-high resolution radiometer (AVHRR), debuted in 1998, is one of two essential satellites created for forest fire detection. The moderate resolution imaging spectroradiometer (MODIS) was introduced in 1999 (Alkhatib et al., 2014) and was first used in China and second in Canada (Benzekri et al., 2020; Roldan et al., 2021).

Moreover, Technology Experiment Carrier 1 (TET-1) and Berlin InfraRed Optical System (BIROS), two microsatellites created by the German Aerospace Center (DLR) for the FireBird project, survey the Earth for extreme temperature occurrences. TET-1 debuted in 2012, while BIROS debuted in 2016. The latter satellite is based on BIRD, the first microsatellite designed to identify and investigate hot regions such as forest fires and volcanic activity. The BIRD microsatellite was launched in 2001 and was operational until 2006 (Lorenz et al., 2015). More recently, advancements in infrared remote sensing technologies have occurred. Measurements of non-refrigerated microorganisms have received a lot of attention in terms of detecting land-based fires in space. This technology's applicability in space has previously been presented, like with ALOS-2, a Japanese satellite released in 2014 by JAXA. As a payload, the spacecraft includes the 3 kilogram microbolometer camera CIRC (Barschke et al., 2017).

The operating principle of these systems involves using satellite sensors to monitor forested areas and detect signs of wildfires. The detection algorithm is the core of the system, and it can use various techniques such as multi-temporal information, multi-spectral information, and deep learning to process images and detect fires. The expected background temperature of a pixel is commonly derived based on spatial-contextual information. The thermal imagery data obtained from the global system of the geostationary orbit (GEO), which is a circular orbit located at an altitude of 35,786 kilometers and with a zero slope, shows that in this orbit, the satellite remains motionless relative to the ground, offering a constant view of the same surface area. This feature allows GEO satellites to consistently stay above a specific area, providing continuous coverage for various applications; this imagery is the most appropriate satellite-based data for early fire detection in the non-polar regions of the earth (Ghali et al., 2023). The system carries out automated data acquisition, processing, and reporting on locations of active fires present during the satellites' twice-daily overpasses. The system can detect fires early and warn users, which can help prevent or minimize damage caused by forest fires (Payra et al., 2023; James et al., 2023), as shown in Figure 1.

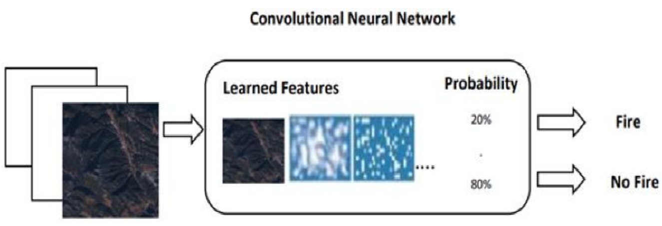

Figure 1. Architecture-based images satellite for early fire detection. (James et al., 2023)

Numerous studies on detecting land fires from space suggest using constellation of multiple satellites to maximize the revisit rate (Table 1), thus increasing the accuracy of observation data. Using nanosatellites, like the TUBIN satellite based on the TUBiX20 platform, is equipped with two infrared microbolometer sensors and a CMOS camera, which are used to achieve its goal of monitoring and detecting fires (Bbarschke et al., 2017). In addition, Barmpoutis et al. (2020b) presented a system comprised of a constellation of nanosatellites outfitted with multi-spectral visible-to-infrared cameras and a base station, allowing all surface places on the world to be visited a minimum of once per hour. According to simulations, a fire of around 400 square meters can be recognized within 30 minutes. Furthermore, photos can be relayed to the ground station every 90 minutes.

Satellite images offers broad coverage and detection on large scale. Satellite images have been routinely employed in recent years to identify wildfires, and they have been used along with deep learning for classification, object detection, and semantic segmentation. Several researchers have recently employed deep learning for land use classification with satellite images. The Phan et al. (2019) suggested a unique bushfire detection methodology based on the GOES-16 satellite image. It cleans and evaluates the data from initial images of areas between regions, then employs deep learning to capture spatial and spectral patterns in order to identify more accurate and robust detection. Dashboard to visualize real time data to obtain timely notifications about probable forest fires. Experiment results show that technology outperforms baselines by a 94% F1 score.

Xie et al. (2018) provided a spatio-temporal contextual model (STCM) that fully leverages the spatial and temporal features of geostationary data using Himawari-8 satellite data. They used an enhanced robust fitting approach to describe each pixel's daytime temperature cycles (DTC) with the intermediate and long infrared bands. A Kalman filter was used to mix the DTC for each pixel in order to approximate the real background brightness temperature.

SmokeNet, a novel CNN model that blends spatial and channel-wise attention in CNN to improve feature representation for scene categorization, was suggested by Ba et al. (2019). The study introduced USTCSmokeRS, a new data set for satellite smoke imagery consisting of RGB images from more fire-related disasters and more complex ground, containing 6225 satellite images divided into six groups: cloud, dust, haze, land, coastline, and smoke. Using 64% of training images, the SmokeNet obtains the highest accuracy of 92.75% and the highest Kappa coefficient of 91.30%.

A practical example of deep learning algorithms is Fully Connected Network (FCN) algorithm, able to predict the existence of fire smoke in high-resolution satellite data in near real time (NRT). It used images measured by the Advanced Himawari Imager (AHI) aboard satellite Himawari-8. The FCN detects fire smoke utilizing training information from operational smoke identification techniques, utilizing verified smoke products in a framework that can be implemented in NRT. The method has a high classification accuracy of 99.5%(Larsen et al., 2021). Another study Vani et al. (2019) presented a successful technique based on a Convolutional Neural Network (CNN), Inception-v3, based on transfer learning. A collection comprising 534 RGB satellite photos from various sources, including MODIS images from NASA's Worldview platform and Google, was used. Based on their datasets, the accuracy is 98%.

2.2. Camera based system

2.2.1. Fixed Cameras

Today, ground cameras can be used to detect wildfires, whether they have a single sensor or multiple sensors. They are usually optical, thermal, or infrared cameras. The latter is able to detect temperatures and produce thermal images that can be used to identify areas with heat sources. These cameras must be carefully placed to provide optimal sight. As a result, they are typically housed in watchtowers. Infrared cameras are able to detect temperatures emitted by objects and produce thermal images that can be used to locate areas with heat sources. Optical cameras work by capturing visible light and producing color images. Optical cameras can detect fumes and flames by analyzing color and shape changes in the image (Barmpoutis et al., 2020a).

Table 1. List of the state-of-the-art studies (Satellite based system)

Study	Year	Satellite- Sensor used	IA Technique used	Accuracy %
Bbarschke et al.	2017	TUBIN infrared microbometric measures CMOS photographer	/	/
Barmpoutis et al.	2020b	constellation of nanosatellites multi-spectral visible-to-infrared (IR) cameras	/	/
Phan et al.	2019	GOES-16	Deep learning	F1-score 94
Xie et al.	2018	Himawari-8	/	/
Ba et al.	2021	Himawari-8	CNN	92.75
Vani et al.	2019	MODIS	CNN	98

Flames and fumes are detected by analyzing the color changes in the images captured by ground cameras. Bright yellow, orange, or red colors indicate flames, while white or gray color indicates fumes. In the case of forest fire detection, these images are processed by advanced detection algorithms. These algorithms, which employ machine learning and deep learning approaches (Gaur et al., 2020), are capable of scanning enormous volumes of data and learn to distinguish between fire and noise signals.

The operating principle of the camera-based forest fire detection system involves the use of cameras with specialized technology to monitor forest areas and detect signs of forest fires. The forest fire detection system operates through a sequence of key steps. Initially, cameras equipped with thermal infrared and/or visible light sensors are strategically positioned within forested areas, often elevated in fire watchtowers or masts, to maximize their field of view. These cameras continuously capture images and live video footage, subjected to real-time analysis through image processing or deep learning. This software actively scans for visual signs that might indicate the presence of a wildfire, such as flames, smoke, or hotspots. After detection, the software triggers an automatic alert that is promptly relayed to the relevant authorities and firefighting teams. Fast response is critical, as firefighting teams are dispatched to the location indicated by the camera's alert, enabling rapid reaction to potential fire outbreaks. The cameras maintain ongoing monitoring, providing a continuous data stream on the fire's progression. This continuous surveillance aids authorities in making informed decisions regarding evacuations, resource allocation, and effective fire management strategies. Fig 2 presents an architecture-based camera system for early fire detection (Geetha et al., 2021; Labed et al., 2023).

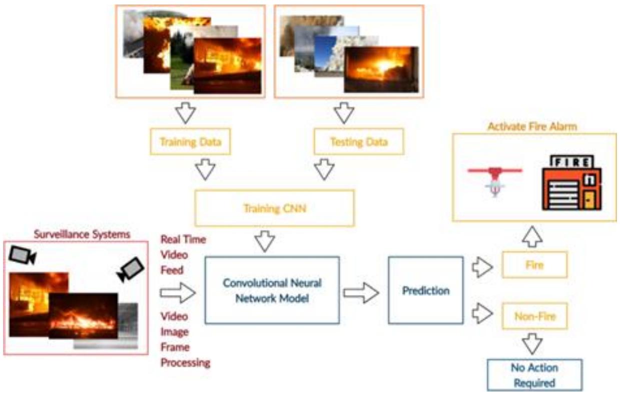

Figure 2. Architecture-based Camera fixed system for early fire detection (Geetha et al., 2021)

There are several systems used to detect and monitor forest fires (Table 2), as previously mentioned in the study of Alkhatib et al. (2014) such as AlarmEYE, UraFire, the ForestWatch system, EYEfi SPARC, FireHawk, and FireWatch. One of the new systems is the ADELIE system, a forest fire surveillance system that identifies the presence of smoke in the natural environment using a novel capture and image processing method. This automatic forest fire detection system enables monitoring from one or more elevated locations, covering a 360-degree view up to the horizon, both day and night (Figure 3).

Figure 3. Camera fixed for forest fire. (URL-2, URL-3)

Detection systems that employ optical sensors combine physical attributes of flame and smoke, such as color, velocity, and spectral, spatial, temporal, and textural characteristics (Barmpoutis et al., 2020b). For the final fire presence occurrence judgment, a probabilistic color-based model was employed to detect fire zones and motion characteristics (Zhang et al., 2014). A study by Toreyin et al. (2006) offered an optical camera-equipped system and a methodology combining feature extraction. Chen et al. (2010) used motion detection utilizing a Gaussian mixture model, integrating color analysis using RGB color filtering, and flickering temporal analysis. The system was applied to a video dataset that included various daylight and evening conditions; however, color analysis is less effective at night, and night smoke is less evident. As a result, motion analysis is commonly used to identify wildfires at night.

To address the limitations of optical cameras in detecting low-brightness simulated flames, an innovative approach was taken. Infrared video was employed, and hidden Markov models (HMMs) were used for a temporal-spatial analysis of the wave field. This analysis was performed after determining the boundaries of moving bright spots in each frame (Toreyin et al., 2007). Sousa et al. (2020) presented a transfer learning approach combined with data augmentation techniques. Retraining and testing of technology previously trained on ImageNet model Inception-v3 on the Corsican Fire database with 93.6% accuracy. Ya'acob et al. (2021) employed an infrared camera to identify wildfires by using the RGB and YCbCr color models to isolate fire pixels from the backdrop, separated glitter and color from the original image to detect fire, and processed photos using a MATLAB analyzer.

Qi et al. (2021) used a convolutional neural network attempts to extract and categorize picture information for fire recognition. The authors developed a framework for a fire recognition system based on fire video images (FVIFRS) and identified both static and dynamic flame attributes. Guede et al. (2021) created a deep learning model according to the Detectron2 platform. They used a data set of forest images captured with the same system they had used in previous work. The image was captured using a bi-spectrum temperature measurement pan and an optical camera, the IQinVision IQeye 7 Series (IQ762WI-V6). They utilized 1500 smoke images classified as mid- and low-level, as well as 1500 cloud images and 1500 empty images.

Table 2. List of the state-of-the-art studies (Camera based system)

Study	Year	Dataset	Technique used	Accuracy %
Sousa et al.	2020	Corsican Fire database	Inception-v3	93.6
Qi et al.	2021	video images (FVIFRS)	CNN	/
Guede et al.	2021	forest images	Detectron2	/
Chen et al.	2023	BowFire	YOLOv5	87.7
Almeida et al.	2023	Kaggle and FLAME, plus frames of videos	ANN CNN	82
Srinivas et al.	2020	/	CNN AlexNet	95
Jandhyala et al.	2023	Imagenet Aerial photos	classification and object recognition	Classification: 88 Detection : 91
Lee et al.	2017	UAV image data RGB camera data	CNN AlexNet, GoogLeNet, VGG-Net, and customized versions of GoogLeNet and VGG-Net	94.8, 99, 86.2, 96.9, and 96.2
Hossain et al.	2020	airborne platforms	artificial neural network and a color and multi-color space	F1 scores: 0.84 for flame 0.90 for smoke.
Li et al.	2022	Data sets from the Internet	CNN and standard computer vision algorithms	/
Anh et al.	2022	/	image processing and a correlation coefficient	97.89
Namburu et al.	2023	Kaggle and FLAME	MobileNet deep learning	97.22
Guan et al.	2023	UAV image data	MS R-CNN	/
Jiao et al.	2019	UAV image data	YOLOv3	/
Zhang et al.	2023	FLAME	MS R-CNN Faster RCNN was	MS-FRCNN : 82.9 Faster RCNN : 77.8

To solve the issue of limited detection accuracy produced by various mechanical fluctuations and shifting forest fire structures. Chen et al. (2023) suggested YOLOv5s-CCAB, an enhanced YOLOv5s-based target detection method. A coordinate attention (CA) technique is introduced to overcome the problem of inadequate extraction of accessible features from wildfire images. In addition, contextual transform (CoT) was merged into the C3 module in order to build the CoT3 module, which extracts richer characteristics. The authors used 2976 images for training, validation, and testing acquired from the dataset BowFire. The actual findings demonstrate that the model described in this research can achieve 87.7% of accuracy.

Almeida et al. (2023) presented a novel algorithm enabling the monitoring of tiny parts of forest protected areas using real-time video flow. Two types of cameras was used: IP cameras with a WiFi connection, HD resolution, and RTSP remote access functionality, and PC cameras with VGA resolution. 5209 images were employed to train the ANN and 24725 images to train each CNN. Their model achieved a consistent accuracy of 82%.

Finally, Prasanna et al. (2023) devised a low-level forest fire warning system using cameras positioned in towers. The fire informs the forestry department concerned with the location of a unique node group with a long-range network (LoRa) that has the real-time fire detection algorithm implemented. Raspberry Pi is designed with a fire detection algorithm to detect the presence of fire or smoke.

2.2.2. Unmanned Aerial Vehicle (Drone)

Camera-based solutions are costly since towers and communications equipment must be created in remote forests regions. In addition, it is sometimes impossible to see flames in the forest from a ground camera or a camera placed on a tower. To achieve that goal, a drone, also known as an Unmanned Aerial Vehicle (UAV), is a remote-controlled flying device that can be utilized for aerial photography, mapping, surveillance, parcel delivery, and forest fire detection. It flies with an electric battery or a gas engine. Drones are outfitted with a various of sensors and technological equipment, including cameras, thermal sensors, and GPS systems (Kinaneva et al., 2019; Patel et al., 2023).

Drones can cover a vast area effectively. Work for long periods and at all times. It is easily refundable and affordable, and most importantly, operations can be carried out automatically, with or without a pilot or operator. Resource research and environmental monitoring have greatly benefited from the recent rapid development and implementation of UAV technology for applications such as catastrophe monitoring, precision agriculture, and biological surveillance. Drones have enormous potential for identifying and monitoring wildfires because they provide high flexibility, flexible perspective and resolution, and reduced dangers for individuals (Roldan et al., 2021).

A forest fire detection system based on drones operates through a series of well-defined steps. It begins with deploying drones that are equipped with cameras, thermal imaging sensors, and potentially other specialized sensors to areas requiring monitoring for potential forest fires. These drones perform aerial surveillance by flying over the forested terrain, capturing real-time images and videos from an elevated vantage point. The drones continually collect data from their onboard sensors, including temperature, smoke levels, and other environmental factors that may signal the presence of a fire. This data is subjected to rigorous analysis through onboard software and algorithms that search for visual and thermal indicators of a fire. When potential fire signs are detected, the analysis software triggers an automatic alert. The alert is communicated in real-time to the relevant authorities and firefighting teams, often accompanied by precise GPS coordinates indicating the suspected fire's location. This fast response capability is crucial in forest fire management, as firefighting teams can be rapidly dispatched to the alerted area to take immediate action (Sherstjuk et al., 2018; Tehseen et al., 2021) (Figure 4).

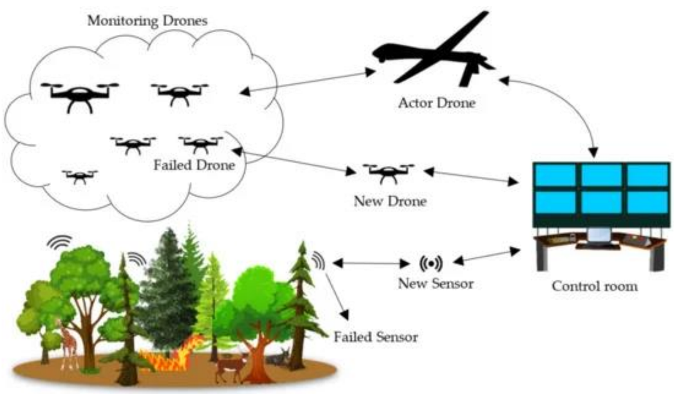

Figure 4. Architecture based on drone system for early fire detection. (Tehseen et al., 2021)

The United States Forest Service's (USFS) Forest Fire Laboratory implemented the UAV system for forest fire detection in 1988. Wardihani et al. (2018) presented a real-time wildfire surveillance system utilizing UAVs. The system employs five sensors: a temperature, a compass, a barometer, a GPS, and an inertial measurement unit (IMU). The UAV has a tiny CPU (a Raspberry Pi) and a flying controller. The results were sent to the server via the Transmission Control Protocol (TCP) system. This drone can monitor temperatures from a height of 20 meters above the surface of the earth.

Hossain et al. (2020) contributed a unique approach to identifying forest fires by utilizing a single artificial neural network and a color and multi-color space local binary pattern of both flame and smoke characteristics. The photos used in this work were largely collected from airborne platforms under difficult conditions. With the processing rate preserved at 19 frames per second, the suggested technique produced F1 scores of 0.84 for flame and 0.90 for smoke.

A number of studies have recently used CNN to categorize UAV-based forest fire photos. Srinivas et al. (2020) recommended using a rudimentary CNN architecture to categorize photographs of wildfires. In an AlexNet-like architecture, they layered convolutional and pooling layers, followed by flattening and two dense layers with sigmoid activation functions for binary classification. They attained an accuracy of 95% with such a design.

For disaster management agencies to respond quickly and appropriately, Jandhyala et al. (2023) suggested a hybrid strategy for detecting forest fires in aerial photos by combining classification and object recognition algorithms. For classification, they utilized the Inception-V3 model from the Keras framework, which was pre-trained on the ImageNet dataset, and trained it on aerial photos using transfer learning. It categorizes photos as fire if they contain fire or smoke, and a single-shot detector model, which identifies the regions of fire or smoke in the picture. The classification accuracy was around 88%, while the detection accuracy was approximately 91%.

The authors Lee et al. (2017) used five different CNN architectures to categorize photos collected by UAVs as fire or non-fire and captured by an RGB camera. AlexNet, GoogLeNet, VGG-Net, and customized versions of GoogLeNet and VGG-Net were utilized, and they attained an accuracy of 94.8, 99, 86.2, 96.9, and 96.2% sequentially.

Object detection techniques, instead of image classification, may identify and localize the object desired in an input picture or video by constructing a rectangular circle around the desired object, in this case, the flames and fumes of a fire (Bouguettaya et al., 2022). Li et al. (2022) developed an online early forest fire detection system using a drone platform. Various sensors are used to detect multiple aspects of fire and smoke. Deep convolutional neural networks (CNN) and standard computer vision algorithms are used to interpret visual (RGB) and infrared (thermal) pictures. However, precision, accuracy, and other metrics were not defined. Their software architecture took advantage of ROS (Robot Operating System) and the DJI on-board software development kit.

Anh et al. (2022) suggested a new forest fire detection approach based on image processing and a correlation coefficient. Initially, two fire detection criteria are used in the RGB color space to discriminate between fire pixels and the background. In addition, the RGB picture is transformed into the YCbCr color system, where two fire detection criteria are implemented. Ultimately, the correlation coefficient is utilized to differentiate between flames and items with fire-like hues. There are achieving up to 97.89% accuracy in performance evaluation.

For accurate wildfire smoke detection, Zhan et al. (2022) presented an adjacent layer composite network (ARGNet) based on a recursive feature pyramid with deconvolution, dilated convolution, and global optimal nonmaximum suppression. The proposed method uses an adjacent layer composition network to improve the extraction of smoke characteristics as well as SoftPool to keep additional information on smoke characteristics. GO-NMS is presented, to enhance the detection capabilities of various smoke places under UAV aerial photography and effectively decrease missed and false detections. It sets the goal function under the global viewpoint and selects the ideal anchor frame through a number of iterations. For training, 13838 images obtained by UAVs were used.

Chowdary et al. (2022) were presented the Barrier Coverage Networks as a method for early identification of wildfires and supporting authorities in adopting actions to prevent them as soon as possible. Drones that fly over the monitored area act as sensor nodes in this system. The drones are furnished with the necessary technology to detect forest fires and communicate data to other nodes. The X-Bee protocol used for communication.

Namburu et al. (2023) suggested a less expensive UAV with expanded MobileNet deep learning capacity and communicate wildfire detection and GPS position with state forest agencies for prompt action. The authors used two datasets for training, which contain images obtained using the designed drone, extracted from videos of wildfires gathered in Kaggle and FLAME, plus frames of videos taken by drone, resulting in 97.22 % accuracy.

Researchers presented several fire detection approaches using UAV imagery, such as models based on the Faster RCNN. Guan et al. (2022) suggested an early forest fire semantic segmentation approach based on an MS R-CNN model. These models can fully utilize the benefits of UAV image data to enhance the detection of wildfires. Jiao et al. (2019) proposed a YOLOv3 wildfire detection system based on UAV aerial image data to increase the real-time identification efficiency of wildfires.

By upgrading the traditional Faster RCNN target detection model, the study by Zhang et al. (2023), provided a multi-scale feature extraction model (MS-FRCNN) for small target wildfire identification. ResNet50 is utilized in the MS-FRCNN model in lieu of VGG-16 as the fundamental network of Faster RCNN to relieve the gradient dispersion phenomena observed with VGG-16. In addition, MS-FRCNN used FBN to increase its capacity to gather comprehensive feature data.

MS-FRCNN was also incorporated the parallel attention module (PAM) into the RPN. The FLAME dataset is used in training, where the average detection accuracy of MS-FRCNN was 82.9 %, while the average detection accuracy of Faster RCNN was 77.8%.

2.3. Wireless Sensor Network based system

WSN is also technology used to monitor wildfires and is deployed in forest areas to detect fires in real time. These sensors can detect changes in temperature, smoke, flame, or humidity, as well as chemical parameters such as carbon monoxide and carbon dioxide that may indicate the presence of a fire. A WSN consists of several components that work together to enable data collection: sensor nodes to measure different environmental parameters.

The base station is the central point of the network at which the data collected by the sensor contract is assembled and processed, in addition to a telecommunications network to transfer aggregated data to the base station where it is generally used: WiFi, Bluetooth, ZigBee, and LoRa. In the latter, each previous components receives power from the power unit (Sairi et al., 2023). The Wireless Sensor Network (WSN) forest fire detection system works by deploying a network of wireless sensors in forest areas to monitor and detect potential fires. The sensors, equipped with various environmental sensors, such as temperature, humidity, gas, smoke, and motion, are strategically positioned to cover the region effectively, as seen in Figure 5.

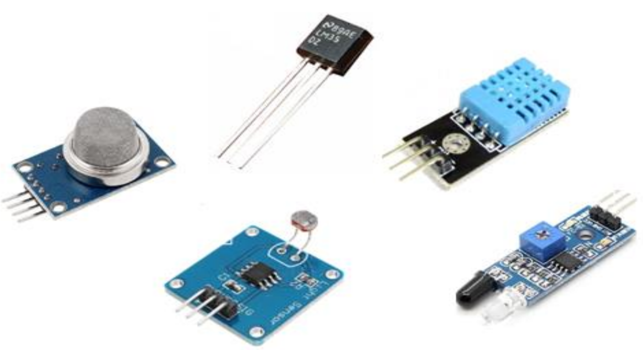

Figure 5. Sensors types (Benzekri et al., 2020; Dampage et al., 2022)

These sensors continuously collect environmental data in real-time. The data collected is continuously analyzed by specialized software and algorithms for anomalies or patterns indicating the potential presence of a fire, such as rapid increases in temperature, high levels of smoke or pollutants, or unusual environmental conditions. When potential fire signs are identified, the software triggers an automatic alert, transmitted in real time to a central monitoring station or fire management authority. It ensures a rapid response of firefighting teams deployed on the site, as indicated by the alert for early intervention and fire control (Benzekri et al., 2020; Dampage et al., 2022) (Figure 6).

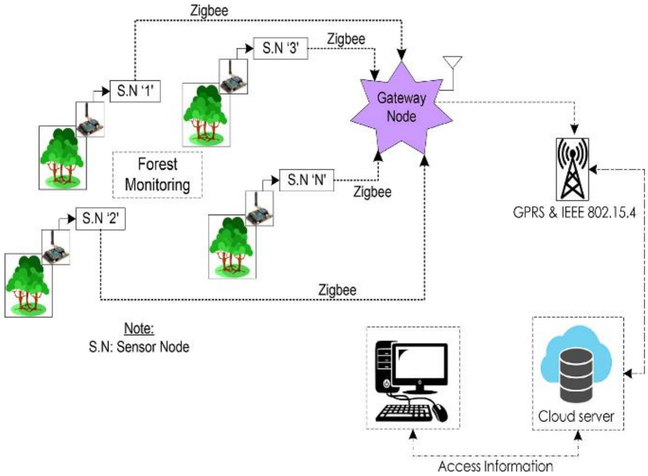

Figure 6. Architecture based on WSN system for early fire detection. (Benzekri et al., 2020)

At first, several systems were proposed, such as the Pennsylvania Project (Conrad et al., 2009), FireWxNet (Hartung et al., 2006), FIRESENSE (Kose et al., 2010) is a complex system that includes multisensors, optical, infrared, and PTZ cameras, as well as temperature sensors and weather stations. The current technological development in WSN has resulted in the prospect of using this technology to identify forest fires early, mainly when used in the IoT system. Several studies have looked into the use of WSN in wildfire systems.

A study by Molina et al. (2016) presented a hierarchical wireless sensor network connected with firefighting command centers, geographical information systems, and fire simulators to detect fires early in high-risk locations. This design has been successfully tested in two fire simulations that included all essential participants in firefighting operations.

Devadevan et al. (2019) created the Forest Fire Information System (FFIS) study to offer an interface for monitoring, assessing, and analyzing forest fire data generated by WSN, an Intelligent Forest Fire Detection System component. It also comprises a decision support system that forest administrators may use for strategic planning. PHP and MySQL were used to create this.

Kadir et al. (2019) suggested employing WSNs to detect forest fires in peat regions. The sensor nodes, which contained temperature, humidity, fire and smoke sensors, and particle sensors, were utilizing sensor nodes with many integrated sensors for reliable fire detection. The researchers used intelligent software to study the incident and obtain precise facts. Furthermore, using the Raspberry Pi computer and numerous sensors, a model for early fire detection was presented (Dubey et al., 2019). The GPS tracker was used in conjunction with the alert message to relay the location of that specific region. To predict, use the neural network with 96.7% accuracy. Varela et al. (2020) presented a simple algorithm based on temperature and humidity. They generated two base functions using regression analysis. D et al. (2020) aims to warn of forest fires faster than traditional methods while also assisting in predicting the directional movement of the fire. They suggested a system for continuous monitoring and real-time detection of forest fires based on temperature, humidity, and gas sensors incorporated in MICAz engines, as well as a surveillance IR camera sensor.

Noureddine et al. (2020) used a field experiment with low-cost hardware and software to create a forest fire warning system based on wireless multimedia sensor network (WMSN) technology in the Mesele Forest, Oran City, Algeria. Budiyanto et al. (2020) proposed a system based on Sugeno's mysterious logic and wireless sensor networks. Two sensor contracts, and one central contract are part of the proposed system. The NRF24L01 transceiver module transmits all data.

Dampage et al. (2022) recommended combining machine learning and WSN to detect wildfires early on. Temperature, oxygen concentration, humidity, and light intensity were gathered from sensors at different times of day and under different climate conditions. The model was enhanced by including a machine learning method to decrease false warnings with 81% accuracy.

Anshad et al. (2023) implements an effective strategy for predicting and detecting forest fires in real-time. Using a wireless sensor network built using tree topology, real-time forest fire detection is accomplished by taking into account several characteristics such as temperature, humidity, and smoke intensity. To predict forest fires, they combined machine learning models of the neural prophet with logistic regression. Taking into account characteristics such as ground temperature, wind speed, relative humidity, and precipitation resulted in a forecast accuracy of 86.67%.

Aldahoud et al. (2023) offers a low-cost wildfire detection system. The system monitors environmental factors such as temperature, humidity, and smoke using a network of sensor nodes. Sensor data is sent to a central computer, where powerful algorithms predict wildfires. The technology sends real-time notifications to forest officials and users via a mobile app. Experiments were used to assess the suggested system, and the findings demonstrate that it can efficiently detect forest fires with high accuracy, low false alarms, and a low cost (Table 3).

2.4. Hybrid systems

Hybrid systems for forest fire detection represent a promising approach to enhance the reliability and efficiency of forest fire surveillance. By combining different techniques and technologies, these systems offer a comprehensive approach to detecting fires as soon as they occur and monitoring the situation's evolution in real time. For instance, integrating drones equipped with optical and thermal cameras with wireless sensor networks (WSNs) makes it possible to cover vast geographical areas efficiently and rapidly. The data collected by drones and sensors can be analyzed together to detect early signs of fires and confirm detected incidents. Lloret et al. (2009) described all the procedures taken to design, research, and construct a wireless multisensor network that combined sensors and IP cameras in a wireless network to detect and verify fire in rural and forest regions of Spain.

Table 3. List of the state-of-the-art studies (WSN based system)

Study	Year	Sensor used	Communication type	Technique used	Accuracy %
Dampage et al.	2022	Temperature, humidity, light intensity and CO sensors.	NRF24L01	Linear regression	81
D et al.	2020	Temperature, humidity and gas sensors.	/	/	/
Dubey et al.	2019	Temperature, humidity, gas and flame sensors.	GSM	Neural network	96.7
Varela et al.	2020	Temperature and humidity sensors.	/	Regression analysis	/
Molina et al.	2016	Temperature, humidity smoke, CO and CO2 sensors.	ZigBee	ANN	82.5
Anshad et al.	2023	Temperature and humidity, smoke sensors.	nRF24L01	neural prophet with logistic regression	86.67
Aldahoud et al.	2023	Temperature, humidity, smoke sensors.	WiFi	/	/
Budiyanto et al.	2020	Temperature, fire and smoke sensors.	NRF24L01	Sugeno Fuzzy Logic	100

The authors evaluated the number of cameras, sensors, and access points required to cover a rural or woodland region, as well as the system's scalability. They created a multisensor that detected fires and transmitted a sensor alarm to a central server over a wireless network. Based on a software program, the central server chose the nearest wireless cameras to the multisensor, rotated them to the sensor that triggered the alert, and sent them a message. Sujith et al. (2022) proposed a novel method for identifying forest fires. An aerial vehicle equipped with cameras would capture images of the fire, and machine learning techniques were utilized to analyze the data. By integrating data from the sensor network, the wireless sensor network improved the accuracy of fire prediction. A key feature of this system was its capability to swiftly and efficiently make decisions by analyzing images captured by UAVs.

Li et al. (2018) presented an autonomous forest wildfire early warning system employing an advanced UAV that systematically traverses forested areas along predefined routes, adhering to strict protocols. The UAV gathers environmental data from sensors installed on trees, continuously monitoring and predicting wildfire occurrences and issuing early warnings should any danger be detected. Bluetooth Low Energy (BLE) technology facilitates data transmission between the UAV and various sensors. The collected monitoring data, including temperature and humidity readings, accurately reflects the forest's current condition, enhancing the potential for early wildfire detection.

Kizilkaya et al. (2022), the authors presented a unique hierarchical technique for detecting forest fires. The suggested architecture took a novel approach, hierarchically using multimedia and scalar sensors to reduce visual data transmission. A lightweight deep learning model was also created for network edge devices to boost detection accuracy while reducing traffic between the edge devices and the sink. Real-world testbed, network simulations, and 10-fold cross-validation were used to assess the framework's energy efficiency and detection accuracy. Based on their trials, the suggested system had a validation accuracy of 98.28% and an energy savings of 29.94%.

3. Results and Discussion

This literature review carefully examined and contrasted four types of early fire detection systems: satellite-based systems, camera-fixed systems, drones, and WSNs (Table 4). Cameras fixed in general are more effective in terms of precision and response time to forest fire occurrences and provide excellent spatial resolution depending on camera resolution and viewing angle, Srinivas et al. (2020) can achieve 95 %.

In contrast, the coverage area of the camera fixed is restricted compared to the other three systems due to the placement of cameras in fixed locations. The satellites provide broad-scale space coverage and can monitor enormous regions of forest. The spatial coverage is determined by the satellite orbit and the spatial resolution of the collected images (Bbarschke et al., 2017; Ba et al., 2021). However, the accuracy of the positioning of fires detected by the satellite can be relatively low due to the spatial resolution of the images. This can make it difficult to accurately locate a fire in a given area. The coverage in the case of drones is large. It provides a comprehensive view of a fire by providing high fire localization accuracy and providing more visibility. Its effectiveness depends on the flight time and range, as thermal cameras can detect the hottest areas and determine the fire area with precision, especially in inaccessible or dangerous areas. However, the accuracy of the drone's location can be influenced by factors such as its air movement, its quality, and weather conditions. A WSN, which allows for more comprehensive spatial coverage, it depends on the number of sensor nodes deployed in the forest. Sensor networks can provide high localization accuracy and detect fire signals from multiple points based on their quality and spatial arrangement.

Table 4. Comparison between Intelligent Technologies for Forest Fire Detection

Comparison	Satellite system	Fixed cameras	Drone	WSN
Spatial coverage	Large-scale coverage (the earth)	Restricted Coverage	Large coverage	large coverage
The speed of detection	Within hours or longer.	Detect fire in real time if it passes through its field of view.	Detection in real time	Detection in real time
Reliability of detection	Low	High	High	High
Cost	Very expensive	Expensive	Expensive	Medium
False alarm rates	High	Low	Low	Very low
Devices sensors and satellite used	MODIS, GOES, AVHRR, NOAA, CubeSats	Thermal, infrared, or optical cameras	Thermal, infrared, or optical cameras and GPS	Various Sensors: Temperature, humidity, smoke, flame, wind speed, precipitation, CO and CO2 sensors, GPS, microcontroller arduino and raspberry
IA techniques used	Machine learning, deep learning			
Accuracy Range %	92.75 - 99.5	82 - 93.6	82.9 - 97.22	81 - 96.7
Advantages	- Spatial coverage is extensive, allowing detection across wide areas. - Unlike CubeSats, its size is small, its cost is reduced, Improved time resolution time: less than 1 hour. - Specialized sensors are used to detect indicators of fire. - Satellite imagery is an effective way to identify hot spots and provide accurate estimates of fire-affected areas in forests. These images help equip us with the necessary possibilities to reduce the spread and control of fires. In addition, it contributes to assessing the impact of fires on the number of affected hectares, identifying the necessary response, and directing rescue efforts more efficiently.	- The ability to monitor continuously in the places where it is deployed. - Depending on camera resolution and viewing angle, give great spatial resolution. - Capability to detect smoke or flames visually and detect hotter regions using a thermal camera.	- Mobility and the capacity to cover huge regions rapidly. - For more precise detection, use thermal cameras or specialized sensors. - Use to limit the number of false positives. - Capability to fly over inaccessible or risky places for personnel.	- It can cover any space and this is depending on the number of sensors and distribution in the forest. -They may be used everywhere - Its network is extensible. - They may be linked to a variety of devices such as camera and drone and equipped with a variety of sensors to monitor a variety of factors. - There is no need to construct towers or set up complex communication networks. - High detection accuracy. - Environmental monitoring that is continuous and real-time. - Detection of various fire signals such as smoke, flame and heat through specialized sensors.
Limitations	-Low spatial resolution, which might make accurate fire localization difficult. - Data delivery delays. - Sensitivity on meteorological conditions, including cloud and smoke. - Satellite system does not work in real time to provide information about a forest fire. - Satellites cannot detect radiation from a tiny flame caused by a fire in the forest. Unless it is spread over a large area - The costs are very high	- This technology only allows for a line of sight. - Camera Fixed systems require development in order to decrease the frequency of false alarms caused by obstacles such as trees, cloud shading, and so on. - The camera's accuracy is affected by the weather and night vision. - is very expensive and need infrastructure. - In case of optical cameras the reliance is on vision and light conditions. - Range and geographical coverage are limited. -The need for precise positioning for successful monitoring.	-Sensitivity to weather conditions. - Costs related to the purchase and maintenance of drones are relatively high when they are of quality. - Limited flight time.	- Sensor network complexity and data management, especially if sensor density is very high. - Power problem consumed by sensors nodes. - Problem of increasing the number of sensors nodes and thus increasing the cost.

The detection time for each technology varies based on several parameters, such as weather conditions, the distance between the detection location and the fire source, real-time data processing capability, and the speed of the devices. Forest fires may be detected in real-time through sensor networks. When the sensor detects fire signals, it promptly provides a warning, minimizing detection time. On the other hand, the distance between the sensors and the fire source might alter the detection time. Drones can also identify threats in real-time. In addition, the detection time is determined by the distance between the drone and the fire, the speed of the drone, and the data processing capability. Conversely, fixed cameras detect fire if it passes through their field of vision. However, the detection time may be affected by how frequently photos are processed. Satellites can detect forest fires on a broad scale, but the detection time varies depending on the frequency with which photos are acquired and the capacity to analyze data from satellite photographs. In certain circumstances, images may be analyzed and fires discovered in a matter of hours (Barmpoutis et al., 2020b), whereas current AI-driven systems can detect fires within minutes (Lee et al., 2017; Namburu et al., 2023; Zhang et al., 2023).

The cost of each approach differs greatly based on numerous aspects, including the technology employed, the quality of the devices, operational costs, maintenance, and coverage area. Fixed cameras may be expensive in terms of installation and maintenance infrastructure, electricity, and continual monitoring, because there is a need to build towers and install telecommunications infrastructure in remote areas of forests. Furthermore, expenses may rise due to picture quality, precision, sophisticated detection capabilities, and networking. For drone-based technology, costs can vary depending on the type of drone, the quality of the camera or sensors on board, additional batteries, accessories, training and maintenance fees, and the licenses required to fly over forests. In addition, utilizing satellite data might result in greater expenses since it requires access to high-quality, up-to-date satellite photos. Costs may vary based on the data provider. Finally, sensor network costs are determined by the number of sensors required, the technology employed, the installation of sensors and communication systems, maintenance expenses, network deployment, network monitoring and management. WSNs have the lowest cost for detecting forest fires compared to other approaches.

Faulty alert rates for sensor networks are determined by sensor sensitivity, dispersion in the forest, and detecting techniques utilized. It can help improve detection accuracy and decrease false alarms. In contrast, fixed cameras and drones can have relatively low false alarm rates when correctly designed. Furthermore, sensor networks in the area with widely dispersed sensors can attain extremely low false alarm rates. However, they are susceptible to false alarms. Unlike satellites, they have a greater false alarm rate owing to their greater spatial resolution. They are influenced by weather conditions such as clouds or fog, which can confuse, as well as the difficulty of discriminating between fire signals and other heat sources. It is vital to highlight that by utilizing modern data processing techniques, complex detection algorithms, and taking into consideration the unique particulars of the forest environment, false alarm rates may be decreased.

They combined several techniques to reduce the error rate (Li et al., 2018; Kizilkaya et al., 2022; Sujith et al., 2022). In recent years, the field has been transformed by integrating AI, ML, and IoT. These intelligent technologies leverage vast amounts of data from satellites, drones, and ground-based sensors to provide real-time monitoring and predictive analytics. Advanced algorithms now enable rapid detection of fires, prediction of fire spread, and optimization of firefighting strategies. These modern systems not only enhance detection capabilities but also contribute to more efficient resource allocation and response planning.

Despite the impressive technical capabilities of modern intelligent technologies, their implementation is challenges, such as data privacy, high costs of deployment, the need for specialized training, and the integration of diverse data sources present significant barriers to widespread adoption. Furthermore, the reliability of these systems in diverse and challenging environments, as well as the potential for false alarms, must be addressed to ensure their effectiveness and acceptance.

In addition, implementing effective communication protocols for wildfire management is difficult due to factors such as reliable real-time data transmission from diverse sources, ensuring reliability, security concerns, and low-latency communications. Balancing these requirements while ensuring scalability, adaptability, and cost-effectiveness is a major challenge.

4. Conclusion

The detection and management of forest fires have undergone a significant transformation over the decades, driven by advancements in technology and a deeper understanding of fire behavior. From the early days of human observation from lookout towers and ground patrols to the sophisticated integration of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT). The evolution of forest fire detection methodologies reflects a continuous effort to improve accuracy, response time, and overall effectiveness. In this paper, we did a comparative study of various techniques for forest fire detection. According to documented research in the literature, fixed cameras, drones, satellites, and wireless sensor networks (WSN) are among the technologies used to detect forest fires. Each approach has benefits and drawbacks, particularly regarding geographic coverage, detection time, false alarm rates, detection rates, cost, and light localization precision. Cameras fixed with adequate resolution and range of view allow continuous surveillance of high-risk regions. For airborne surveillance, drones provide greater freedom and mobility. Satellites give worldwide coverage and can identify large-scale fires. Wireless sensor networks continuously monitor environmental conditions for indications of fire. For more extensive detection and monitoring of forest fires, it is frequently desirable to employ a mix of methods. Future research should focus on data fusion by integrating information from various sources and using machine learning and AI to enhance forest fire detection, making systems more adaptable to changing environmental conditions. Additionally, evaluate the effects of climate change on wildfire frequency and intensity and incorporate these findings into the design and deployment of early detection systems. Finally, low-cost and sustainable solutions that are simple to apply, especially in resource-constrained areas, should be develop to ensure widespread acceptance and efficacy. By investing in these areas, we can work together to create a safer and more resilient approach to wildfire prevention and control, protecting our ecosystems and communities.

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