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A Review on Fire Detection Architectures and Techniques in Indoor and Outdoor Spaces

Una Revisión sobre Arquitecturas y Técnicas de Detección de Incendios en Espacios Interiores y Exteriores

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Technological innovation: Fire detection systems powered by artificial intelligence.
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Resumen

Los incendios en zonas residenciales y áreas forestales son eventos que pueden causar una serie de problemas catastróficos cuando se descontrolan, desde la destrucción total o parcial de estos lugares hasta causar muertes, pérdidas materiales y contaminación del aire. La investigación abarca métodos dedicados a detección de incendios tanto en espacios exteriores e interiores. Estos se basan en técnicas computacionales, como la visión por computadora, aprendizaje automático (ML), sistemas de detección de variables como humo, CO, y CO_2, verificados mediante redes de sensores inalámbricos (WSN) y sistemas de información geográfica (GIS). También se presenta lo relacionado con la tecnología satelital que ofrece soluciones para detectar incendios mediante sensores y algoritmos de inteligencia artificial (IA). De los métodos de detección analizados, se observa una notable influencia de la IA para aumentar el nivel de confianza en los procesos de detección y predicción de incendios en diferentes contextos. Uno de los algoritmos más recurrentes es el uso de redes neuronales convolucionales (CNN), que integran sistemas de sensores, sistemas satelitales, vehículos autónomos no tripulados, entre otros.

Palabras clave: Visión artificial, Aprendizaje profundo, Punto de calor, Incendios forestales, Redes de sensores inalámbricos.

Abstract

Fires in residential and forested areas can escalate rapidly, causing catastrophic consequences such as partial or total destruction, loss of life, economic damage, and air pollution. This review compiles research on fire detection in outdoor and indoor environments. The surveyed approaches leverage computer vision, machine learning (ML), and sensing systems that measure variables such as smoke, CO, and CO2, often validated through wireless sensor networks (WSN) and geographic information systems (GIS). Satellite-based monitoring is also discussed as a complementary solution that uses sensors and artificial intelligence (AI) algorithms. Across the literature, AI significantly improves the reliability of detection and prediction in diverse contexts; convolutional neural networks (CNNs) are among the most frequently used methods, and are commonly integrated with sensor networks, satellite platforms, and unmanned autonomous vehicles.

Keywords: Computer vision, Deep Learning, Heat point, Wildfire, Wireless Sensor Networks.

1. Introduction

Uncontrolled fires pose a significant threat, causing injuries, fatalities, and extensive material damage, particularly in indoor environments (CONAPCI, 2020; García et al., 2022; Velasco et al., 2024). The World Health Organization (WHO) reports approximately 268,000 fire-related deaths annually, with children under five accounting for 60% of these victims (Koudenoukpo, 2023). In the case of wildfires, human activity is the primary cause, responsible for 98% of occurrences (Semarnat, 2018). While fire is a natural and essential part of ecosystem renewal (He et al., 2012; McLauchlan et al., 2020), modern wildfires have severe environmental consequences. They release an estimated 6.375 billion tons of carbon dioxide (CO_2) each year (Greenpeace, 2019) and burn between 30 and 42 million square kilometers of land globally (Randerson, 2012). Furthermore, the smoke from these fires contains hazardous particulate matter (PM10 and PM2.5), which, when inhaled, can enter the bloodstream and lead to serious lung and cardiovascular diseases (Vicente et al., 2013; Adetona et al., 2016; DeFlorio-Barker et al., 2019).

The complexity of heat sources can be assessed using methods ranging from simple instruments (e.g., thermometers and hygrometers) to more sophisticated electronic and computer-based systems (Hossain et al., 2019). The main approaches include:

- Classification through artificial intelligence.
- Detection by sensor reading.
- Forecasting by geographic systems.

Artificial Intelligence (AI) generates highly reactive monitoring systems that enable actions to be taken in a manner close to human response. In the case of spatial monitoring, Machine Learning (ML) is used, which helps to see large extensions or bounded extensions by extracting information in real-time. Advances within ML include deep learning (DL), which excels at analyzing vast datasets to identify specific patterns, an application demonstrated in urban fire prevention (Alapatt et al., 2021).

Convolutional neural networks (CNNs), inspired by the visual cortex, are powerful function approximators that excel at extracting visual features from images (Venkatesan and Li, 2017). These networks can learn patterns of varying complexity in

digital images for classification (Masegosa et al., 2018). Pre-trained CNN architectures (Stančić et al., 2022) can expand the effective field of view and simplify data collection; the captured information is then processed to identify anomalies in the monitored area and support timely decision-making in the event of an unforeseen contingency. Figure 1 shows the classic structure of a CNN.

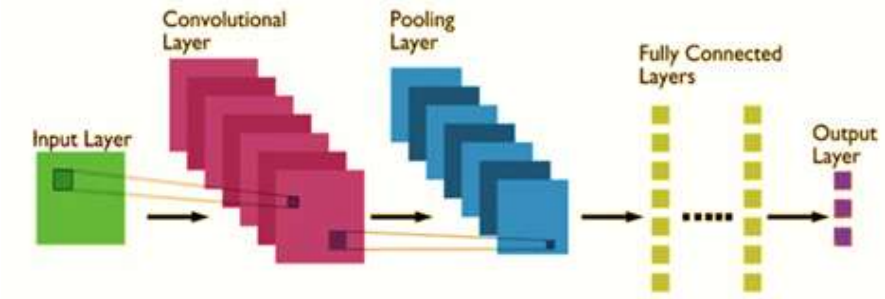


Figure 1. The basic structure of a CNN (Chen and Lee, 2020).

ML algorithms require specific validation; common metrics include precision, evaluating model quality in classification (Equation 1), recall, indicating the ML model's retrieval quantity (Equation 2), F1 score, combining precision and recall performance (Equation 3), and accuracy, recording the successful model percentage (Equation 4).

$$Precision = \frac{TP}{TP + FP} \quad \textbf{(Eq. 1)}$$

$$recall = \frac{TP}{TP + FN} \quad \textbf{(Eq. 2)}$$

$$F1 = (2\cdot)\frac{precision \cdot recall}{precision + recall} \quad \textbf{(Eq. 3)}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \textbf{(Eq. 4)}$$

Where:
TP = True Positive, *TN* = True Negative, *FP* = False Positive, *FN* = False Negative.

The most common type of grouping of electronic sensors is the Wireless Sensor Network (WSN), this type of device allows the propagation of a signal using the nearest neighbors reducing costs and communication mechanisms, where a central node coordinates and manages the information that is transmitted by each of the devices (Sharma and Bhatt, 2022). In this type of network, it is essential to reduce the level of energy consumption to prolong the life of the network (Sharma et al., 2023) and maintain its level of confidence and operability (Oprea et al., 2020; Marrero et al., 2019). Figure 2 shows the basic structure of a WSN. Other important tools for detecting fire outbreaks are geographic information systems (GIS), whose information comes from the Earth's surface from satellites, which have sensors (Liang and Wang, 2019), in turn, satellites. Satellites make up systems responsible for obtaining information about the planet (Tricart, 1979) through radar waves, and infrared sensors, among others, to be processed by mathematical and AI models.

This study was developed due to the catastrophic and multifaceted threat of uncontrolled wildfires, which cause hundreds of thousands of deaths annually, immense property damage, and severe environmental degradation due to massive CO_2 emissions and dangerous air pollution. To address this critical issue, the research aims to conduct a comprehensive analysis of modern fire detection technologies, particularly those using artificial intelligence, numerical methods, and image processing. The goal is

to identify and analyze the most effective techniques for indoor and forest environments, to inform future research to optimize existing solutions, adapt them to specific contexts, and drive innovation to create more accurate and robust fire prevention, early detection, and mitigation systems.

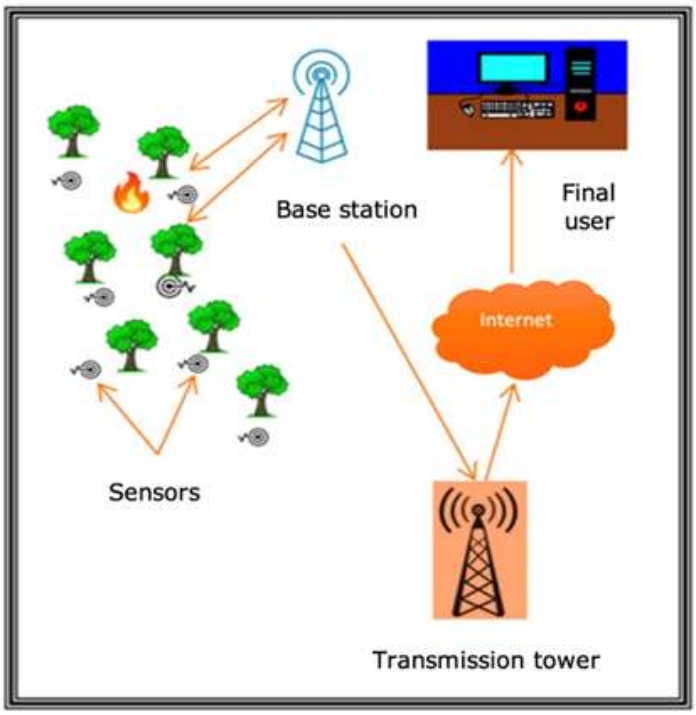


Figure 2. The basic structure of a WSN (Mohamed et al.,2018).

2. Materials and methods

This review focuses on research that develops theoretical models and electronic devices for fire detection from different perspectives, including prediction models, damaged-area estimation, and rapid-response alerting systems. To evaluate and compare these approaches, we adopted a structured methodology, shown in Figure 3, which outlines the stages used to compile and analyze the literature on fire detection.

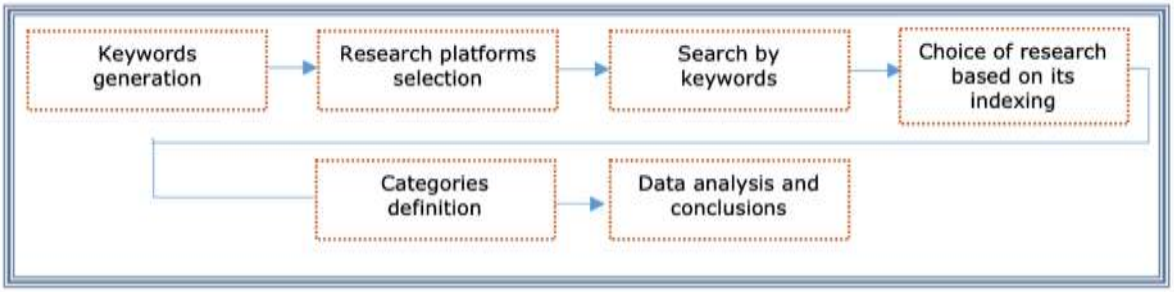


Figure 3. Work methodology proposed.

- Keyword generation. Key terms referring to fires are defined, considering the detection mechanism and the context in which the fire occurs.

- Research platform selection. A search is conducted in databases to find works related to fire detection. The search engines consulted include IEEE Xplore, Wiley, Scopus, Springer, and Google Scholar. The search structure is composed of basic terms, secondary search terms, and finally, the other parameters that are relative to the year and the relevance of the investigation per citation (see Table 1).
- Search by keywords. The generated search terms are used to search for research works in the selected databases, according to a base term structure and its complements.
- Selection criteria based on indexing. Journal articles indexed in Scopus or Web of Science (WoS) were prioritized; papers indexed in ROAD or DOAJ were also considered if they had received at least one citation within the last six years. Conference papers and book chapters were included only when published by recognized publishers such as IEEE, Springer, or ACM, among others.
- Categories definition. From the set of research work collected and filtered, the generation of fire detection categories is carried out based on the context in which the fires occur, forestry or interior of buildings, subsequently, the technology or methodology used to detect the fire is considered.
- Data analysis and conclusions. According to the data collected, an analysis of research works classified into forest fire detection systems and indoor detection systems is carried out. From the analysis developed, the construction of a contrast between the advances and current challenges with fire detection systems is considered.

Table 1. Basic term combinations are used in this investigation to generate in State-of-the-art.

Basic terms	Secondary terms	Other terms
Fire detectors	Interiors, buildings, house	Year, relevance
Fire detectors	Outdoor, forestry	Year, relevance
Fire prediction	Interiors, buildings, house	Year, relevance
Fire prediction	Outdoor, forestry	Year, relevance

Figure 4 shows the process to filter the research work investigation obtained in the first search process, using the question investigation and criteria filters, the research works obtained belong to the period 2017-2023. The research questions that were proposed for this investigation to select the articles investigated were: what impact does the research presented have? How important has it been for the international community? What has been the novelty concerning another research? The general terms were combined to determine the research to be analyzed. In the first instance, 350 works were found, of which they were filtered according to the proposed methodology. From the final works obtained, a division based on outdoor fire detection was carried out, from these it is derived the detection of fires based on computer vision and ML, detection by unmanned aerial vehicles, detection by satellite systems, detection by WSN, fire prediction systems, while the detection of indoor fires is subdivided into fire risk detection systems, computer vision-based sensing in ML and sensor-based systems. From this process, a total of 105 articles were obtained, and selected to be analyzed in the document. Figure 5 presents the distribution of the works cited in this

research considering the year in which they were published, as can be seen, the years in which most of the publications to be analyzed are concentrated are from the years 2020-2022, other years in which the rest of the concentration of publications is presented are the years 2019 and 2023.

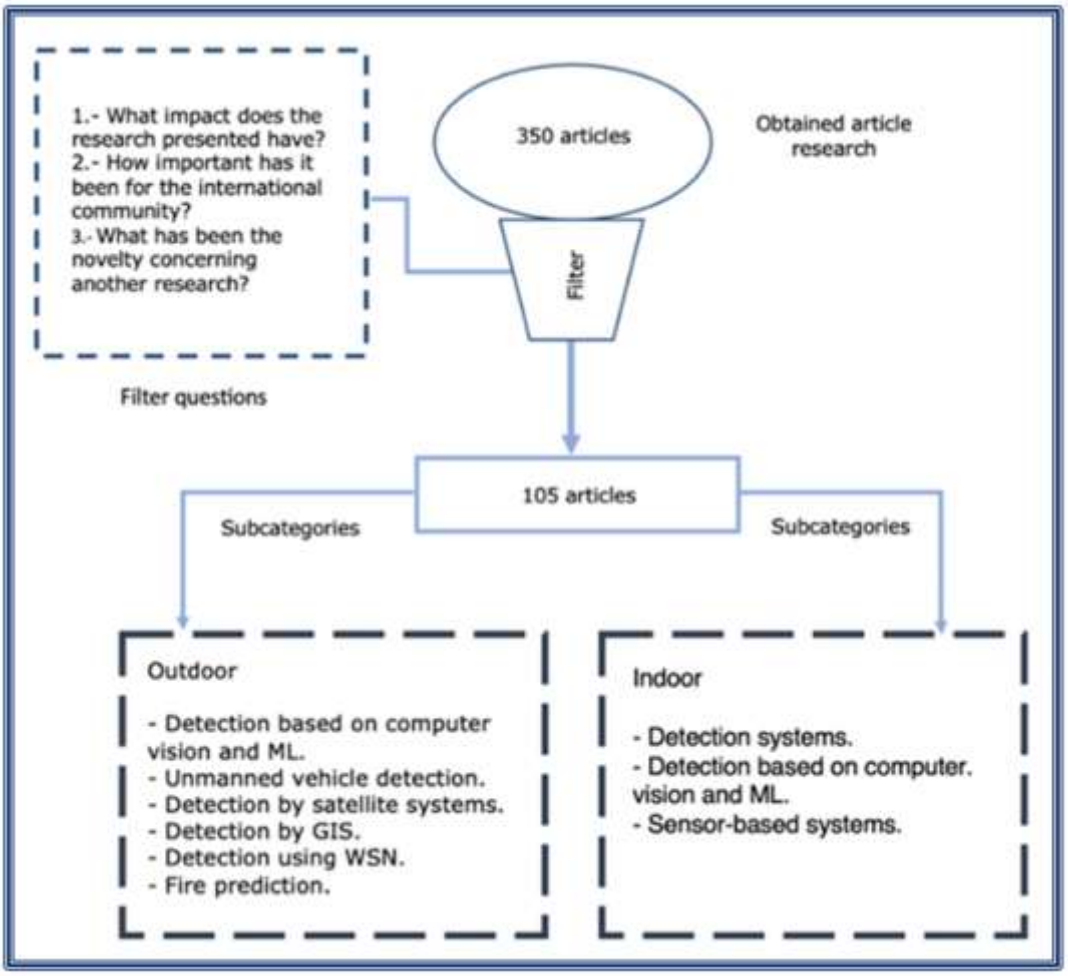


Figure 4. Selection process for articles related to fire detection.

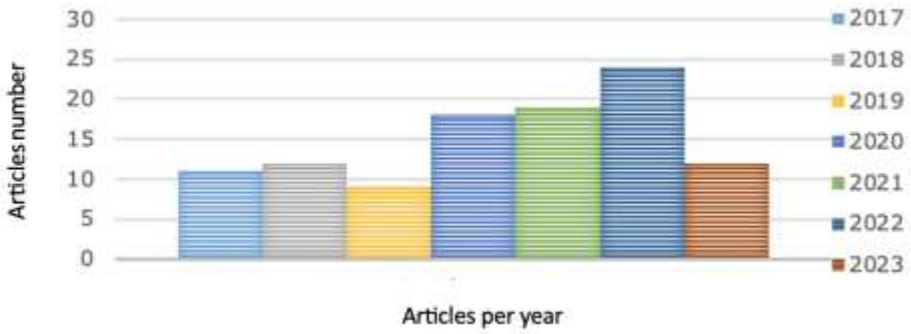


Figure 5. Distribution of publications of this research from the period 2017-2023.

As can be seen in Figure 6, the main distribution of articles used in State-of-the-art and that are indexed in recognized databases such as WoS or Scopus represents 82% (89 articles), while conference articles occupy 16% (17 articles), and finally, 2% (2 articles) correspond to other articles published in databases with a lower category indexing than WoS or Scopus. On the other hand, the articles presented in this research have a sub-distribution, as indicated in Figure 7, 65% (11 articles) of articles are indexed in IEEE, 17% (3 articles) correspond to ACM, while 12% and 6% (2 and 1 articles) respectively correspond to Springer and other publishers.

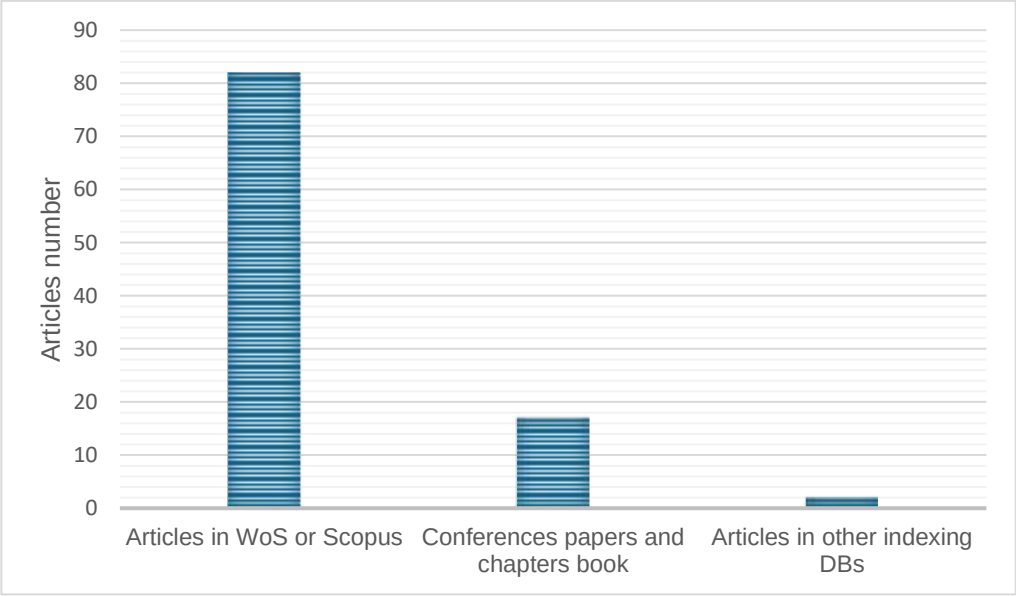


Figure 6. *Article distribution statistics in indexing DB included in State-of-the-art.*

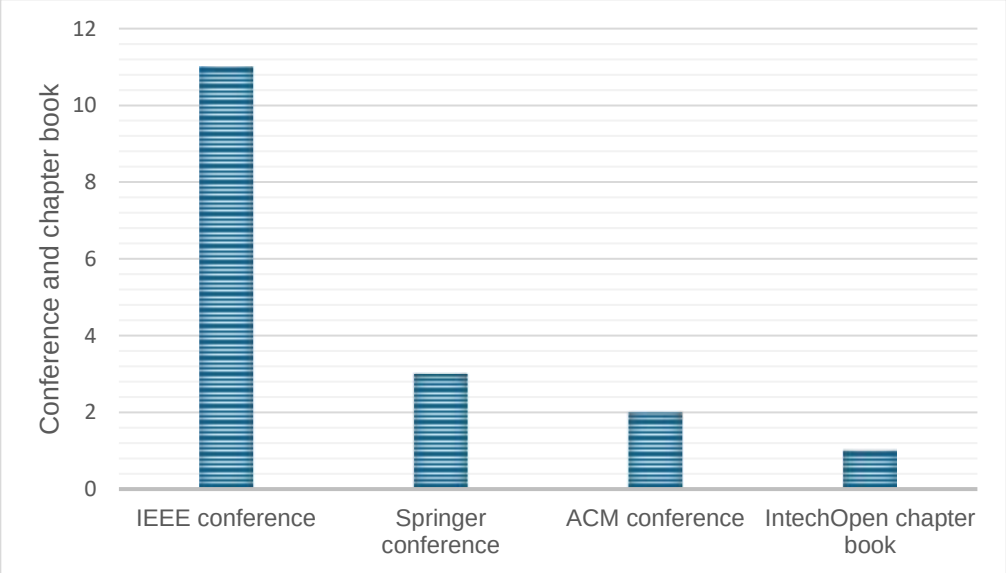


Figure 7. Distribution statistics of conference articles and book chapters by publisher.

3. State-of-the-art

The works presented in this section are based on different methods and techniques to classify indoor and outdoor fire events. The dimensions that will be addressed are detection by computer vision and ML, detection by unmanned aerial vehicles, detection by satellite systems, detection by GIS, detection by WSN, and finally fire prediction investigations.

3.1 Machine learning and deep learning

Computer vision approaches for outdoor fire detection are widely studied. Convolutional neural networks (CNNs) such as Faster R-CNN have been used to detect smoke in video frames (Zhang et al., 2018; Namozov and Im Cho, 2018). Li et al. (2018) developed a CNN for forest-fire smoke detection using 3D parallel analysis. Seydi et al. (2022) proposed Fire-Net, a deep neural network for early fire identification over relatively small areas (around 50 hectares). Hu et al. (2022) introduced MVMNet, which combines multi-oriented detection, a value-attention conversion module, and Mixed-NMS to better adapt to smoke direction. Built on YOLOv5, their model reported an mAP@0.5 of 88.05% and ran at 122 frames per second (FPS).

Research such as Wang et al. (2021), Goyal et al. (2020), and Zhao et al. (2022) rely on the YOLO model for forest fire identification due to the effectiveness of such a model. An et al. (2022) used YOLOv5 as a base and applied the K-means++ algorithm and dynamin convolution for fire detection with a precision of around 80% to 95%, depending on the scenario. Other proposals such as Zhang et al. (2023), use the basis of the Faster R-CNN model for fire detection, while Park et al. (2021) and Nguyen et al. (2021) use VGG-16 and MobileNets, respectively, the latter with a detection effectiveness of 92%. Guede-Fernández et al. (2021) present a system for the classification of smoke columns; using independent tests an F1 score of approximately 80% was achieved with a detection rate of around 90%. Huang and Du (2020) proposed a classifier for fire detection using rough set theory and a support vector machine, considering that the developed classifier improves fire recognition.

Xu et al. (2021) based their investigation on two different conditions, first considering YOLOv5 and EfficientDet, they obtained a model that is more robust for the detection of forest fires considering different scenarios.

3.2 Unmanned Vehicle Detection

Several investigations have focused on the use of unmanned aerial vehicles (UAVs) for the detection of forest fires, including studies by Kinaneva et al. (2019), Liu et al. (2020), Wardihani et al. (2018), and Lin et al. (2018). Cao et al. (2019) and Al-Kaff et al. (2020), of which Al-Kaff et al. (2020) for taking advantage of cell phone transmission stations stand out to send data regarding the progress of fires that are occurring. The work of Calderón de León et al. (2021) presents a distributed ROS (Robotic Operating System), which is composed of several UAVs controlled from a command center, that collect information about a forest fire. Innocente and Grasso (2019) developed a proposal based on the Particle Swarm Optimization (PSO) method, to fight against forest fires with a swarm of drones with self-organized decentralized cooperative behavior.

Aydin et al. (2019) developed a system composed of a set of scanning unmanned aircraft systems (UAS) to detect fires in buildings, as well as the ability to deploy spheres capable of fighting forest fires. Kim and Muminov (2023), developed a smoke detector for forest fires using UAVs for forest fire smoke imaging which, were used to train

a YOLOv7 model. In this model, a CBAM mechanism and a SPPF+ layer were implemented to improve the detection capability.

Pham et al. (2018) developed a real-time fire detection solution for large area surveillance using an unmanned aerial vehicle using a lightweight camera and telemetry modules. Fire detection is based on the Single Shot MultiBox Detector (SSD) algorithm, as well as the CNN MobileNets network, which achieves an average of 92.7%.

3.3 Detection by Satellite Systems

Various research has focused on fire detection through the support of satellite technology, as shown in Seo et al. (2017) combining UAVs with the Landsat 8 OLI satellite system for rapid-fire response. Byer and Jin (2017) used the Moderate Resolution Imaging Spectroradiometer (MODIS) system to detect fires in the Sierra Nevada. This system is also used by Marchese et al. (2017) and Chatterjee et al. (2017). Xu and Zhong (2017), Zhao et al. (2018), and Xie et al. (2018) use the Himawari-8 satellite in Australia to evaluate the behavior of forest fires. Other studies, such as those by Pandey et al. (2017), use satellites like Landsat 8, while Meng et al. (2017) apply the Multiple Endmember Spectral Mixture Analysis (MESMA) technique to study the behavior of forest fires. Due to the potential of satellite systems, several investigations have been developed for outdoor fire detection, as shown in the work of Santi et al. (2022) used the NASA CyGNSS (Cyclone Global Navigation Satellite System) system was used for wildfire detection in Angola. Its method consists of obtaining the signal-to-noise ratio (SNR), the equivalent reflectivity of the Global Navigation Satellite System (GNSS-R), the angle of incidence, and the forest biomass through a binary classification of a 5 km area, to obtain 98% detection accuracy. A solution to the detection of smoke sources by satellite is presented by Zhao et al. (2022), who developed an investigation for the detection of smoke from fires at the scene level based on satellites, using a dataset of multispectral images from the satellite Landsat 5 TM and Operational Land Imager. The authors design a lightweight model structure Variant Input Bands for Smoke Detection (VIB_SD), training your model with three added Infra-Red (IR) bands to detect fire and smoke early in various scenarios. Castro et al. (2022) used multiple remote sensing datasets to compare forest loss and fires over 16 years in Talassemtane National Park, finding severe wildfires.

The study by Rashkovetsky et al. (2021) used satellite images in the visible, infrared, and microwave domains for fire detection. This is achieved through the U-Net architecture, which takes various atmospheric conditions into account. Additionally, the study explores the combination of different models. Wooster et al. (2021) carry out an analysis of different approaches, that have been carried out in fire detection using satellite images.

3.4 Detection by Geographic Information Systems

GIS systems, which have a large amount of data, it is possible to use them as tools to deal with forest fires, as shown in Zhang (2019), presents a case study of mapping the suitability of habitats Yunnan region (China) using statistical data, to prove the usefulness of integrating GIS in wildlife habitat assessment. Nasiri et al. (2022) found areas of forest fire risk predicted by a GIS, the implementation developed detected 64.7% of the areas where there are high degrees of fires. The research of Güllüce and Çelik (2020) presents a fire detection system in forested areas at an early stage by using the geolocation and propagation of the fire (speed and direction of propagation) are calculated

using spatial resolution by superimposing the detection areas of multi-IR detectors, called FireAnalyst, and implementing DBTC (detection towards the center) geometry overtook other fire detection methods.

The research of Bartholomäus et al. (2022) presents an analysis of data from the TUBIN microsatellite, which has detected forest fires and volcanic activity in different biomes around the world as well as an evaluation of light pollution in specific night-time imaging campaigns. Thangavel et al. (2022) present an examination of wildfire monitoring using satellite systems, through feasibility analysis, as well as a model and a prototype scenario for a satellite AI system to enable rapid action and provide alerts quickly, using DSS architecture in geographic locations to demonstrate system-wide coverage. In Shao et al. (2023), work was conducted that integrates DL, geographic information, and other data like topography, climate, vegetation, and society, finding that the risk of forest fires can increase according to the season of the year and varies from the regions where fires occur.

3.5 Detection using WSN

The WSN can be deployed in diverse types of terrain, as demonstrated by Kandris et al. (2020) and Tsipis et al. (2020). Additionally, this is highlighted in the work of Jain (2020), where the combination of IoT with WSN stands out. The researchers of Ayele & Seraj (2020) and Curtin et al. (2019) used WSN for the remote observation of forest fires. Research such as Dampage (2022) and Varela et al. (2020) apply ML with the data collected for the information collected (Varela et al., 2020) and raise the level of precision in detection. Bharany et al. (2022) base their work on a clustering algorithm to optimize routing tables to extend the life of UAVs for forest fire detection. Santos et al. (2023) propose a LoRa, for fire detection with WSN and UVA, taking data from urban and forest environments, with an average tracking root mean square error (RMSE) of 0.0381. Elias et al. (2022) suggest a system based on wireless sensor nodes based on technology for packet-oriented Wi-Fi by obtaining a low-cost WSN with low power consumption. Paidipati et al. (2023) implement the emperor penguin algorithm, taking the data from a WSN and treating it using DL, the data is cleaned by guided filtering (GF) and root mean square propagation optimization (RMSPro) to fire detection. Kanwal et al. (2017) developed a WSN in combination with a machine vision technique through a camera node that implements a model HIS to detect fire.

Brito et al. (2020) developed a system that uses LoRaWAN for communication between the nodes and the central system. The data collected by the sensors are temperature, air humidity, solar radiation, and barometric pressure, among others. The developed system is evaluated through simulations and field tests. Baek et al. (2021) a fire detection algorithm is proposed taking into consideration a network of sensors that are in distinct positions based on the k-out-of-P rule by combining the signals from multi-channel sensors, for testing, they use data from the National Institute of Standards and Technology.

Barmpoutis et al. (2020) the authors propose RGB cameras with 360-degree sensors for early fire detection, applying two DeepLab V3+ networks to perform flame and smoke segmentation, respectively, in this way, they can reduce costs in the assembly of sensors in the ecosystem. The parameter F score achieved is 94.6%, thus reducing the number of sensors required.

3.6 Fire Prediction Systems

Due to the complexity of fires, a useful tool is drought forecasting, which allows for

estimating the duration of the absence of water as shown in Castillo-Castillo et al. (2018), Liu et al. (2022), Tian et al. (2021) and Poornima and Pushpalatha (2019), in these works highlight the implementation of techniques such as the Kalman filter, regression, and CNN networks. AI algorithms allow to detection of different patterns, as shown in Moayedi and Khasmakhi (2023), present two different hybrid algorithms of ANN for the spatial analysis of forest fires in northern Iran. The evolutionary algorithms such as ant colony optimization (ACO) and biogeography-based optimization (BBO) are synthesized with an ANN. ML fire prediction models increase the range of possibilities for wildfire prevention presented by Bottero et al. (2020), McCarthy et al. (2020), and Naderpour et al. (2021).

Monaco et al. (2021) present an experimental solution based on CNN for the estimation of areas damaged by forest fires and the assessment of damages without the need for previous images of fires, using a two-stage method with a double-pass deep learning framework (APDP) based on the UNet segmentation model (Ronneberger et al., 2015) and the interoperability analysis of the multichannel model, the results obtained show high ability in the prediction and evaluation of damages.

3.7 Analysis of Outdoor Fire Detection Systems

As can be seen in Table 2, the works related to the use of CNN use pre-trained models to develop the basis of recognition, among the most widely used pre-trained models are YOLO, GoogLeNet, and Faster R-CNN among others, this type of CNN are highly efficient for the detection of events in real-time, achieving at best 95% effectiveness (Zhao et al., 2022).

Table 2. Outstanding work in the detection of outdoor fires.

Authors	Main techniques
Hu et al. (2022)	Network based on YOLOv5
Xu et al. (2021)	Combination of YOLOv5, EfficientNet, and EfficientDet
Zhao et al. (2022)	YOLO based network
An et al. (2022)	CNN Network
Calderón de León et al. (2022)	System distributed ROS
Innocente et al. (2019)	Numerical methods
Aydin et al. (2019)	Drone Equipment
Santi et al. (2022)	Satellite detection
Meng et al. (2017)	
Castro et al. (2022)	GIS
Nasiri et al. (2022)	GIS
Sivrikaya and Küçük (2022)	GIS, statical analysis
Castillo et al. (2018)	
Liu et al. (2020)	Statistical processes neural networks
Tian et al. (2021)	
Bottero et al. (2020)	ML
McCarthy et al. (2020)	Statistical models
Zhao et al. (2018)	Drone with CNN and GPS
Monaco et al. (2021)	Estimation based on CNN with APDP

One of the most relevant recent applications is the use of unmanned aerial devices that require the calculation of routes to perform planned flights due to the limitations present in the autonomy (Innocente and Grasso, 2019), these devices allow a series of routines based on the use of sensors and digital image capture devices to detect forest fires (Aydin et al., 2019). GIS allows the creation of mathematical models for fire detection (Güllüce and Çelik, 2020), while information from satellite systems allows different exploration tasks, and detects fires by showing flame or smoke, one of the key features is that the information is analyzed by edge classification algorithms (Santi et al., 2022; Castro et al., 2022) running with 98% effectiveness. WSN networks supply great advantages over the area where they are deployed, due to their ability to measure temperature, and humidity, as well as the detection of flame and smoke (Kandris et al., 2020; Ayele and Seraj, 2020; Dampage et al., 2022). Finally, models that calculate the amount of precipitation in times of drought (Castillo-Castillo et al., 2018; Liu. et al., 2022, Tian et al., 2021; Poornima and Pushpalatha, 2019) allow for estimating the areas that can be presented as more likely, and fire forecasting systems (Bottero et al., 2020; Park, 2021; McCarthy et al., 2020) are tools that allow planning to be created in advance.

4. Investigations of intended for indoor fire detection

Indoor fire detection proposals are based on different perspectives, including risk estimation systems, computer vision-based detection, and sensor-based systems, as presented below.

4.1 Fire Risk Estimation Systems

Works such as Hahnemann et al. (2017), conducted a study to visualize the best method of fire risk assessment, this work proposed Gretener's method to quantify fire risks and thermal loads, and thus decide the position of systems that mitigate the effects of a fire. The works of Choi and Jun (2020) compare their model against the KFRI (Korea Fire Protection Association Fire Risk Index), in the experimental results obtained an accuracy of 0.7514 (to 1), which represents a significant effort considering the number of variables that exist for a fire to occur in a building. An interesting proposal for fire control is presented by Wang et al. (2022), who use digital images to make predictions based on the evolution of detected smoke. In an evaluation of more than 1,800 simulated fire scenarios, the images are analyzed using a CNN, considering the Heat Release Rate (HRR), and achieving an error rate of less than 20% during the experimental phase. Other works such as Nazir et al. (2022), carried out detailed experimentation on the components that exist in closed spaces and analyzed and analyzed factors such as temperature, and the concentration of gases such as CO_2, to measure the alert levels that may occur.

Sivrikaya and Küçük (2022) based on multi-criteria analysis based on geographic information systems, an analytical hierarchy process, and a statistical index established a forest fire risk map of a Mediterranean region, to make the map they used four main criteria and 16 sub-criteria. The work carried out will serve to make decisions and thus minimize the risk of forest fires in the region. It is considered that the success of the evacuation depends on the risk conditions of the evacuees, which are determined by the stage of development of the fire (Cao et al., 2023).

4.2 Detection based on Computer Vision and ML

Several investigations have focused on the analysis of digital images from the point of view of heat intensity, using infrared technology, such as the research of Rostami

et al. (2022), Wang et al. (2018), Yang et al. (2020) and Saponara et al. (2021), being remarkable the use of advanced models of digital image recognition with RGB images and digital images taken with infrared cameras. Other studies, such as those by Sharma et al. (2017), Mwedzi et al. (2019), Iqbal et al. (2020), and Muhammad et al. (2018), present similar proposals based on CNNs for fire detection inside buildings. The most advanced of these is the work of Muhammad et al. (2018), which developed a fire video surveillance framework for buildings, residential rooms, forest fires, and vehicle fires. This framework, based on GoogLeNet (Szegedy et al., 2015), achieved an accuracy of 94.43%, even in 80% of noisy scenes. Xu et al. (2017) use a scheme based on deep learning for different forms of fire in synthetic images. Munshi (2021) developed an investigation in which they decided that the technique for fire detection, using distinct color models such as RGB (Red Blue Green), HSI, CIE L*a*b, and YCbCr along with detection algorithms such as Gaussian filter. Nicolas-Mindoro et al. (2019) ran 3999 iterations of 210 images, to obtain train accuracy and cross-entropy with 100% accuracy in training, 96% in validation, and 99% accuracy with new data. Other models such as that of Zhong et al. (2018) present a CNN to detect the shape of the flame to activate an alarm in indoor places, by training it on a database with extensive examples.

The work of Sankarasubramanian and Ganesh (2022) presents a real-time fire detection system, this system achieved moderately high classification accuracy using CNNs, due to the over-fitting that exists in the network to learn about fire and smoke functions, with a 94% accuracy. Other works based on computer vision such as that of Lestari and Kosasih (2022), developed methods to detect fire access points through Faster R-CNN (Ren et al., 2015) and YOLO. The authors measured the F1 score, which is close to 1, therefore, the balance is best. In the experimental results, the authors found that YOLO has an accuracy of 100%, a recovery of 54.54%, an accuracy of 66.67%, and an F1 score of 0.70583667. While Faster R-CNN obtained 87.5%, 95.45% in the recovery, and the accuracy was 86.67%, and the hand an F1 score was 0.913022. Joshila Grace et al. (2022) have used many CNN-based strategies aimed at finding a fire somewhere with the right accuracy and season of activity, using a non-heavy deep neural organization without fully packed layers, generating a low computational cost, and testing the model in insecure IoT (Internet of Things) environments.

Khamdamov et al. (2021) present the contour method for fire detection based on contour analysis and complemented by color verification to reduce the rate of false negatives and false positives rates. Taspinar et al. (2021) combine CNN algorithms with brightness reduction filtering, HSL (Hue, Saturation, Intensity), and YCbCr (Luminance; Chroma: Blue; Chroma: Red), they developed a data set with 1141 fire images and 1900 images without fire zones. The CNN algorithms used were Inception V3 (Szegedy et al., 2016), SequeezeNet (Iandola et al., 2016), VGG16 and VGG19 (Simonyan and Zisserman, 2014). In the experiments, thanks to the Inception V3 model, it obtained 98.8% in the classification, SqueezeNet 97.3%, VGG16 and VGG19 with 96.8%.

Instance segmentation is present in the research of Zhou et al. (2021) and is based on DL for indoor fire load recognition, the base was developed three Mask R-CNN models (He et al., 2017) implement a learning technique, in the validation obtains an AP, AP50, and AP75 of 40.5%, 59.2%, and 44.2%, with a real-time fire load monitoring, and risk assessment. Wang et al. (2023) developed an image classification system based on the Reduce-VGGnet algorithm,

which consists of detecting forest fire regions aimed at the characterization of temporary environments with a detection accuracy greater than 97%. Jain and Srivastava (2022) investigation present a system for indoor smoke and fire detection developed based on three existing models in the literature. The authors consider the method useful for detecting smoke and fires indoors. Roque and Padilla (2020) and Ahn et al. (2023) propose the identification of indoor fires using infrared cameras and camera circuits, respectively, to detect the presence of flames.

4.3 Sensor-Based Systems

Active monitoring systems such as the work of Meidelfi et al. (2022), developed a device for detecting and monitoring LPG (Liquefied Petroleum Gas) gas leaks and fire with an Android-based MQ-6 in real-time. In their research, Nivennesh et al. (2021) developed an autonomous robotic system controlled by Android-based software to help people in building fires, with the ability to carry a water pump to extinguish the fire. Al Rakib et al. (2022) developed a prototype robot to clear obstacles and fight fires; this device is a firefighting robot with water spraying and uses a sensor to offer a fast reaction and high sensitivity when checking the temperature of the fire.

The work of Radke et al. (2020) presents the development of a system called RFire to detect fires using a deep learning model and an mm-wave (millimeter wave) radar, with 90% of fire detection. Khan (2023) in his research presents a WSN dedicated to detecting variables such as the amount of rain, wind, CO_2, temperature, and humidity, these variables are sent through a cellular network connection to be processed by a central server and displayed in a mobile app, as well as presented on maps of the location of forest fires. Abdusalomov et al. (2021) through YOLOv3 to detect fires using fire detection cameras as sensors. According to the authors, modifying the algorithm, they found immediate and highly accurate detection of fires whether during the day or at night, or their fire size. In Liu et al. (2023), a series of sensors are organized to detect temperature changes during a fire. Using the collected data, a prediction model is developed using a neural network to provide an early warning in case of fire. A DL algorithm was proposed to locate fire sources by fusing temperature and smoke sensor data, considering the different combustion stages. The evaluation of the proposed algorithm is performed using a simulator (Li et al., 2023).

4.4 Analysis of Indoor Fire Detection Systems

Table 3 presents the most relevant studies regarding indoor detection. In the first instance, the works dedicated to the estimation of fire risks have an accuracy ranging from 80% to 95% Choi and Jun (2020), which is an acceptable level due to the substantial number of elements involved. On the other hand, detection based on computer vision and ML presents many solutions in fire detection Muhammad et al. (2018), Nicolas-Mindoro et al. (2019), Lestari and Kosasih (2022), with recognition rates exceeding 90% in real applications. Proposals based on the use of CNN such as YOLO and Faster R-CNN predominate. While in other words it was shown that it is possible to use filters for digital images and CNN network models to obtain a high detection accuracy, greater than 97% (Taspinar et al, 2021.). Sensor-based systems can run on firefighting robots (Nivennesh et al., 2021; Al Rakib et al., 2022), as well as employ radio frequency waves (Radke et al., 2020). The different methods used to detect fires indoors can easily exceed 90% accuracy, most of them are still limited to presenting alerts about this type of event, which are oriented to the presence of fire and smoke, while a smaller

group is dedicated to aiding people who can be found inside a fire.

Table 3. Works related to indoor fire detection.

Authors and main techniques	Main techniques
Hahnemann et al. (2017)	Fire prediction
Choi and Jun (2020)	Statistical model
Wang et al. (2022)	Model of 1800 scenarios analyzed by a CNN
Muhammad et al. (2018)	CNN on GoogLeNet
Ahmad and Osman (2021)	Image filtering with Sobel
Nicolas-Mindoro et al. (2019)	Neural networks
Lestari and Kosasih (2022)	CNN YOLO and Faster R-CNN
Taspinar et al. (2021)	Digital Image Filtering CNN
Nivennesh et. al. (2021)	Systems Robotic with sensors
Al Rakib et al. (2022)	Systems Robotic with sensors
Radke et al., (2020)	Infrared radiation

5. Discussion

In the investigations dedicated to the detection of fires in indoor and outdoor spaces, the following general methods coincide.

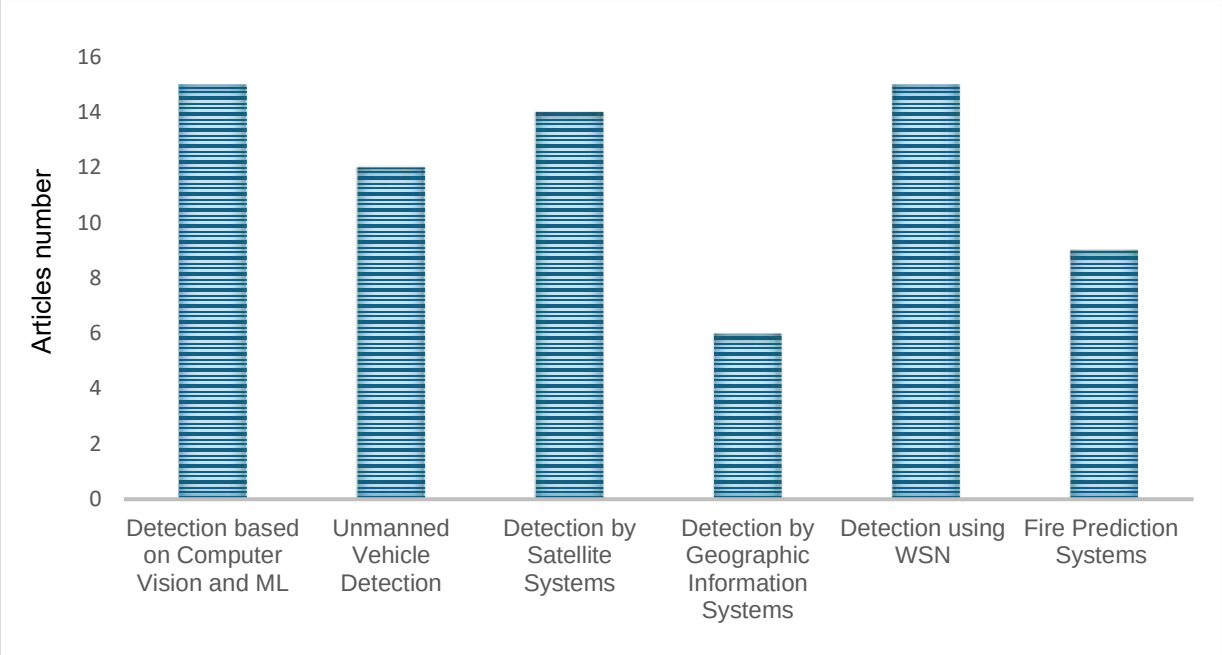
- Detection based on computer vision.
- Sensor-based detection.
- Analysis of estimation of potential risks.

Table 4 shows the advantages and disadvantages of indoor and outdoor fire detection methods. As can be seen, the different proposals analyzed in the past sections dedicated to the detection of fires in indoor and outdoor spaces use various methods and techniques for the detection of fire and smoke highly effective, such as computer vision and ML, sensor networks, robotic systems, and among others. Still, it is possible to note that there is no advanced contextual analysis for the detection of the presence of people, as well as the emotional and health conditions when in the middle of a fire, the latter is crucial to avoid deaths or serious injuries that condition the quality of life of a human being.

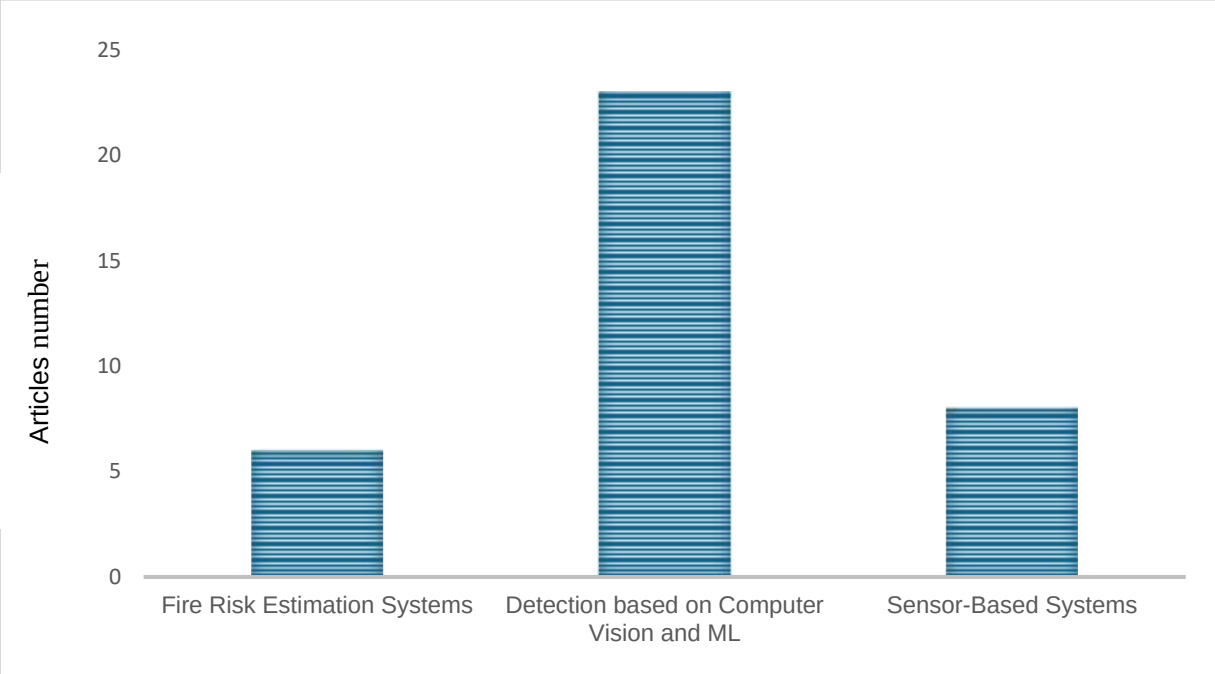
Figure 8 presents the number of research works by classification area and subarea, for the works corresponding to fire recognition in exterior spaces, Figure 8 a), 71 in total were examined, of which 15 correspond to Detection based on Computer Vision and ML, 12 correspond to Unmanned Vehicle Detection, 14 correspond to Detection by Satellite Systems, 6 correspond to Detection by Geographic Information Systems, 15 correspond to Detection using WSN and 9 correspond to Fire Prediction Systems, while the classification of fire recognition in interior spaces was analyzed 35 investigations, Figure 8 b), 6 investigations corresponding to Fire Risk Estimation Systems, 23 investigations to Fire Risk Estimation Systems and 8 investigations to Sensor-Based Systems. It should be noted that research related to fire and smoke recognition models is based on deep neural networks, while sensor-based systems for fire detection in different spaces are widely effective in detecting fire events, due to their wide effectiveness.

Table 4. Advantages and disadvantages of fire detection methodologies.

General detection proposal	Methods	Advantages	Disadvantages
Fire estimation	Neural networks Genetic algorithms Statistical models	Allow to decide risk factors such as materials present in the environment and generate an evolution of fire. Can estimate based on statistical data the areas where a fire may occur.	Requires a large amount of statistical data, as well as correct indices on the heat capacity of objects found in a medium.
Computer vision-based	Detection by CNN Digital image filtering detection	CNN-based systems can detect many objects in digital images or real-time video with conventional or infrared cameras. CNN networks can be adapted to a wide variety of platforms, from PCs to IoT devices.	The training process of a CNN is long and requires devices with ample computational power, preferably requiring GPU. CNN models, despite optimization, consume high computational resources as well as energy.
Computer vision-based	Detection by CNN Digital image filtering detection	The filters allow us to obtain special characteristics of the images such as the edges of the fire and the smoke. Can be applied without excessive consumption of computational resources.	Its implementation in IoT devices requires thorough control of the use of batteries. When using filters for contour recognition, a selection of several of these is needed for a correct analysis due to the fires' characteristics.
Detection by WSN	Regression systems Various methods of AI	It has the advantage of being distributed in different ecosystems and covering great distances. The devices where the sensors are deployed can remain in operation for extended periods.	The sensors must be distributed at strategic points to avoid false positives. Require batteries.
GIS-based discovery	Neural networks Genetic algorithms	Due to the complexity of the house, a large amount of information allows prediction models to be applied at focused points where a fire can be generated.	Require a constant updating of information. When generating predictions and probabilities of fires requires hardware of great computational power.
Detection by satellites	Specialized sensors such as radiometers Neural Networks Image Filters	These systems can obtain images and video from any area, making them ideal for verifying events such as wildfires.	Usually, its effectiveness decreases in areas smaller than 50 hectares for early detection of fires with high precision.



a) Graphic exterior spaces



b) Graphic interior spaces

Figure 8. Distribution by classification investigation works in exterior spaces and Distribution by classification investigation works in interior spaces.

Table 5. Most cited investigation works.

Authors	Cites number	Main detection method
Xu et al. (2021)	443	CNN
Barmpoutis et al. (2020)	289	WSN
Sharma et al. (2017)	222	CNN
Zhang et al. (2018)	211	CNN
Zhao et al. (2018)	203	UAV
Pham et al. (2018)	139	UAV
Saponara et al. (2021)	137	CNN
Innocente and Grasso (2019)	126	CNN
Meng et al. (2017)	121	Information from satellite
Lin et al. (2018)	110	UAV
Aydin et al (2019)	108	Drone
Namozov and Im Cho (2018)	108	CNN
Cao et al. (2019)	102	LSTM
Wooster et al. (2021)	97	WSN
Xu et al. (2017)	97	Deep learning
Dampage et al. (2022)	86	WSN and ML
Byer and Jin (2017)	84	Information from satellite
Poornima and Pushpalatha (2019)	82	CNN
Chatterjee et al. (2017)	81	Information from satellite
Xu et al. (2017)	79	Information from satellite
Sivrikaya and Küçük (2022)	73	GIS, statical analysis
Abdusalomov et al. (2021)	71	CNN
Li et al. (2018)	70	CNN
Zhong et al. (2018)	69	CNN
Rashkovetsky et al. (2021)	69	Information from satellite
Liu et al. (2020)	68	Sensors
Hu et al. (2022)	60	CNN
Naderpour et al. (2021)	54	DL
Xie et al. (2018)	52	Information from satellite
Seydi et al. (2022)	51	CNN

5.1 Challenges for fire detection systems

There are still numerous challenges to solve to guarantee the detection and prevention of fires in different contexts. The current challenges facing these systems are presented below.

- Despite the efforts of various investigations, the development that exists to calculate the risk of a fire occurring in various contexts remains precarious due to the substantial number of variables that intervene as variables in the environment, as well as the number of fuels available. In this sense, algorithms such as CNNs can perform detection and classification tasks, but their implementation should be extended to devices such as UAVs, thermal vision cameras, and systems with sensors that are not sensitive to diverse types of noise, among others.
- Although satellite systems have indeed evolved in such a way that they allow the construction of fairly accurate weather forecast models, access to these is not allowed for the entire public, but it is possible to regionally integrate monitoring units that combine the WSN with drones with fire detection and mitigation functions, both in outdoor and indoor spaces.
- The proposals that suggest the use of drones to detect and mitigate fires present a series of drawbacks when it is necessary to use many of these because they must use various coordination algorithms to take advantage of their autonomy.
- Various databases extensively contain fire scenes in various contexts, but there is

still a lack of inclusion of information related to elements such as wind direction, natural or artificial barriers, and thermal indices of materials, which would allow the development of new fire detection and prediction models. Fires with greater precision in complex environments.

6. Conclusions

Fires in urban and forest areas continue to be a problem addressed by different public and social sectors due to the amount of human losses and damage to ecosystems due to the copious amounts of CO_2 released. From this perspective, AI proposes different techniques to control and make decisions according to the environmental conditions in short response times, allowing the prevention of material and especially human damage. Flame and smoke recognition models based on CNN have had a notable development, due to their effectiveness in recognizing this type of event, achieving more than 97% accuracy in the most advanced proposals. It should be noted that several of these models come from pre-trained CNNs such as YOLO, Faster R-CNN, VGG-16, and GoogLeNet, among others.

The versatility of CNNs allows them to operate on different IoT devices, UAVs, systems that integrate WSNs, and systems with connection to satellites, this is because they can work on various platforms. Of referenced research with more than 50 citations, at least 12 are directly related to CNN models. WSN-based systems guarantee that information is transparent even when distances are considerable, generating high availability and persistent systems at any time, allowing the use of advanced AI models to detect and help estimate fire risks. The use of hybrid architectures for fire detection allows the incorporation of techniques from different areas of AI such as neural networks, and genetic algorithms, among others. UAVs have had a prominent development in the last 7 years because they can incorporate sensors to capture the presence of smoke and fire, as well as tools to help fight fires in forest environments or buildings.

The integration of color models such as RGB, and HSI, among others, as well as the use of filtering techniques such as Kalman, has allowed the development of new proposals for the identification of fires in forest areas and interior spaces effectively.

Currently, satellite systems continue to be widely used for fire recognition tasks, due to their ability to use different sensors, among which Landsat, CyGNSS, and MODIS stand out. GIS data systems use information from satellites to manage fire estimation models. These systems use contour detection techniques, as well as genetic algorithms to obtain results from the models.

As has been observed in this research, the role of AI is predominant in the detection of fires in indoor and outdoor spaces, because the outstanding proposals that use artificial vision systems, sensor networks, unmanned vehicles, fire estimation fire probability, as well as geographic and satellite systems, have incorporated AI models and techniques to increase their detection efficiency.

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