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A Systematic Literature Review of Vision-Based Fire Detection, Prediction and Forecasting

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ABSTRACT

The primary method used by conventional fire detection systems is sensor-based detection, which has limitations in terms of accuracy and detection time. Traditional approaches and techniques could be improved by the latest advancements in computer vision-based technologies for fire prediction and detection. Consequently, this paper aims to provide a comprehensive literature analysis of earlier research on fire detection and prediction using the computer vision techniques. The Preferred Reporting Items for Systemic Reviews and Meta-Analyses, or PRISMA 2020, are applied in this systematic review. Three databases such as the Web of Science, Scopus, and IEEE were searched for pertinent publications to include in this review for this study. The systematic review reveals that existing studies predominantly focused on fire flame rather than smoke detection. Moreover, the majority of research has centered on forest fires in the particular context of occurrence, neglecting indoor or interior environments. Video surveillance systems emerge as the primary source of hardware and datasets utilized in these investigations. Notably, convolutional neural networks (CNNs) stand out as the most frequently employed deep learning approach for classification purposes. The systematic review clarifies the state of fire detection research using computer vision techniques by combining data from several academic sources. Through a systematic approach, this study contributes a deeper understanding of the opportunity and challenges in leveraging vision-based technologies for fire detection and prediction.

Keywords: Systematic literature review; vision-based; fire detection; fire prediction; machine learning

INTRODUCTION

Fire incidents pose serious threats to both life and property. The alarming number of fire related deaths and financial losses suffered annually across the world call for improved response to fire risks. Early fire detection, prediction, and forecasting are critical to minimizing fire-related losses and ensuring public safety (Yuming et al., 2022). Despite significant advancements in traditional fire detection systems, they often fall short in detecting fires quickly and accurately, leading to delayed responses and substantial damages (Rodriguez-Conde et al., 2022; Diaconu, 2023; Khan et al., 2019; Rabiu, 2022).

In recent years, machine learning has become a very useful tools in several fields such as fire detection and prediction (Abid, 2021). By using sophisticated algorithms and large volumes of data, it has the potential to increase the speed and accuracy of fire detection. Especially when combined with vision-based techniques, machine learning can enable systems to "see" and interpret visual cues indicative of a fire, such as smoke or flames, much like a human observer might (Enis et al., 2013; Gaur et al., 2019; Calderara et al., 2011)

The two primary categories of fire alarm systems are computer vision-based fire detection systems and conventional fire alarm systems. Conventional fire alarm systems use temperature, flame, and smoke detectors, among other physical sensors (Wang et al., 2020). In the event of an alarm, these types of sensing equipment need human action to validate the existence of a fire. These systems also need various instruments in order to detect fire or explosive or flammable gases and inform people by indicating the location of the designated area and the size of the flames. Additionally, because smoke detectors cannot tell the difference between smoke and fire, they frequently go off unintentionally.

For clear detection, fire detection sensors require a large volume of fire, which might lengthen the detection period and result in severe loss and damage. An alternative strategy that can improve the reliability and security of fire detection systems is the application of visual fire detection techniques. To overcome the limitations mentioned above, a number of researchers have looked at combining computer vision-based methods with sensors (Qiu et al., 2012; Liu and Ahuja, 2004). A vision-based detector's benefit is that it can make up for the shortcomings of sensor-based methods.

Vision-based fire detection, prediction, and forecasting have emerged as promising avenues for enhancing the capabilities of fire management systems. By leveraging the power of machine learning algorithms, these approaches offer the potential to not only detect fires in their incipient stages but also forecast their behavior and spread, thereby enabling proactive decision-making and timely response (Carta et al., 2023).

The objective of this paper is to conduct a systematic literature review on vision-based fire detection, prediction, and forecasting. It is essential to emphasize that the primary focus lies in providing a comprehensive understanding of the current state of research in this field. Through an extensive review, we aim to clarify trends, identify gaps, and offer insights into the advancements and challenges encountered in vision-based fire detection methodologies. This work seeks to contribute to the ongoing efforts aimed at developing more effective, efficient and reliable technologies for predicting and detecting fires.

METHODOLOGY

This section describes the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) procedure, which is the publication standard that was used. According to Page et al. (2021), the PRISMA guideline recommends developing research questions first, then methodically developing search techniques for databases and search phrases. The selection procedure for the papers' exclusion is then carried out using their abstract, title, and exclusion criteria. The validity of the collected papers was confirmed by the authors during the quality appraisal phase. The final step involves data extraction and analysis, as shown in Figure 1.

PREFERRED REPORTING ITEMS FOR SYSTEMATIC REVIEWS AND META–ANALYSES (PRISMA)

A structured and methodical strategy used in research is known as a research methodology. It entails a theoretical investigation of pertinent concepts associated with the research topic, including models, phases, and qualitative as well as quantitative methods. The writers used PRISMA, a widely used standardized publication in the fields of public health and medicine, to build this Systematic Literature Review (SLR). PRISMA provides an organized method with a 27-point checklist and a four-stage organizational diagram. The flowchart delineates standards for locating, vetting, ascertaining suitability, and integrating pertinent reports (Liberati et al., 2009). Including topics like as title, abstract, introduction, methods, findings, and discussion, the checklist consists of 27 recommendations. These PRISMA components serve as a valuable resource for authors, editors, and writers, aiding them through the diagram and checklist (Selcuk, 2019). Even though this SLR pertains to engineering, PRISMA remains pertinent for shaping precise research questions and facilitating methodical searches. This SLR started with the formulation of research questions and worked its way up to a structured search strategy, evaluation of article quality, and data extraction and analysis from selected publications, all based on the PRISMA framework.

SOURCE OF REFERENCE

Three main electronic databases were chosen in order to find related articles and resources which are the Web of Science, Scopus and Institute of Electrical and Electronics Engineers. The Web of Science (WOS) database is now owned and managed by Clarivate Analytics and was produced by the Institute for Scientific Information (ISI) until the year 1997. Since 1900, WOS consists of over 75 million records including more than 20,900 journals. (website: Web of Science Collection, 2023). The second database, Scopus, was used for the review.

Scopus is managed by Elsevier which consists of over 80 million records (website: Scopus - document search, 2023). The Institute of Electrical and Electronics Engineers (IEEE) produced IEEE Xplore digital library containing a research database for discovery and access to articles, proceedings papers and related research on computer science, electrical and electronics engineering and allied fields. IEEE has over 5 million of records on its database (website: IEEE Xplore, 2023)

FORMULATING RESEARCH QUESTIONS

The identification of research questions is the first stage in the SLR process. There are six research questions related to the vision-based fire detection system.

RQ1 – What type of fire occurrence have been used in the study?
RQ2 – What type of visual data has been used in this study?
RQ3 – What are the hardware and software involved in this study?

RQ4 – What type of algorithms are used for processing and analyzing visual data in the study?
RQ5 – What is the percentage recognition rate of accuracy in the previous study?
RQ6 – What are the challenges and limitations using machine learning techniques for fire prediction based on visual data?

SYSTEMATIC SEARCH APPROACH

The five primary processes of doing a systematic review are identification, screening, eligibility, quality assessment, and data extraction and analysis. These phases are comprised of multiple discrete actions. The five steps of the systematic searching methods process are shown in Figure 1.

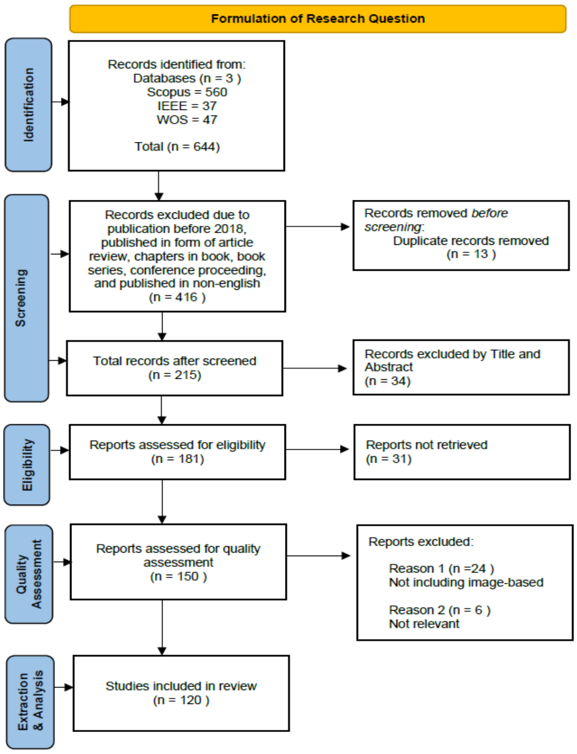

FIGURE 1. PRISMA 2020 flow diagram

IDENTIFICATION

The procedure of choosing and diversifying appropriate keywords is crucial in order to find the relevant content.

During the search process, keywords are essential since they can increase the quality of the articles and references found for SLR references. Three primary keywords which are fire detection, machine learning, and vision-based were chosen in accordance with the previously mentioned study topics. Synonyms, related terms, and variations of the primary keywords were looked for in order to broaden the pool of possible keywords. This search was carried out using an online thesaurus, the Scopus database, references to previous research terms, and expert opinions. Table 1 presents the results obtained using this identifying procedure.

TABLE 1. Search string created for relevant articles and reference research

Database	**Search String**	**Total**
Web of Science	TS=(("fire prediction" OR "fire forecasting" OR "fire detection") AND (image* OR "vision based" OR vision OR "video -based" OR video*) AND ("machine learning" OR "computational learning") AND ("algorithm" OR "method" OR "technique"))	47

Scopus	TITLE-ABS-KEY ("fire prediction" OR "fire forecasting" OR "fire detection") AND (image* OR "vision based" OR vision OR "video -based" OR video*) AND ("machine learning" OR "computational learning") AND ("algorithm" OR "method" OR "technique")	560
IEEE	(("fire prediction" OR "fire forecasting" OR "fire detection") AND (image* OR "vision based" OR vision OR "video -based" OR video*) AND ("machine learning" OR "computational learning") AND ("algorithm" OR "method" OR "technique"))	37

A total of 644 articles were successfully acquired based on the search strategies, databases, and keywords that were employed. The following step in the methodical search approach, known as screening, will be applied to these articles.

SCREENING

After completing the identification procedure successfully, 644 articles will now go to the screening phase. In the screening procedure, references and articles that are relevant for the SLR to be produced are chosen based on predetermined inclusion and exclusion criteria. In other words, as the primary goal of this systematic literature review (SLR) is to identify and ascertain the results of previous research, review articles are excluded. A minimum of one machine learning technique must be applied to published work selected between 2018 and 2022. Findings from the chosen publication should focus on vision-based fire prediction or detection. This is necessary to enable all chosen publications to provide insights into the formation of the SLR (see Table 2). 416 publications were rejected and only 215 studies (33.4%) were included based on the aforementioned criterion. Not to add the 13 articles (or duplicate items) that were discovered in these three databases.

TABLE 2. Search string formed for related article and reference research

Criterion	**Eligibility**	**Exclusion**
Literature type	Journal	Review paper, book series, book, chapter in book, conference proceeding
Language	English	Non-English
Timeline	Between 2018 and 2022	2017 and earlier

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ELIGIBILITY

A second screening procedure known as eligibility will be used to all selected publications. To make sure every article chosen is appropriate for this SLR and relevant, eligibility is checked. This procedure is carried out based on the titles of particular papers and abstracts. The technique, results, and discussion sections of the chosen article will be consulted in case the results regardless of their relevance, cannot be found after perusing the study abstract and title. Throughout the process, a total of 181 articles were included due to their emphasis on machine learning approaches, fire detection or prediction, and vision-based content.

QUALITY ASSESSMENT

To ensure high quality content, the remaining articles will be assessed carefully. The authors used two criteria for each article: 1) Is the research question stated clearly? and 2) Do the collected data provide answers to the study questions? Evaluators choose either "Yes" or "No" for each criterion. All agreements from the evaluators are considered high quality for the next step. This procedure identified 120 articles.

EXTRACTION AND ANALYSIS OF DATA

The 120 full papers article underwent a thorough analysis and evaluation. It is essential to read the abstracts first and then have a thorough comprehension of all the papers in order to find the pertinent response for the research issues at hand. To make the synthesis process easier, all of the retrieved data were organized into a table and figures.

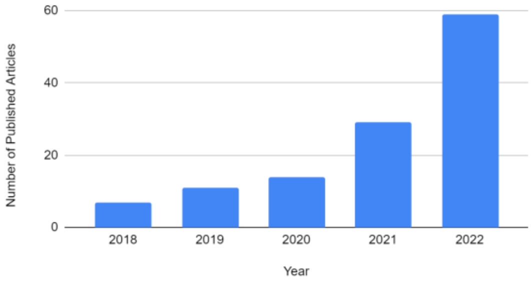

FIGURE 2. Increasing articles published between 2018 to 2022

RESULT

The selected studies were analyzed based on the research questions and discussions were made in the field of vision-based in fire protection and prediction.

BACKGROUND OF THE SELECTED ARTICLES

The background of the selected articles in the SLR will be covered in this section before discussing the findings. From the 120 articles that were chosen, 7 came out in 2018, 11 came out in 2019, 14 came out in 2020, 29 came out in 2021, and 59 came out in 2022. The quantity of research publications found annually is depicted in Figure 2. The number of research publications published increased considerably between 2018 and 2022.

Figure 3 shows flame is the main topic focusing on the type of image studied with the highest article published with a total of 52 articles. 22 studies concentrated on fire pixel, 15 studies concentrated on flame and smoke. Followed by 13 studies related to flame image. Seven studies discussed flame or smoke, while two studies concentrated on fire pixel or flame, two studies on fire hotspot, and another two studies mentioned about either flame and smoke, flame or smoke. While each study discussed in using thermal image; fire and smoke pixel; fire spread rate; fire motion; and fire pixel or smoke.

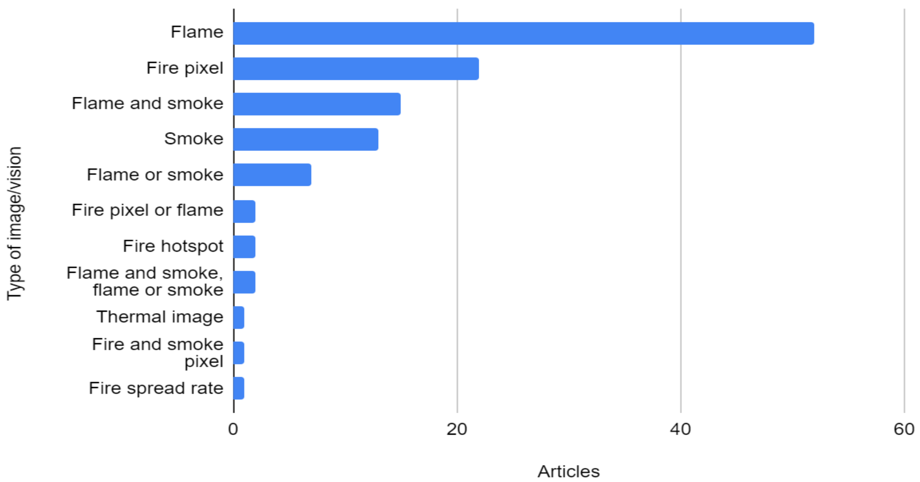

FIGURE 3. Number of articles based on type of image or vision chosen

ANSWERING RESEARCH QUESTION

All the research questions will be discussed in this section.

RQ1 – What type of fire occurrence have been used in the study?

There are a lot of types of fire occurrences encountered during fire detection or prediction as shown in Figure 4. Most fire occurrences made in the study involve forest fires and wildfires which contribute a total of 53.3 percent. Followed by an experiment with 15.8 percent involving an detection by Park and Bae (2020), autonomous ships fire detection method by Kim and Ruy (2022) and unmanned fire-fighting vessel study by Wang et al. experiment by Huang et al. (2022) using ZR-YJV power cable, Xhao et al. (2022) used equipment in another experiment that included a detection system, an electric field application system, and a combustion system. The rest of the experiments include using open-source databases or internet images. Study based on surveillance systems is 13.3 percent while indoor environment study and building fire with a total of is 13.3 percent. Vehicle fire occurrence study with 3.3 percent which includes study from Tao and Lu (2018) discussing smoky vehicle detection, ship engine rooms smoke (2022). The least study was done on virtual reality video images which represent 0.9 percent by Huang and Du (2020).

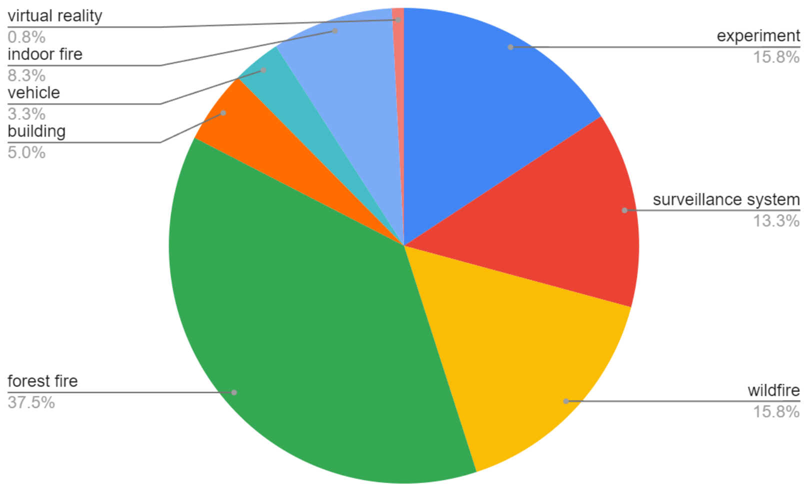

FIGURE 4. Percentage of fire occurrence

RQ2 - What type of visual data has been used in this study?

Visual data including satellite images, drone images and video surveillance footage, has been extensively used in wildfire-related studies. Search engines and online resources such as Google and Baidu provide access to various images and videos from public websites. Notable studies by Zhong et al. (2018); Zhao et al. (2022); Qin et al. (2021) and others have leveraged these search engines to acquire relevant visual content.

Video surveillance systems play a crucial role in security, safety, and behavior analysis. Researchers have tapped into real-time footage captured by these systems to study various phenomena. Noteworthy references include works by Qian et al. (2022), Abdusalomov et al. (2021), and Wei et al. (2022).

Satellite imagery provides detailed views of Earth's surface, aiding geographical, meteorological, and environmental research. Specific satellites like Sentinel-1 and Sentinel-2, as well as Landsat-8, have been valuable data sources. Researchers such as Zhang et al. (2021) and Pletsch et al. (2022) have harnessed these images to analyze patterns and changes.

Drones, or UAVs, offer high-definition photos and videos, especially in challenging terrains or remote areas. Researchers have used drone imagery extensively. Notable studies by Zheng et al. (2022), Wang et al. (2022), and Li et al. (2021) have leveraged UAV data for their research. Various specialized datasets and platforms have contributed to visual data acquisition as displayed in Table 3.

TABLE 3. Visual data

No	Visual data obtained	Reference
1	Search engine such as Google, Baidu platform	Zhong et al. (2018); Zhao et al. (2022); Qin et al. (2021); Abdusalomov et al. (2022); Avazov et al. (2022); Sheng et al. (2021); Khalil et al. (2021); Mao et al. (2018); Mahmoud et al. (2018); Hossain et al. (2020); Yandouzi et al. (2022); Chen et al. (2019); Taspinar et al. (2021); Perrolas et al. (2022)
2	Video surveillance systems	Qian et al. (2022); Baldo et al. (2021); Chen et al. (2021); Kim et al. (2021); Abdusalomov et al. (2021); Wei et al. (2022); Valikhujaev et al. (2020); Saeed et al. (2020); Muhammad et al. (2018); Avazov et al. (2022); Sowah et al. (2020); Yang et al. (2020); Roy et al. (2022); Shakhnoza et al. (2022); Hashemzadeh et al. (2022); Khan et al. (2022); Tao et al. (2018)
3	Satellite image	Sentinel-2 satellites (Zhang et al., 2021); (Pletsch et al., 2022); (Xu et al., 2022), Sentinel-1 and -2 (Rashkovestsky et al., 2021) Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) (Higa et al., 2022); (Bai et al., 2021); (Cheng et al., 2022); (Pletsch et al., 2022); (Bai et al., 2021); (Sharma et al., 2022); (Higa et al., 2022) USGS FIREMON (Tonbul et al., 2022), Landsat Multispectral Scanner (MSS) (Boothman et al., 2022), Himawari-8 (Xie et al.,2018); (Xu et al., 2022); (Jang et al., 2019); (Kang et al., 2022), Global Fire Emissions Database (GFED) (Chen et al., 2020), Landsat -8 (Seydu et al., 2022); (Sofan et al., 2019); (Rostami et al.,2022); (Li et al., 2020), EO-1 (Waigl et al., 2019), Precursore IperSpettrale della Missione Applicativa (PRISMA) (Amici et al., 2019)
4	Unmanned aerial vehicle (UAV)	Zheng et al. (2022); Fouda et al. (2022); Lu et al. (2022); Sharma et al. (2019); Wang et al. (2022); Khan et al. (2022); Muid et al. (2022); Mashraqi et al. (2022); Yang et al. (2022); Li et al. (2021); Chen et al. (2022).
5	ImageNet database from Deng et al. (2009)	Shahid et al. (2022); Khan et al. (2022); Nguyen et al. (2021); Chen (2021).
6	Corsican Fire Database by Toulouse et al. (2017)	Perrolas et al. (2022); Sousa et al. (2020); Ciprián-Sánchez et al. (2021); Ghali et al. (2021).
7	Foggia et al. (2015) dataset	Valikhujaev et al. (2020); Khan et al. (2022); Shahid et al. (2022).
8	Firesense database by Kucuk et al. (2008)	Lu et al. (2022) and Harjoko et al. (2022)
9	VisiFire dataset from Kong et al. (2016)	Lu et al. (2022); Mao et al. (2018); Lu et al. (2022); Harjoko et al. (2022); Xu et al.(2021)
10	ForestryImages database from Daouce et al. (2001)	Lu et al. (2022) and Xu et al. (2021)
11	Open Images by Google Inc.	Kumar et al. (2021) and Sun et al. (2021)
12	BoWFire dataset by Chino et al. (2016)	Xu et al. (2021); Lu et al. (2022); Qian et al. (2022)
13	Fire Dynamic Simulator (FDS)	Xu et al. (2021); Hodges et al. (2019)
14	California Fire Perimeter Database (CAL FIRE1)	Rashkovetsky et al. (2021)
15	Youtube	Wilk-Jakubowski et al., (2022)
16	FiSmo dataset (Cazzolato et al., 2017)	Lu et al. (2022)
17	NTUST fire dataset	Shahid et al. (2022)
18	Portuguese Firefighters Portal Database	Sousa et al. (2020)
19	D-fire by Gaia (2021)	Wang et al. (2022)

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20	Social media platform	Saeed et al. (2020)

RQ3 – What are the hardware and software involved in this study?

Vision-based techniques have been massively implemented in fire detection systems. High technology hardware and software programming has been developed to provide input signals for vision-based detection such as web cameras, DSLR cameras, video cameras, and cameras on smartphones, surveillance camera, satellite, infra-red cameras, thermal camera, UAV camera, smart glasses camera. High-definition camera was used in Huang et al. (2022), High speed industrial camera used in Zhao et al. (2022); infrared thermal (IRT) and RGB cameras was used in Balen et al. (2022), near infra-red camera with modified IR pass filter was used in Jain et al. (2022), Charge-coupled device colour camera was used in smoke detection in ship engine room (Park and Bae, 2020).

Various open software projects in machine learning (ML) libraries have recently been developed and each has its own unique set of features and capabilities. Some of the most popular libraries such as TensorFlow library is a machine learning library developed by Google used in 22 studies including Fouda et al. (2022); Kim et al. (2021) and Apostolopoulos et al. (2022). Pytorch developed by Facebook and was used in 19 studies including Huang et al. (2022) and Zhang et al. (2021). Keras was utilized in 13 studies which includes Fouda et al. (2022) and Rashkovetsky et al. (2021). OpenCV was used in several studies, including Shahid et al. (2022) and Wilk-Jakubowski et al. (2022). Numpy was used in Kim et al. (2022); Wilk-Jakubowski et al. (2022); Guede-Fernández et al. (2021); Martins et al. (2022). Scikit-learn focuses on supervised learning algorithms for classification, regression and clustering. Scikit-learn was used in Fouda et al. (2022); Lai et al. (2022) and Martins et al. (2022). Matplotlib was used in Fouda et al. (2022); Kim and Ruy (2022); Wilk-Jakubowski et al. (2022). Pandas was used in Kim and Ruy (2022) and Martins et al. (2022). The detail list of the machine learning libraries is shown in Table 4.

TABLE 4. Machine learning libraries

No	Machine learning library	Reference
1	Tensorflow	Fouda et al. (2022); Kim et al. (2021); Apostolopoulos et al. (2022); Ciprián-Sánchez et al. (2021); Majid et al. (2022); Valikhujaev et al. (2020); Kim and Ruy (2022); Hodges et al. (2019); Wilk-Jakubowski et al. (2022); Khan et al. (2022); Taspinar et al. (2021); Kim et al. (2021); Wang et al. (2022); Yandouzi et al. (2022); Sowah et al. (2020); Boothman and Cardille et al. (2022); Cheng (2021); Khan et al. (2022); Laptev et al. (2021); Liu et al. (2020); Perrolas et al. (2022) and Rashkovetsky et al. (2021).
2	Pytorch	Huang et al. (2022); Qian and Lin (2022); Wei et al. (2022); Wang et al. (2022); Wang et al. (2022); Guan et al. (2022); Tran et al. (2022); Yan et al. (2020); Lu et al. (2022); Deng et al. (2022); Shakhnoza et al (2022); Ghali et al. (2021); Guede-Fernández et al. (2021); Hashemzadeh et al. (2022); Martins et al. (2022); Shahid et al. (2022); Xu et al. (2021); Yang et al. (2022); and Zhang et al. (2021).
3	Keras	Fouda et al. (2022); Shamsoshoara et al. (2021); Apostolopoulos et al. (2022); Majid et al. (2022); Valikhujaev et al. (2020); Kim and Ruy (2022); Khan et al. (2022); Khan et al. (2022); Mao et al. (2018); Lai et al. (2022); Cheng (2021); Khan et al. (2022); Rashkovetsky et al. (2021).
4	OpenCV	Shahid et al. (2022); Tao and Lu (2018); Fouda et al. (2022); Kim and Ruy (2022); Wilk-Jakubowski et al. (2022); Avazov et al. (2022); Guede-Fernández et al. (2021); Martins et al. (2022).
5	Numpy	Kim et al. (2022); Wilk-Jakubowski et al. (2022); Guede-Fernández et al. (2021); Martins et al. (2022)
6	Scikit-learn	Fouda et al. (2022); Lai et al. (2022) and Martins et al. (2022).

7	Matplotlib	Fouda et al. (2022); Kim and Ruy (2022); Wilk-Jakubowski et al. (2022).
8	Pandas	Kim and Ruy (2022) and Martins et al. (2022

In summary of Figure 5, the highest study uses Tensorflow which represents 29.7 percent followed by Pytorch with 25.7 percent. Keras is in third rank with 17.6 percent of usage and OpenCV usage with 10.8 percent. 5.1 percent using Numpy library and both Scikit-learn and Matplotlib with 4.1 percent. The lowest library usage is from Pandas with 2.7 percent.

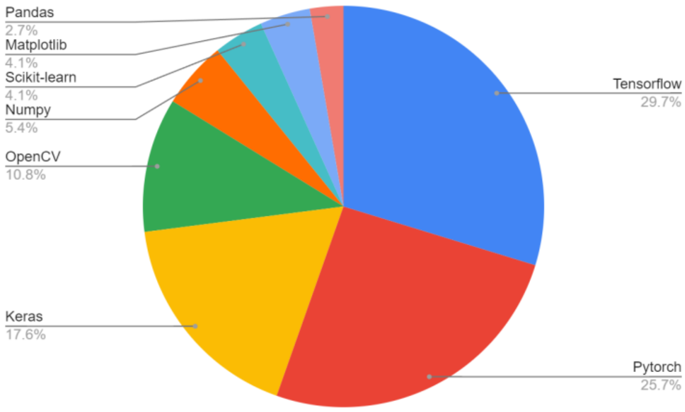

FIGURE 5. Percentage of ML library

RQ4 – What type of algorithms are used for processing and analyzing visual data in the study?

The final analysis of previous studies with methods that used vision-based techniques shown in Table 5. Figure 6 shows three main different approaches utilized in the classification process. Deep Learning (DL) is the most popular approach being used in previous studies with a total of 82 articles. Deep neural networks, or multilayer neural networks, are used in DL. Examples of DL algorithms are Convolutional Neural Networks (CNN), Recurrent Neural Network (RNN), Generative Adversarial Network (GAN), Long Short-Term Memory (LSTM). Followed by Machine Learning (ML) approach with 33 articles. A vast variety of methods, including k-nearest neighbors, support vector machines, decision trees, and linear regression, are used in machine learning. The last approach is Artificial Neural Network (ANN), which was used in previous studies in 5 articles. ANN can only have three layers of neuron; the input layer, the hidden layer and the output layer.

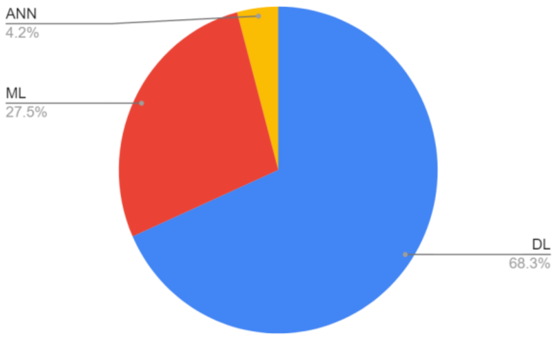

FIGURE 6. Percentage of classification approach

Based on how many times an image is processed with the network, there are two types of object identification algorithms: one-stage or single-shot detection (SSD) and two-stage or two-shot detection. You Only Look Once (YOLO) is an illustration of single shot detection. Two passes of the input image are used in two-shot detection; the first pass generates a group of proposals, while the second pass refines the image and makes the final prediction. Example of two-stage detection are Region-CNN (R-CNN) by Girshick et al. (2014), Fast R-CNN by Girshick (2015), Faster R-CNN by Ren et al. (2015) and Mask R-CNN by He et al. (2017). YOLO introduced by Redmon et. al (2016) uses a fully CNN to process an image. 15 articles were used for this single-stage detection as shown in Table 6.

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TABLE 5. Analysis of previous studies with methods and outcomes.

Author (year)	Method	Outcome
Abdusalomov et al. (2022)	1. Utilize YOLOv5m model for real-time monitoring. 2. Automate manual processes for efficiency.	Successfully detected and notified catastrophic fires with high speed and accuracy.
Apostolopoulos et al. (2022)	1. Employ Convolutional Neural Networks for image classification. 2. Utilize Grad-CAM++ and LIME algorithms for explainability.	Xception network achieved high accuracy in fire/smoke classification.
Avazov et al. (2022)	1. Develop a novel convolutional neural network based on YOLOv4. 2. Modify network structure for real-time monitoring.	Successfully detected and notified fire incidents with high speed and accuracy.
Bai et al. (2021)	1. Utilize logistic regression, backpropagation neural network, and decision tree methods. 2. Analyze influencing factors for fire occurrence.	Achieved accuracies of 68.59% and 79.59% with BPNN and DT methods, respectively.
Baig et al. (2023)	1. Utilize angular and regional area information of fire flame for prediction. 2. Employ machine learning algorithm for distinguishing fire and non-fire objects.	Efficiently distinguished fire and non-fire objects with proposed framework.
Baldo et al. (2021)	1. Design LoRaWAN architecture integrating different services. 2. Test architecture in laboratory and field settings.	Tested architecture in laboratory and field settings, reaching Technology Readiness Level 3.
Balen et al. (2022).	Calibration procedure on seven cameras and two pyrometers resulted in necessary data for input-data correction and anomaly detection, revealing discrepancies between devices of different price ranges.	The observed problem of device deviation can be addressed through improved calibration techniques, ensuring accurate input data for computer analysis and implementation in autonomous robotic systems.
Boothman et al. (2022)	Used deep learning, specifically UNet, to detect historic forest fires in MSS imagery for forest-dominated regions of Quebec, identifying previously unreported burns and increasing total known burned area by 35.30% between 1973 and 1982.	Deep learning applied to MSS data opens new avenues for mapping historic fires, allowing for better understanding of forest structure and ecological processes, and informing land-management decisions.
Chen et al. (2021).	Proposed algorithm considerably outperformed traditional methods in precision, recall, and F1-score, offering a more accurate and less computationally expensive method for fire detection in IoT environments.	Future research can focus on further refining the proposed algorithm and exploring its application in real-world IoT systems to enhance fire detection capabilities and reduce false alarm rates.
Cheng et al. (2022)	Combined forward and inverse modellings successfully integrated real-time observations for parameter adjustment, leading to more accurate future predictions of burned area in wildfires.	Integration of real-time observations in fire prediction models allows for more accurate and timely predictions of wildfire behavior, aiding in effective fire management and mitigation strategies.
Cheng et al. (2022)	Proposed algorithm showed potential for speeding up wildfire forecasting while maintaining accuracy through the integration of reduced-order modelling, machine learning, and data assimilation techniques.	The integration of data assimilation techniques into wildfire forecasting models offers the potential for more accurate and timely predictions, aiding in effective fire management and mitigation strategies in near real-time.
Ciprián-Sánchez et al. (2021)	Different combinations of DL architectures, loss functions, and image types were evaluated to identify parameters most relevant for improving segmentation results, showing promising performance improvements compared to traditional techniques.	Further exploration of attention modules on DL architectures and evaluation of their impact on segmentation results can lead to enhanced performance and robustness of DL-based wildfire segmentation models, improving their utility for wildfire monitoring and management.

TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Deng et al. (2022)	Multi-step implicit Adams predictor-corrector (MIAPC) network is proposed, utilizing Adaptive Feature Fusion (AFF) and Spatial Attention Layer (SAL) to extract hierarchical features.	The method achieves 87% accuracy in a challenging test dataset and demonstrates practical inference speeds. The MIAPC network outperforms existing methods by at least 6% in accuracy and exhibits practical inference speeds, enabling its use in real-world applications.
Fouda et al. (2022)	Propose a lightweight hierarchical AI framework that switches between simple machine learning and advanced CNN models based on a multi-objective optimization approach.	The proposed framework achieves a balance between detection accuracy and computational performance, making it suitable for resource-constrained UAVs.
Ghali et al. (2021)	Utilize vision Transformers (TransUNet and MedT) to explore global dependencies in forest fire segmentation and optimize architectures for improved performance.	Both TransUNet and MedT architectures outperform current methods with F1-scores of 97.7% and 96.0%, respectively, reducing mis-classifications and providing finer detection of fire shapes.
Guan et al. (2022)	Propose a feature entropy guided neural network for forest fire detection, giving larger weight to samples with higher content complexity to improve classification accuracy.	The proposed method outperforms state-of-the-art methods in forest fire detection accuracy by effectively balancing content complexity, achieving superior performance.
Hashemzadeh et al. (2022)	Propose a method involving motion detection, CNN-based smoke region identification, and feature extraction for smoke classification using spatio-temporal features and SVM classification.	The proposed method achieves high performance and accuracy in smoke detection with low false alarm rates across various environmental conditions, outperforming existing techniques.
Huang et al. (2022)	Propose a combined approach using RCNN for fire characteristic extraction and ResNet for fire forecasting, providing real-time information on fire spread position, speed, and flame width.	The proposed approach accurately extracts fire parameters and forecasts fire development trends, providing specific information about fire circumstances in real time for improved industrial fire safety.
Hossain et al. (2020)	Propose a method combining fire-specific color features and multi-color space LBP for flame and smoke detection, trained on challenging UAV-captured images with varying conditions.	The proposed method achieves high F1 scores for both flame and smoke detection while maintaining high processing speed, outperforming several other classification techniques.
Hodges et al. (2019)	Use TCNN to predict temperatures and velocities within compartments based on Fire Dynamics Simulator (FDS) simulations, focusing on simple two-compartment configurations initially and validating with more complex multi-compartment simulations.	TCNN predictions of temperatures and velocities within compartments align well with FDS simulations, demonstrating accuracy within specified error margins for both simple and multi-compartment configurations.
Higa et al. (2022)	Utilize object detection methods with CBERS 04A imagery to map active fires in the Pantanal, employing a post-processing strategy to reduce overlapped detections and evaluate the performance of the approach across multiple images and environmental conditions.	The proposed approach accurately maps active fires in the Pantanal, demonstrating generalization capability to complement existing wildfire databases and research efforts, with accurate results even with recent satellite imagery.
Huang & Du (2020)	Combine rough set (RS) theory and support vector machine (SVM) methods to create an RS-SVM classifier for fire detection and recognition, enhancing performance compared to using SVM alone.	The RS-SVM classifier model demonstrates improved performance in terms of recognition time, efficiency, and accuracy, effectively reducing false fire-detection alarms in VR video images.
Jain & Srivastava (2022)	Utilize a near infrared (NIR) camera to capture images for fire detection while preserving occupants' privacy, and develop a system incorporating spatial and temporal properties of fire for effective detection.	The proposed framework achieves superior fire detection performance while preserving occupants' privacy, validated through experiments and real-world prototypical implementation.

TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Jang et al. (2019)	Propose a 3-step forest fire detection algorithm utilizing thresholding, machine learning-based modeling with random forest (RF), and post-processing using forest maps to improve accuracy and reduce false alarms.	The proposed algorithm successfully detects and monitors forest fires in South Korea with high accuracy, effectively reducing false alarms compared to existing methods, and demonstrating promising results for real-time monitoring and management of forest fires.
Ji, Z., & Han, Q. Q. (2020)	Propose a feature descriptor combining spatter trajectory morphology, spatial distributions, and temporal information, evaluated using real images captured in various conditions and classified using support vector machine (SVM) and random forests.	The proposed feature descriptor achieves high classification accuracy for spattering patterns in SLM processes, providing semantic interpretability and non-contact monitoring capabilities for online anomaly detection, with potential applications in improving manufacturing quality and fault detection.
Kang et al. (2022)	Utilize convolutional neural network (CNN) and random forest (RF) techniques for model development, focusing on incorporating temporal and spatial information to reduce detection latency and false alarms in forest fire monitoring.	The proposed CNN-based model achieves high accuracy in detecting forest fires with reduced detection latency, outperforming existing methods and demonstrating robustness across varied environmental conditions.
Khalil et al. (2021)	Propose a fire detection method based on Red Green Blue (RGB) and CIE L∗ a∗ b color models, incorporating motion detection and tracking of fire objects to reduce false alarms.	Experimental results demonstrate the effectiveness of the proposed method in reducing false positives while maintaining precision, compared to existing methods.
Khan et al. (2022)	Curate the DeepFire dataset containing real-world forest imagery with and without fire, and evaluate various supervised machine learning classifiers along with a VGG19-based transfer learning approach for forest fire detection.	The proposed approach achieves high accuracy in classifying fire and no-fire images in the DeepFire dataset, outperforming several machine learning classifiers.
Khan, S., & Khan, A. (2022)	Propose FFireNet, leveraging a pre-trained MobileNetV2 model and additional fully connected layers for forest fire recognition, and evaluate its performance against other CNN models using forest fire detection dataset.	FFireNet achieves high accuracy, precision, and recall in classifying fire and no-fire images, outperforming other CNN models in the forest fire detection dataset.
Khan et al. (2022)	Introduce SE-EFFNet, a deep model using EfficientNet as a backbone and stacked autoencoders for feature refinement, with randomly initialized weights to address vanishing gradient problems, and evaluate its performance against state-of-the-art models.	SE-EFFNet demonstrates better recognition abilities and reduced computational complexity compared to recent state-of-the-art models in fire detection.
Khudayberdiev et al. (2022)	Present Light-FireNet, a lightweight network incorporating lighter convolution mechanisms and a novel architectural design, and evaluate its performance in fire detection across diverse environments.	Light-FireNet achieves high detection accuracy while being significantly lighter and more efficient than existing fire detection techniques.
Kim, D. and Ruy, W. (2022)	1. Build fire detection model using deep learning with CNN. 2. Use RGB-IR combined channel data. 3. Tune hyper-parameters.	Increased fire detection accuracy and decreased false alarm rate using RGB-IR data.
Kim et al. (2021)	1. Utilize embedded modules for real-time surveillance. 2. Develop algorithms for various detection tasks.	Achieved high performance in intruder, fire, loitering, and fall detection with reduced processing time for real-time surveillance.
Kumar et al. (2022)	1. Utilize YOLOv4 and YOLOv4-tiny algorithms for detection. 2. Train models using a self-made dataset.	Achieved real-time detection of fire and PPE with high mean average precision (mAP).

TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Lai et al. (2022)	1. Employ sparse autoencoder-based deep neural network. 2. Propose data balancing procedure.	Improved prediction accuracy for large-scale forest fires compared to state-of-the-art methods.
Laptev et al. (2021)	1. Use object detection technology with EfficientDet-D1 model. 2. Implement pre- and post-processing algorithms for image enhancement.	Achieved visual image classification accuracy of 81% and localization accuracy of 87%.
Li et al. (2020)	1. Evaluation of GOES-16 ABI active fire product using Landsat-8, VIIRS, and ground-based data 2. Characterization of fire detection performance 3. Estimation of omission and commission errors 4. Evaluation of ABI FRP	ABI detected 19% and 29% more fires observed by Landsat-8 and 375-m VIIRS, respectively. ABI FRP was ~30–50% larger in individual fire events but was overall similar at a regional scale.
Li et al. (2021)	1. Design of LSTM-based models 2. Outdoor combustion experiments for data collection 3. Construction of progressive LSTM models 4. Cross-Entropy Loss equation for model evaluation	FNU-LSTM determined as the best model for general prediction. Improved real fire prediction demonstrated on historical wildland fires.
Li et al. (2022)	1. Proposal of lightweight fire detection model based on MobileNetV3 and anchor-free structure 2. Evaluation on self-built dataset and public datasets 3. Comparative experiments	Proposed method achieved 90.2% accuracy with 21.4M model size and 29.5f/s running speed. Outperformed other methods in detection accuracy and speed.
Liu et al. (2020)	1. Generation of high-quality forest fire samples with GAN 2. Primary prediction using Adaboost classifier and HOG features 3. Secondary recognition with CNN and SVM	Recognition rate of forest fire images reached 97.6% with 1.4% false alarm rate and 1% missed alarm rate. Average recognition time was only 0.7 s.
Lu et al. (2022)	1. Proposal of MTL-FFDet model with three tasks and shared feature extraction 2. Development of joint multi-task NMS processing algorithm 3. Data augmentation strategy for small fire targets	MTL-FFDet outperformed YOLOv5-s in multiple metrics, including mean average precision and average precision for small objects. Better focus on target region during feature extraction demonstrated.
Mahmoud and Ren (2018)	1. Background subtraction for movement detection. 2. Color space conversion and fire detection rules application. 3. Temporal variation for fire differentiation.	Achieved up to 96.63% true detection rates.
Lu et al. (2022)	1. NanoDet model for fire detection. 2. Binocular stereo vision for depth map calculation. 3. Coordinate frame conversion for LLA coordinates.	Detected 89.34% of suspicious frames with flame targets. Achieved precision in latitude and longitude.
Majid et al. (2022)	1. Custom framework using transfer learning with CNNs. 2. Utilization of attention mechanism for better performance.	Achieved a test accuracy of 95.40% and a very high recall of 97.61%.
Mao et al. (2018)	1. Multi-channel CNN for fire recognition. 2. GPU acceleration for model training.	Achieved classification accuracy of 98% or more for various flame scenes and types. Outperformed traditional feature-based methods in terms of performance metrics.
Martins et al. (2022)	1. Instance segmentation algorithm for feature extraction. 2. Ensemble of machine learning algorithms for smoke object identification.	Achieved around 95% removal of false positives with minimal reduction in true positives.

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TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Mashraqi, et al. (2022)	1. Design of a modified MobileNet-v2 model for feature extraction. 2. Application of a simple recurrent unit model for classification. 3. Use of shuffled frog leap algorithm for improved classification outcomes.	Achieved improvements over other recent algorithms in forest fire detection and classification accuracy.
Muhammad et al. (2018)	1. Fine-tuned convolutional neural networks for fire detection. 2. Adaptive prioritization mechanism for surveillance cameras. 3. Dynamic channel selection algorithm based on cognitive radio networks.	Achieved higher accuracy compared to state-of-the-art methods in fire detection. Validated the applicability of the framework for effective fire disaster management.
Muid et al. (2022)	1. UAV photogrammetry for image collection. 2. Color filtration algorithm for hotspot detection.	Achieved almost zero deviation of longitude and latitude from the real location. High accuracy in fire area detection.
Munshi (2021)	1. RGB, YCbCr, and HSV color models for fire detection. 2. Supervised machine learning techniques for model training. 3. Gaussian mixture model (GMM) with expectation maximization (EM) algorithm for parameter estimation.	Achieved satisfactory overall accuracies in fire detection using different color models. Efficient detection of outdoor and indoor fires.
Ngoc Thach et al. (2018)	1. Support Vector Machine classifier (SVMC), Random Forests (RF), and Multilayer Perceptron Neural Network (MLP-Net) for fire danger analysis. 2. GIS-based database establishment and correlation analysis for variable selection.	Achieved high prediction performance with MLP-Net model outperforming SVMC and RF models.
Nguyen et al. (2021)	1. Detection of fire candidates based on salient features in the first stage. 2. Use of pretrained CNN model for feature extraction in the second stage. 3. Utilization of LSTM network for flame classification.	Achieved competitive performance compared to other state-of-the-art methods. Suitable for real-world applications.
Pang et al. (2022)	1. Leveraging artificial intelligence algorithms for data fusion from multiple sources. 2. Identification of thirteen major drivers of forest fires using machine learning algorithms.	Achieved prediction accuracies between 75.8% and 89.2%. Identified high-risk forest fire areas in China.
Park et al. (2019)	1. Multifunctional artificial intelligence framework including multiple machine learning algorithms and adaptive fuzzy algorithm. 2. Introduction of Direct-MQTT based on SDN for minimizing data transfer delay.	Achieved fire detection accuracy of over 95%. Reduced end-to-end delay by an average of 72%.
Park and Bae (2020)	1. Creation of a dataset for smoke detection scenarios within ship engine rooms. 2. Use of motion detection and support vector machine classifier for smoke detection.	Seldom produced false positive windows in non-smoke regions. Processing time sufficiently fast for real-time smoke detection.
Perrolas et al. (2022)	1. Proposal of a multi-resolution iterative quad-tree search algorithm for fire and smoke segmentation. 2. Application of classification and segmentation CNNs to focus on informative parts of the image.	Achieved higher accuracy in detecting and segmenting fire and smoke regions. Efficient for segmenting small incident regions in high-resolution images.

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TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Pletsch et al. (2022)	1. Development of a Machine Learning (ML) algorithm based on GOES-16 ABI sensor for NRT active fire detection. 2. Analysis of optimal ML algorithms and historical time series for accurate predictions.	Achieved overall accuracy rate of approximately 80% for the final model. Remarkable potential for single and consecutive detections of active fires. Trade-off between accuracy and time for assembling fire indications identified.
Qian et al. (2022)	1. Proposal of FMAS based on channel-wise pruned YOLOv3 to reduce parameter size and improve detection accuracy. 2. Collection of a large fire and smoke image dataset for training and validation.	Achieved satisfactory accuracy with low computational capacity after parameter squeezing. Demonstrated improved detection accuracy and generalization abilities compared to existing methods.
Qian and Lin (2022)	1. Proposal of weighted fusion algorithm to identify forest fire sources using Yolov5 and EfficientDet models. 2. Parallel training and prediction of datasets to achieve fusion frame using weighted boxes fusion algorithm (WBF).	Improved detection performance by 2.5% to 4.5% compared to individual Yolov5 and EfficientDet models. Enhanced feature extraction ability for better recognition accuracy.
Qin et al. (2022)	1. Introduction of FGL-GAN with hierarchical Global-Local generator structure for rendering high-quality flame images. 2. Incorporation of fire mask and data augmentation techniques to enhance rendering quality.	Achieved better performance in qualitative and quantitative evaluation compared to mainstream GAN. Effective features such as hierarchical Global-Local generator structure and fire mask demonstrated through ablation study.
Qin et al. (2021)	1. Implementation of depthwise separable convolution for fire image classification and YOLOv3 for fire position regression. 2. Integration of classification and regression models to improve detection accuracy and speed.	Achieved detection accuracy of 98% and detection rate of 38 fps. Improved detection accuracy, reduced computational cost, and increased detection rate compared to traditional methods.
Rashkovetsky et al. (2021)	1. Workflow development for fire detection using convolutional neural networks (CNNs) on satellite imagery. 2. Training of single-instrument models using U-Net architecture on datasets from different satellite instruments.	Fusion of Sentinel-2 and Sentinel-3 data provides best detection rate in clear conditions, while Sentinel-1 and Sentinel-2 fusion is beneficial in cloudy weather.
Saeed et al. (2020)	1. Hybrid model combining Adaboost and MLP neural networks for fire prediction. 2. CNN model for immediate fire detection.	Achieved near 91% fire detection accuracy with low false positive rate.
Seydi et al. (2022)	Development of Fire-Net framework trained on Landsat-8 imagery, leveraging optical and thermal modalities and residual convolution and separable convolution blocks.	Achieved overall accuracy of 97.35% in detecting active fires, including small fires.
Rostami et al. (2022)	Development of MultiScale-Net with multiple convolution kernels of various sizes and dilated convolution layers (DCLs). Introduce an innovative Active Fire Index (AFI) for improved performance.	Achieved highest F1-score and IoU of 91.62% and 84.54%, respectively, using MultiScale-Net with AFI and specific input variables.
Ryu and Kwak (2021)	Utilize HSV color conversion and Harris Corner Detection for image preprocessing. Extract regions of interest (ROIs) using CNN trained on flame appearance characteristics.	Achieved higher accuracy and precision in fire detection compared to conventional methods, reducing false detection rates.

TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Roy et al. (2022)	Utilize LeNet5 CNN model for fire and non-fire image classification. Employ L2 regularization to manipulate the complexity of the CNN model and reduce overfitting.	Achieved train accuracy of around 87%, validation accuracy of 71%, and test accuracy of 70% after 10 epochs.
Saeed et al. (2020)	Hybrid model combining Adaboost and MLP neural networks for fire prediction, followed by Adaboost-LBP model and CNN for fire detection from images and videos.	Achieved an accuracy of almost 99% with low false alarm rate using the proposed model.
Shahid et al. (2022)	Self-attention mechanism for spatial-temporal features	Significant enhancement in F1-score for large scale fires and relative improvement for small fires
Shakhnoza et al. (2022)	Attention feature map in capsule network	High classification accuracy achieved, robust and stable classification of outdoor CCTV images with different viewpoints
Shamsoshoara et al. (2021)	1. Binary classification using ANN method, 2. Fire detection using segmentation with U-Net approach	Achieved classification accuracy of 76%, precision of 92%, and recall of 84%
Sharma et al. (2019)	Utilization of Wireless Sensor Networks and Unmanned Aerial Vehicles (UAVs)	Presented accurate detection rate and suitable for early event detection
Sharma et al. (2022)	Comparison of six machine learning algorithms for fire prediction	Support Vector Machine (SVM) and Artificial Neural Network (ANN) showed excellent performance
Sharma et al. (2020)	Implementation of eight Machine Learning algorithms	Boosted decision tree model with AUC value of 0.78 identified as most suitable candidate for fire prediction model
Sheng et al. (2021)	Deep belief network (DBN) based on statistic image features	DBN achieved superior classification accuracy compared to SVM and CDBNs
Sofan et al. (2019)	Tropical Peatland Combustion Algorithm (ToPeCAl) based on Landsat-8 images	ToPeCAl achieved an overall mapping accuracy of 93% with reduction of errors after masking urban areas
Sousa et al. (2019)	Fuzzy modeling approach based on thermal imaging data	Proposed algorithm demonstrated performance comparable to state-of-the-art methods
Sousa et al. (2020)	Transfer learning coupled with data augmentation techniques	Proposed framework demonstrated improved performance and provided insights into misclassifications
Sowah et al. (2020)	Multisensor data fusion with Convolutional Neural Network (CNN) fire detection	CNN achieved an accuracy rate of 94% and fuzzy logic unit 90%
Sun et al. (2021)	1. Train YoloV3 network to detect lamps 2. Mask lamp regions with Local Grabcut segmentation method 3. Compare methods with InceptionV4 networks	34.6% reduction in false alarm rate Effectiveness verified among different CNN architectures
Taspinar et al. (2021)	1. Extract flame regions using image processing algorithms 2. Utilize mobility feature of flame 3. Employ CNN for fire detection with transfer learning	Achieved classification success rates of 96.8% to 98.8% Potential reduction in fire damage through early detection and intervention

TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Tonbul et al. (2022)	1. Analyze burn severity using RF, RotFor, and CCF classifiers 2. Apply classification to fire-affected areas using Sentinel-2A images	CCF classifier outperformed RF and RotFor classifiers Significant variation in burned area estimates between pixel- and object-based classifications
Tran et al. (2022)	1. Implement DetNAS for optimal backbone selection 2. Compare DetNAS backbone with ResNet, VoVNet, and FBNetV3 3. Develop damage area estimation using BNN	DetNAS achieves higher mean average precision BNN estimates damage area with less error and increased generalization
Udahemuka et al. (2020)	1. Assimilate brightness temperatures into a Diurnal Temperature Cycle model 2. Implement data assimilation using EnKF, SIR particle filter, and 4D-Var	High detection rate achieved with EnKF and SIR particle filter Consideration of diurnal variation enables detection of low-power fires
Tao and Lu (2018)	1. Utilize Vibe background subtraction algorithm 2. Extract LHI features from key vehicle regions 3. Employ ensemble back-propagation neural networks (E-BPNN) for classification	Better performance of E-BPNN with multi-feature fusion Lower false alarm rates compared to common detection methods
Valikhujaev et al. (2020)	Deep learning approach using a convolutional neural network with dilated convolutions	Superior performance and complexity compared to state-of-the-art methods, effective generalization, reduced false alarms
Waigl et al. (2019)	1. Metric based on potassium emission, 2. Continuum-interpolated band ratio (CIBR), 3. Hyperspectral Fire Detection Index (HFDI)	Modified HFDI produces well-defined map of active fire areas, CO2 CIBR contributes to detection performance
Wang et al. (2022)	Novel dilated efficient channel attention module (DECA) with weight-sharing method applied	DECA module enhances performance by more than 4.5% compared to baselines, holds great generalization ability
Wang et al. (2022)	1. Improved dark channel prior algorithm for image preprocessing, 2. Coordinate attention (CA)-based deep learning network	Prototype system achieves 96.1% accuracy and 60fps frame rate for fire situation detection
Wang et al. (2021)	1. Lightweight MobileNetV3 model, 2. Channel-level sparsity-induced regularization, 3. Knowledge distillation algorithm	Model parameters reduced by nearly 95.87%, inference time decreased by nearly 75.68%
Wang et al. (2022)	1. Construction of forest fire dataset from UAV-captured remote-sensing images 2. Selection of four FCNN models and two backbone networks	U-Net model with Resnet50 backbone achieves highest segmentation accuracy, DeepLabV3+ with Resnet50 balances accuracy and speed
Wei et al. (2022)	Improvement of YOLOV5S architecture with MobilenetV3 structure for lightweight design	Novel model achieves excellent detection accuracy and real-time performance on wildfire dataset
Wilk-Jakubowski et al. (2022)	1. Deep Neural Networks for flame detection, 2. Acoustic extinguisher with high-power loudspeaker	Development of techniques for flame extinguishing using Deep Neural Networks, determination of minimum power and sound levels for extinguishing
Xavier et al. (2022)	1. Collection of PIR sensor data for fire and human motion, 2. Feature extraction using wavelet transform, 3. Deep Convolutional Neural Network	ShuffleNet architecture achieves highest prediction accuracy, real-time strategy achieves high detection accuracy levels
Xie et al. (2018)	1. Improved robust fitting algorithm for diurnal temperature cycles modeling, 2. Kalman filter for background brightness temperature estimation	Proposed STCM effectively utilizes spatial and temporal information for forest fire detection, outperforms traditional algorithms

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TABLE 5. Analysis of previous studies with methods and outcomes (continued)

Author (year)	Method	Outcome
Xiong and Yan (2019)	Superpixel merging algorithm for image segmentation using SLIC	77% accuracy in smoke detection in forest scenes
Xu et al. (2022)	1. MPU-PSA model for mixed-pixel unmixing and pixel-swapping	FFLS locations were much closer to actual OriFFs than M-HWFP
Xu et al. (2021)	Deep LSTM neural networks combined with variational autoencoder	LSTM-VAE outperforms other detection methods in simulation and real-world experiments
Yandouzi et al. (2022)	DL model with transfer learning from pretrained architectures	Detection rate of more than 99.9% achieved using various DL architectures
Yang et al. (2019)	CNN inspired by MobileNet with depthwise separable convolution and squeeze and excitation modules	95.44% accuracy achieved for fire detection with 38.50% fewer parameters than MobileNetV2
Yang et al. (2022)	1. Construction of a one-class model relying solely on fire samples 2. Batch decision-making strategy for speed-up	Superiority in high-fire detection rate, low-error warning rate, accurate fire location, and real-time detection
Yang et al. (2020)	1. Combination of lightweight CNN with SRU for dynamic flame characteristic extraction	Accuracy of proposed models above 96%, 25% higher than single-frame image methods
Yang et al. (2022)	1. Generative adversarial network (GAN) for flame image synthesis and migration into specified scenes 2. Evaluation using Unet and SA-Unet fire segmenting networks	Enhancement of fire segmentation accuracy with F1-scores reaching 0.9082
Zhang et al. (2021)	1. Dual-domain channel-position attention (DCPA)+HRNetV2 model for deep-learning-based detection	Detection accuracy surpassing other models with an average IoU of 70.4% to 71.9%
Zhao et al. (2022)	1. Improvement of Fire-YOLO deep learning algorithm with expanded feature extraction network and feature pyramid promotion	Excellent results in detection of small fire and smoke targets with real-time capabilities
Zhao et al. (2022)	1. Simplified weighted Bi-FPN in Yolo-v4 for feature fusion 2. Improved ViBe algorithm for sudden light changes	98.9% fire detection accuracy with reduced false detection rate
Zheng et al. (2022)	1. Improved DCNN model trained with transfer learning and PCA reconstruction technology	Improved detection accuracy with true positive rate of 7.41% and false positive rate of 4.8%
Zhong et al. (2018)	1. Candidate target area extraction algorithm for suspected flame areas 2. Classification using deep neural network model based on CNN	Effective real-time fire warning with higher alarm rate in experimental database

TABLE 6. Detection classification

No	Detection algorithm	Type of detection	Reference
1	One-stage detection	YOLO	Huang et al. (2022); Qian et al. (2022); Wang et al. (2022); Zhao et al. (2022); Qian and Lin (2022); Baldo et al. (2021); Abdusalomov et al. (2021); Wei et al. (2022); Qin et al. (2021); Avazov et al. (2022); Wang et al. (2022); Abdusalomov et al. (2022); Balen et al. (2022); Kumar et al. (2021); Sun et al. (2021); Xu et al. (2021)
2	Two-stage detection	Mask Region CNN (Mask R-CNN)	Wilk-Jakubowski et al. (2022)
		Fast Region-Based CNN (F R-CNN)	Balen et al. (2022); Cheng (2021)
		Faster R-CNN	Balen et al. (2022); Guede-Fernández et al. (2021)

Field of image processing in CNN increased more attention due to its massive economic potential and accuracy rate. Loads well known CNN architectures or pre-trained models which are very popular in the area of image processing and classification namely AlexNet, GoogleNet, MobileNetV2, VGG16, InceptionV3 and ResNet, which have been trained on big datasets like ImageNet. These models can be used for different tasks without starting from scratch. Only some features need to be adjusted. Few reasons mentioned if data is limited due to large datasets needing expensive computers, the training consumes longer time while the pre-trained models help with the generalization and faster learning process (Alzubaidi et al., 2021). He et al. (2016) developed ResNet (Residual Network) which was invented by Microsoft was used by Huang et al. (2022); Higa et al. (2022); Majid et al. (2022); Valikhujaev et al. (2020); Wang et al. (2022); Khan et al. (2022); Yandouzi et al. (2022); Yan et al. (2020); Nguyen et al. (2021); Chen et al. (2022); Sun et al. (2021). Krizhevesky et al. (2017) first proposed AlexNet in 2012 was used in Valikhujaev et al. (2020). VGGNet was proposed by Simonyan and Zisserman (2014) featured nineteen more layers compared to the AlexNet model. VGGNet was used in Majid et al. (2022);Valikhujaev et al. (2020); Wang et al. (2022); Khan et al. (2022); Taspinar et al. (2019); Yandouzi et al. (2022); Chen et al. (2022); Cheng (2021). The list of pre-trained model used in these studies is shown in Table 7.

TABLE 7. Pre trained models used

No	Machine learning library	Reference
1	ResNet	Huang et al. (2022); Higa et al. (2022); Majid et al. (2022); Valikhujaev et al. (2020); Wang et al. (2022); Khan et al. (2022); Yandouzi et al. (2022); Yan et al. (2020); Nguyen et al. (2021); Chen et al. (2022); Sun et al. (2021).
2	AlexNet	Valikhujaev et al. (2020)
3	VGGNet	Majid et al. (2022);Valikhujaev et al. (2020); Wang et al. (2022); Khan et al. (2022); Taspinar et al. (2019); Yandouzi et al. (2022); Chen et al. (2022); Cheng (2021).

RQ5 – What is the percentage recognition rate of accuracy in the previous study?

High accuracy is crucial in the early fire detection stage to allow for a faster response and to help reduce false alarms. The primary concern in any fire incident is the safety of human lives. Accurate fire detection ensures that alarms are triggered promptly, allowing occupants to evacuate the building safely before the fire becomes life-threatening. The method has attained accuracy of 70–96% and above over the last five years of research. Table 8 shows the summary of accuracy achievement in previous study. It has been discovered that the majority of vision-based fire detection systems have accuracy levels of at least 90 percent. The high accuracy of 99 percent and above was found in a study made by Avazov et al. (2022) using Banana Pi M3 board with improved YOLOv4 algorithm based on the surveillance control system. Saaed et al. (2020)

proposed model achieved more than 99 percent by using three machine learning methods with sensor data for prediction accuracy. Abdusalomov et al. (2021) achieved 99.7 percent accuracy by using Banana Pi M3 board with improved YOLOv3 algorithm. Study by Wang et al. (2021) using a combination of YOLO, MobileNetYOLO and MobileNetV3 to achieve 99.57 percent accuracy. Low accuracy found on Bai et al. (2021) using MODIS satellite fire data in back propagation neural network (BPNN) achieved 54.48 percent accuracy. Roy et al. (2022) achieved 71 percent accuracy using the LeNet5 algorithm.

TABLE 8. Accuracy achievement of the existing vision-based fire detection system

Accuracy Percentage	Reference
96 >	Wang et al. (2021); Zheng et al. (2022); Kang et al. (2022); Valikhujaev et al. (2020); Zhao et al. (2022); Saeed et al. (2020); Masharaqi et al. (2022); Amici and Piscini (2021); Taspinar et al. (2021); Qin et al. (2021); Avazov et al. (2022); Khalil et al. (2021); Mao et al. (2018); Wang et al. (2022); Seydi et al. (2022); Ryu and Kwak (2021); Yandouzi et al. (2022); Yang et al. (2020); Khudayberdiev et al. (2022); Lu et al. (2022); Nguyen et al. (2021); Deng et al. (2022); Chen et al. (2019); Cheng (2021); Park and Bae (2020); Shahid et al. (2022)
91 - 95	Baig et al. (2021); Zhao et al. (2022); Gong et al. (2019); Sheng et al. (2021); Kim et al. (2021); Apostolopoulos et al. (2022); Abdusalomov et al. (2021); Majid et al. (2022); Kim and Ruy (2022); Khan et al. (2022); Park et al. (2019); Muhammad et al. (2018); Almoussawi et al. (2022); Wang et al. (2022); Guan et al. (2022); Sowah et al. (2020); Saeed et al. (2020); Booth and Cardille (2022); Yang et al. (2019); Shakhnoza et al. (2022); Chen et al. (2022); Jain and Srivastava (2022); Khan et al. (2022); Rashkovetsky et al. (2021); Sousa et al. (2020);
86 - 90	Qian and Lin (2022); Lu et al. (2022); Wei et al. (2022); Xavier and Nanayakkara (2022); Munshi (2021);
81 - 85	Sofan et al. (2019); Laptev et al. (2021);
76 - 80	Shamsoshoara et al. (2021); Xiong and Yan (2019); Bai et al.(2022); Pang et al. (2022); Pletsch et al. (2022); Ngoc et al. (2018)
< 75	Bai et al. (2021); Roy et al. (2022);

42.4% of the research on vision-based fire detection and prediction recognition systems has obtained 96% to 100% accuracy, as indicated in Figure 7. The remaining 34.8% of the study has attained 91% to 95% accuracy. Of the work, 7.8% has an accuracy of 86% to 90%, and 3% has an accuracy of 81% to 85%. However, 9.1% of the research had accuracy rates between 76% and 80%. 75% and lower is the lowest that may be attained with only 3% of the work.

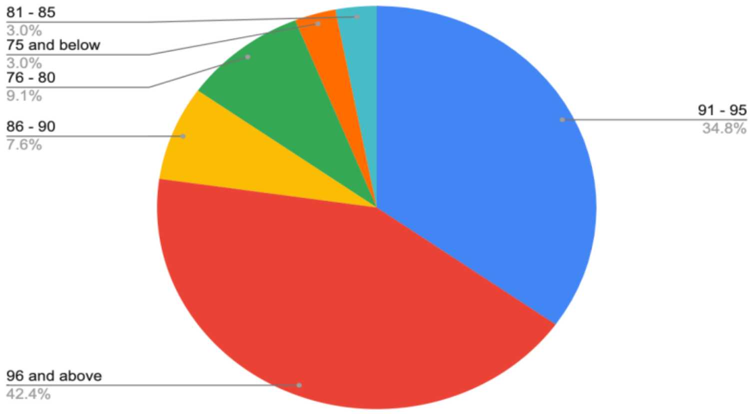

FIGURE 7. Percentage of recognition accuracy rate

DISCUSSION

Comparison with Earlier Research and Its Drawbacks

This section examined and provided a summary of the findings in Table 9 by comparing this study with three review studies. Shaharuddin et al. (2023) reviews the literature for indoor fire hazard based on IoT sensors application for 10 years from 2012 to 2022. The authors describe integrating IoT sensors with deep learning in smart automation for early fire detection using machine learning algorithms and proposed sensing elements which exceed the predetermined value. Vision-based cameras with deep learning only to determine the integrity of the fire incident to avoid false alarm. The authors created a table with the number of metrics used and provided definitions for these metrics in the study. They do not include how the fire image is extracted with the correct machine learning approach. Shidik et al. (2019) work reviewed integrating computer vision, image processing and artificial intelligence into surveillance system applications for 10 years from 2010 to 2019. The paper identified application areas for using video surveillance systems, machine learning methods and network infrastructure design. This paper also did not include fire detection features explanation as in details. However, the authors discussed surveillance framework for local authority or government regarding visualization of global disaster surveillance systems. Geetha et al. (2021) summarizes 4 years from 2017 to 2020 of algorithm models with performance rate of flame or fire and smoke detection using vision-based methods. The paper focuses on feature extraction and selection techniques comparison between smoke or fire detection. In summary, our study covers a wide variety of areas in vision-based fire detection which include software and hardware used in the existing studies.

TABLE 9. Evaluation of Previous Reviews

Articles	Databases	Analysis of Research Trends	Description ML Model	Description of Evaluation Accuracy	Time - Span
Shaharuddin et al. (2023)	4 (Web of Science, Science Direct, IEEE and Scopus)	YES	NO	YES	2012 to 2022
Shidik et al. (2019)	4 (ACM, IEEE Xplore, Science Direct, Springer Link	YES	YES	NO	2010 to 2019
Geetha et al. (2021)	NO	YES	YES	YES	2017 to 2020

RESEARCH SUGGESTION

There are not many publicly accessible datasets for indoor environments like residential homes, according to the SLR of earlier studies suggested by

Rina Tasia et al. (2023) in sign languages outside from American region. As suggested by Nazir et al. (2023), a number of factors, including slow-burning fires, quickly spreading fires, potential fire locations, and flammable materials, must be taken into account when addressing the variability in fire types and sizes. Pincott et al. (2022) recommended taking into account factors including the type of building, the size of the indoor space, and the position of the camera placement for detection. Future research may examine the viability of integrating a vision-based detector and a physical sensor (such as a smoke sensor) into a single system. Additionally, the detector developed for this study might be further trained to distinguish between controlled smoke (such as smoke from toaster or cigarettes) and uncontrolled smoke (such as smoke from a fire). The domestic context would benefit most from this. Since object detection can be used to determine the source of smoke (if smoke from cigarettes is identified, no alarm), this can only be done with vision systems. The likelihood of false alarms is extremely low when physical and visual detectors are combined.

Other features of fire for vision-based systems to look for such as the flame colour and brightness, smoke plumes, flame motion due to flickering flames, heat or flame shape design which contribute to fire occurrence. Integration of conventional fire detector and vision-based detector with multiple combination of algorithm able to increase the accuracy of fire detection and prediction with zero false alarm. However, it is essential to manage integration of multiple machine learning approaches in term of higher computational resources to handle the workload which may consume time. Setting up the system for remote monitoring such mobile phone application allowing the house owner or fire fighter to access live camera feeds for quick action responds.

CONCLUSION

In this study, 120 publications pertaining to vision-based fire detection and fire prediction from the years 2018 to 2022 underwent a thorough SLR based on PRISMA 2020 guidelines. Finding the research trend closely associated with fire detection and prediction methods and algorithms was the aim of this study. In order to ensure the validity and reliability of this result for future research, this review adhered to the systematic approach outlined by the PRISMA 2020 guideline. The search term presented in Table 1 was utilized to retrieve a total of over 644 articles from three electronic databases, namely Web of Science, Scopus, and IEEE Xplore, for this SLR. A small number of duplicates were initially discovered and removed from this SLR; 524 articles were excluded in accordance with Table 2's exclusion criteria. Six primary topics emerged from the investigation conducted: type of fire, dataset, type of hardware and software, type of method and classification, and accuracy attained. Most of the studies utilize video surveillance system to recognize fire flame rather than smoke. Most classification method has been used was Deep Learning which include Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Generative Adversarial Network (GAN), Long Short-Term Memory (LSTM). The study expected to help other researchers to understand works that have been done by previous researchers.

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DECLARATION OF COMPETING INTEREST

None

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