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Intelligent Surveillance Systems for Fire Detection in Open Areas: A Survey

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Abstract

With the growth of open areas comes an ever-increasing risk of fire. However, there is a problem with the present approaches to fire detection, which rely on smoke sensors for wide regions. The advent of video surveillance systems has greatly improved our ability to detect smoke and flames coming from a distance and reduced this risk. Point sensors are slower at detecting fires than cameras when image processing is used. Moreover, using this video and image data presents processing challenges due to the enormous volume of data involved. Several approaches have recently been put forth to address this issue and distinguish between fire and smoke. Earlier methods included image processing algorithms for flame and smoke detection as well as motion-based estimation of smoke. Recently, a variety of techniques have been put forth using deep learning and convolutional neural networks (CNNs) to predict and automatically identify fire and smoke in videos and images. In this study, we review previous studies of fire/smoke detection systems based on machine vision and deep learning. The foundations of image processing techniques, CNN, and their applicability to video smoke and fire detection are explained. A discussion of current data sets and an overview of recent methods applied in this field The difficulties and potential solutions for advancing the application of CNN in this field are discussed. Then a comparison for researchers in the last years based on the dataset, year, technique, limitation, and accuracy they got The CNNs have been found to have a high potential for detecting open areas, and improved development can help create a system that would significantly reduce the loss of human life and property. Remarks for future work were concluded.

Keywords: Fire Detection System, Intelligent System, CNNs, Computer Vision, Deep Learning.

أنظمة مراقبة ذكية لاكتشاف الحرائق في المناطق المفتوحة: دراسة بحثية

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الخلاصة

مع نمو المناطق المفتوحة، يتزايد خطر نشوب حريق. ومع ذلك، هناك مشكلة في الأساليب الحالية للكشف عن الحرائق، والتي تعتمد على أجهزة استشعار الدخان لمناطق واسعة. أدى ظهور أنظمة المراقبة

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بالفيديو إلى تحسين قدرتنا على اكتشاف الدخان واللهب القادم من مسافة بعيدة وتقليل هذه المخاطر. تكون مستشعرات النقاط أبطأ في اكتشاف الحرائق من الكاميرات عند استعمال معالجة الصور. علاوة على ذلك، فإن استعمال بيانات الفيديو والصور هذه يمثل تحديات في المعالجة بسبب الحجم الهائل للبيانات المعنية. تم مؤخراً وضع عدة طرق لمعالجة هذه المشكلة والتمييز بين النار والدخان. تتضمن الطرق السابقة خوارزميات معالجة الصور لاكتشاف اللهب والدخان بالإضافة إلى تقدير الدخان المستند إلى الحركة. في الآونة الأخيرة، تم طرح مجموعة متنوعة من التقنيات باستعمال التعلم العميق والشبكات العصبية التلافيفية للتنبؤ بالحرائق والدخان في الفيديو والصور والتعرف عليها تلقائيًا. في هذه الدراسة، نستعرض الدراسات السابقة لأنظمة الكشف عن الحرائق / الدخان القائمة على رؤية الماكينة والتعلم العميق. ثم يتم شرح أسس تقنيات معالجة الصور وشبكات CNN وإمكانية استعمالها في دخان الفيديو واكتشاف الحرائق. ومن ثم مناقشة مجموعات البيانات الحالية ونظرة عامة على الأساليب الحديثة المطبقة في هذا المجال. بعدها يتم عرض الصعوبات والحلول المحتملة للنهوض بتطبيق الشبكات العصبية التلافيفية. ثم نستعرض مقارنة للباحثين في السنوات الأخيرة بناءً على مجموعة البيانات والسنة والتقنية والدقة التي حصلوا عليها في عملية الكشف. اثبتت CNNs لديها إمكانات عالية للكشف في المناطق المفتوحة، ويمكن أن يساعد التطوير المحسن في إنشاء نظام من شأنه أن يقلل بشكل كبير من الخسائر في الأرواح البشرية والممتلكات. كما نختم بعض الملاحظات للعمل المستقبلي.

1. Introduction

Human safety, health, and property are far more negatively impacted by the fire. The cost of fires in terms of money and human suffering has significantly increased in recent years. Some unexpected factors, such as shifting fuel management regulations, climate change, and rapid rural growth, are to blame for them [1]. A crucial part of surveillance systems is the fire detection system. It monitors various environments, like buildings, as the main part of an early warning system to report, ideally, the beginning of a fire. The majority of fire detection systems in use today use point sensors for smoke analysis, temperature sampling, and particle sampling. They do not have much use in outdoor surveillance and detect fire probabilities slowly, usually in minutes. To prevent false alarms, the smoke and heat detectors activate when enough smoke particles enter the device or when the temperature rises significantly. In addition, one of the key elements in reducing fire damage is time. To maximize the likelihood of putting out fires and so lessen the financial and humanistic damages, the response time of detecting systems should be slowed down [2].

In recent decades, researchers have made an effort to duplicate the sluggish response time of point detectors. The alternate solution, fire sensor-based computing for intelligent surveillance systems, illustrates this issue. They have concluded that obtaining images and/or video frames from vision sensors is one of the most recent and effective methods for detecting smoke and flame [3]. Techniques based on vision sensors can significantly increase coverage of wide areas (such as open areas), decrease response time, and increase the probability of the detection process. More details regarding the size, growth, and direction of fire and smoke can be obtained using vision sensors [4, 5]. Additionally, with minimal implementation costs, we may enhance the current monitoring systems established in a variety of settings, such as parks, open areas, public gardens, and farms, using video processing and deep learning. This procedure can be used to recognize flame and smoke as well as deliver fire early warnings using machine vision techniques.

The three main components of intelligent fire detection systems, which make use of vision sensors, include flame or smoke blob detection, candidate object segmentation, and motion detection. Although the cameras in these systems are typically thought of as fixed, the initial motion is identified using a few different image subtraction and background modeling approaches [6]. Candidate object segmentation can occur after motion detection utilizing color information [6, 7]. Image separation methods or mathematical modeling of the fire or smoke can both be used to locate blobs of flame and smoke. By using pretreatment morphological image processing techniques after motion detection, the geographic locations of fire can be discovered. The depth of a particular scene and the camera's field of view both affect a fire system's ability to detect it. Additionally, the physical characteristics and dynamic behaviors of smoke and flame differ. As a result, a fire system that can locate both smoke and flame can significantly detect a fire earlier than a system that can just discover smoke or flame [8].

Researchers have developed several intelligent and vision-based flame and smoke detection systems, particularly in the last ten years. They employ a variety of methods and structures, including cameras [9], intelligent techniques and neural networks, wireless networks using fuzzy logic, particle swarm optimization, wireless sensor networks, and satellite systems [10]. Most fire detection systems use intelligent ways to organize themselves based on the many characteristics of the fire, such as flame, smoke, and color [11]. These systems share a lot of characteristics. As a result, they are divided into categories in this study based on the different types of habitats, such as systems for detecting forest fires, systems for detecting smoke in open areas, and systems for detecting fires and smoke in forests [7].

The rest of the survey is organized as follows: Section 2 presents a review of the most important research in recent years. Section 3 illustrates the challenges of an intelligent surveillance system for fire detection. Fire detection classification models are presented in Section 4. Section 5 provides a brief comparison of fire detection system research. In the end, we offer some suggestions for future work.

2. Related Works

Systems for fire detection can be formed for use in different environments. Since each environment has its own unique requirements, several fire detection methods can be employed in different contexts. Some can be used to detect fires in open areas and forests, while others can be used in outdoor environments. As a result, this part explains the intelligent and vision-based fire and smoke detection systems in open areas and all environments that were covered in several studies.

In Vipin V in 2012 [12], the author proposed a classification of fire pixels. A color model-based image processing technique is employed; the RGB and YcbCr color spaces are used in the suggested algorithm, and utilizing the YcbCr color space has the advantage of more efficiently separating luminance from chrominance than RGB. Two sets of images, one with fire and one without it, are used to test the performance of the proposed method. A flame detection rate of 99% and a false alarm rate of 14% are achieved by the proposed approach, which qualifies it for use in a system that monitors wildfires in real-time.

Pasquale Foggia et al. [13] suggested a technique that uses video footage from security cameras to identify fires, with the introduction of two significant novelties: in the beginning, a multi-expert system utilizes motion analysis, color, shape variation, and complementary information to combine. The key benefit of this strategy is that it considerably improves the system's overall performance with only a tiny amount of additional work on the part of the designer.

Rui Chi et al. in 2016 [14] developed a multi-feature method that gathers information from the chromatic properties, dynamic features, texture features, and contour characteristics of flames. The method extracts moving regions by fractal dimension and gradient motion history picture analysis of contour information. The experimental findings demonstrate the extremely sensitive, high reliability, and quick response times of the suggested approach for fixed monitoring and video fire detection.

Sebastien Frizzi et al. in 2016 [15] presented a CNN for detecting fire in videos. It has been demonstrated that CNNs excel at object classification, and within the same architecture, this network can carry out feature extraction and categorization. The suggested approach performs better in terms of categorization when tested on actual video sequences.

In 2016 [16], Chongyuan Tao et al. suggested CNN, which can be trained from initial raw pixel values to final classifier outputs and can automatically extract features from images. Studies reveal that utilizing a large dataset, which includes four manually collected smoke and non-smoke data sets from cameras or the internet, this strategy obtains 99.4% detection rates and 0.44% false alarm rates.

In Teng Wang et al. (2017) [17], the authors proposed a fire detection model based on the color component dispersion of the flames and a tracking technique based on the identified region's flame kinematic properties to further reduce false alarms by incorporating similarity between consecutive video frames of the detected area. The suggested fire detection method has useful properties for interior fire detection and can effectively create fire alarms while removing the influence of common interference sources, according to experimental results.
In 2017 [18], Jivitesh Sharma et al. created a fire detection system using VGG16 and Resnet50, two deep CNNs. The improved VGG16 and Resnet50 models added fully connected layers and were tested on an unbalanced dataset. Results indicate that while adding fully linked layers does boost the detector models' accuracy to above 90%, it also lengthens training time.

In 2017 [19], Y. Vasavi and C. Madhu proposed a model based on data on color, shape, and flame movements on a credit card-sized Raspberry Pi microprocessor. They suggested an edge detection method for fire detection. The primary benefit of this system is that it only activates the nearest sprinkler, as opposed to all of them. This shows that a real-time fire detection, suppression, and warning system is feasible.

In Amin Ullah et al.'s 2017 [20], they employed a deep bi-directional long short-term memory (DB-LSTM) network and CNN to handle the video data, suggesting an action recognition approach. First, every sixth frame of the videos has deep features removed, which helps to simplify and cut down on redundancy. The sequential information between frame characteristics is then learned using a DB-LSTM network, where the depth of the network is increased by stacking many layers during both the forward pass and the backward pass. The suggested technique can analyze longer films by examining features for a predetermined amount of time and can learn long-term sequences.

In Chi Yuan et al.'s 2017 [21], the authors proposed an IR camera for unmanned aerial vehicle (UAV)-based monitoring of forest fires. By exploiting both the brightness and mobility properties of fire in IR images, this technique improves the accuracy and dependability of forest fire detection. With the use of histogram-based segmentation and optical flow analysis, it is possible to distinguish between fires coming from the background and other hot, moving objects that aren't on fire. According to experimental findings, the suggested technique can successfully extract and track fire pixels in IR video sequences.
Khan Muhammad et al. in 2018 [22] suggested an economical CNN fire detection architecture for security camera footage. The model was developed with a particular focus on

computational complexity and detection accuracy and was influenced by the GoogleNet architecture. They used 20% of the whole dataset for training and the remaining 80% for testing. As per the experimental technique of [13], it has been demonstrated through trials that the suggested architecture outperforms both the AlexNet architecture-based and currently used hand-crafted feature-based fire detection approaches.

Khan Muhammad et al. in 2018 [23] employed a model that could analyze 17 frames per second, which is enough to detect fire at an early stage utilizing cameras operating at 25–30 frames per second. They started with Alexnet as a baseline architecture and then adjusted it based on a scenario, taking accuracy and complexity into account. In a range of indoor and outdoor environments, they showed how to increase fire detection accuracy while decreasing false alarms.

Abdulaziz Namozov and Young Im Cho in 2018 [24] demonstrated that even with scant data, deep CNNs may produce extremely high classification performance. Generative adversarial networks (GANs) are used to generate more training samples, which broadens the variety of data that is available and aids in the network's ability to learn fire and smoke features under various environmental and lighting conditions day and night. The adaptive piecewise linear function enables deep CNN models to perform noticeably better without substantially boosting the number of learnable parameters.

Chao Hu et al. in 2018 [25] suggested merging a deep convolutional long-recurrent network (DCLRN) and an optical flow approach to create a neural network of DCLRN for real-time fire monitoring in open space environments. The results demonstrate that the optical flow technique and DCLRN networks have excellent performance on fire monitoring.
Dongqing Shen et al. in 2018 [26], they used the most effective way for flame detection, which will be in charge of the object that falls inside the cell, was determined by comparing the You Only Look Once (YOLO) model with those shallow learning techniques, without a completely connected layer, each cell will forecast the bounding box and the confidence score of this box using nine convolutional layers and an extra layer for pre-training, the network for determining the four parameters is then added directly to the network, the max pooling layer and one activation function ReLU will come after each convolution layer, the attained accuracy of suggested flame identification is up to 76% after using the google platform TensorFlow.

In Zhen Zhong et al. (2018) [27], the authors suggested a neural network be put to the test by categorizing the CNN's output based on the warning signal. The recommended technique outperforms existing methods in terms of accuracy and efficiency when it comes to enhancing the recognition of fire color features based on RGB models, according to experimental results.
Byoungjun Kim and Joonwhoan Lee proposed a Differential Thermal Analysis (DTA) process in 2019 [28]. The Faster R-CNN fire detection model is used in the proposed strategy to select SroF based on its spatial properties. Next, the LSTM collects information from the SroFs and the firing-free zones in subsequent frames to classify whether or not there is a fire in a short time. The sequence of short-term decisions is then linked to the clear majority of the conclusion in the long term. The proposed method has been experimentally demonstrated to effectively interpret the temporal behavior of flame and smoke, which may reduce false transmission and provide higher accuracy in fire detection by reducing false detections and false detections of firefighters.

In Panagiotis Barmpoutis et al.'s 2019 [29], they suggested a method divided into two main steps: First, candidate regions are located by utilizing a faster R-CNN network that has been trained to identify fires, and second, the regions that have been found are validated by studying spatial properties using linear dynamic systems (LDS). The suggested strategy maintains high true positive rates and dramatically lowers false positives caused by things with a fire-colored hue, according to experimental results.

In Arpit Jadon et al.'s 2019 [30], the authors who created FireNet had to start from scratch. The outcomes showed that FireNet is successfully able to provide a real-time fire detection function for up to 24 frames per second, which is practically as fast as human visual cognition. Three convolutional layers and four dense layers make up FireNet, which performs well for applications involving real-time fire detection.

Khan Muhammad et al. in 2019 [31] suggested a computationally efficient CNN architecture modeled after SqueezeNet; it uses smaller, fully linked convolutional kernels and fewer dense layers, which requires less processing. The experimental findings demonstrate that the suggested approach achieves accuracy levels that are comparable to those of other, more complex models, mostly due to its improved depth. Figure 1 shows the characteristics of a deep CNN fire detection system.

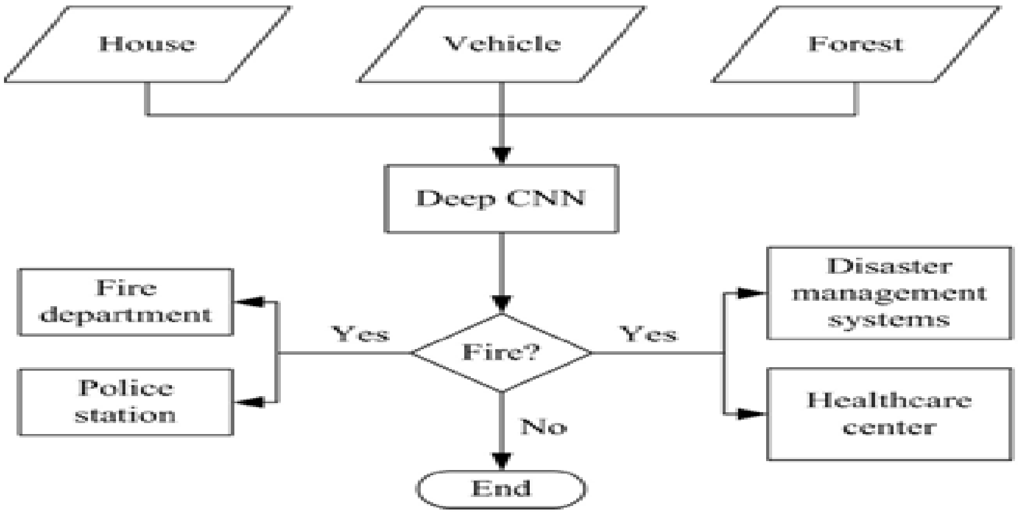

Figure 1: Characteristics of a deep CNN fire detection system in general [31].

In 2019 [32], Angel Ayala et al. suggested an easy-to-use and effective octave CNN to recognize fire in visual images. The databases FireSense, CairFire, FireNet, and FiSmo are the subject of extensive experiments, and according to experimental findings, the model gets greater recognition accuracy.

In 2020 [33], Pu Li and Wangda Zhao proposed image fire detection methods employing the sophisticated object detection CNNs of Faster-RCNN, R-FCN, SSD, and YOLO v3 to enhance the performance of image fire detection technologies. The provided techniques can reliably detect fire in a range of circumstances and can automatically extract sophisticated images of fire properties. The YOLO v3 algorithm has a higher average precision than the other available algorithms, at 83.7%. The YOLO v3 also meets the requirements for real-time detection thanks to its 28 FPS detection speed and improved detection performance robustness.

In 2020 [34], William Thomson et al. looked into various CNN architectures and their variations to detect fire pixel boundaries in real-time, nontemporal video, or still images. To boost computational efficiency for this problem, NasNet-A-OnFire and ShuffleNetV2-OnFire, two reduced-complexity compact CNN architectures, are used. Superpixel localization accuracy is 97%, with a full-frame binary classification accuracy of 95%. The results outperformed current fire detection techniques.

In Sebastien Frizzi et al.'s 2021 [35], they used a network to segment an RGB image to create fire and smoke masks. In a comparison with the best segmentation networks, regarding location accuracy and segmentation rate time, this network performs better than U-Net and Yuan networks when using a semantic segmentation strategy for fire and smoke.
In Rasool D. Haamied et al.'s 2021 [36], the authors designed a system for an automated UAV for object detection, labeling, and localization using deep learning. This system takes images with a low-cost camera and a Global Positioning System (GPS) unit and uses a Raspberry Pi4 with communication protocols to transfer images to the ground station. According to the performance evaluation conducted, the implemented system is capable of meeting the targeted requirements.

In Saima Majid et al.'s 2021 [37], they proposed a novel approach for detecting fires that makes use of transfer learning and images of real fire occurrences. The EfficientNetB0 emerged as the best suitable network because of the model's attention mechanism, which has considerably improved the network's performance and helped the model better localize the fire in the images. The Grad-CAM approach is also used by the framework to highlight a specific area or part of the image and to visualize and localize fire in the images. The model has a test accuracy of 95.40% for the chosen real-world fire image dataset, and a very high recall of 97.61 highlights that the model has only a few false negatives.

These pieces of literature primarily discuss image-level evaluation, but some also include patch-level detection precision. To find a fire, the authors employed the following equations:

$$Accuracy = \frac{NTP+NTN}{POS+NEG} \tag{1}$$

$$Detection\,rate = \frac{NTP}{POS} \tag{2}$$

$$False\,alarm\,rate = \frac{NFN}{NEG} \tag{3}$$

where POS is the number of positives, NEG denotes the number of negatives, NTP denotes the number of true positives, NTN denotes the number of true negatives, and NFN denotes the number of false negatives [4].

3. The Challenges Intelligent Surveillance Systems for Fire and Smoke Detection [9].

CNNs have greatly advanced research and significantly raised the early detection rate. However, there is room for improvement because of a few current issues, which are described below.

● The lack of datasets that can be used as benchmarks and to train and test the neural network is the main obstacle to the advancement of deep learning and CNN techniques in the field of open-area smoke and flame detection. The majority of research to date has focused on data sets generated using images and videos taken directly or taken from publicly available data sets and other sources. It took a lot of resources to illustrate fire and flame in videos and images. Datasets are a major impediment to the efficient and rapid development of specialized deep-learning technologies for this and many other reasons.

● Because CNNs have innate capabilities and have been successful in recent literature, it is crucial to use them to address the difficulty of simultaneous multi-spot smoke and fire flame detection. As a result of CNN's success on big datasets with thousands of classes, it is widely acknowledged that they are a natural candidate for the simultaneous identification of multi-class categories. As a result, creating CNN-based machine vision for intelligent surveillance systems is a key area for future research. The conventional CNN-based methods might not produce the best results in difficult situations where an image scene has multiple patches of smoke and fire with a high degree of variability. A combination of CNNs can accomplish this.

● The difficulties of using CNNs to detect fire in actual situations in addition to the flame, it also picks up smoke. For extended viewing distances, it makes use of a little flame, and the alarm's trust is increased by the alarm's massive smoke.

● Because there are no standard datasets available, it is impossible to choose one method over another and use it in the detection process. Additionally, one method might be superior at identifying fire alone but not smoke, and vice versa, due to the use of specialized datasets. We are still waiting for the accuracy to increase and the false-positive cases to decline.

● Another significant issue is that the system cannot be relied upon to grant complete control to fire suppression equipment. This system operates entirely on camera inputs and makes decisions based on an algorithm. Imagine that the system misidentifies a red object as a fire flame or a gray object as smoke, causing the suppression systems to incorrectly activate and cause unexpected damage. If directly connected to the present sensor-based systems, it would either make both systems unreliable or inefficient.

Open-area fires result in significant financial loss, irreparable harm to the environment and atmosphere, and irreparable harm to the ecology. Open area fires are a serious threat to ecological stability and environmental preservation since they not only result in the tragic loss of lives but also priceless natural environments. Additionally, forest fires have dreadful repercussions and long-term, calamitous implications, including hurting local weather patterns and global warming [7].

4. Fire Detection Classification Models

4.1 Simple Image Processing Models

The widely used feature extraction and segmentation methods are employed in traditional image processing methods to extract the required features from the images. Following that, these features are compared with another set of features that relate to the intended object to be discovered. The image can be regarded as having the same object if the features retrieved from it resemble or match the features of the necessary object. Machine learning techniques like support vector machines (SVM) classifiers can be used as an additional way of categorizing the retrieved data [9].

4.2 CNN architectures

In Figure 2, the CNN-based image fire detection method flow is shown, following the object detection algorithm's premise. The finding Region suggestions, feature extraction, and classification are features of CNN. In the beginning, CNN uses an image as an input and produces region suggestions through convolution, pooling, etc. The second is region-based object detection. CNN employs fully connected layers, pooling layers, convolutional layers, etc. to determine whether there is a fire in the proposal regions or not [33].

CNNs' fundamental component is the convolutional layer. The convolutional layer creates feature maps from the raw images using image transform filters known as convolution kernels, unlike other neural networks that employ weighted summation and connection weights. The convolutional layer has several convolution kernels. The weighted total of the pixels the convolution kernel floats over is added when computing a new pixel as it moves across the images, creating the feature map. The aspect of the original image's features is reflected in the feature map.

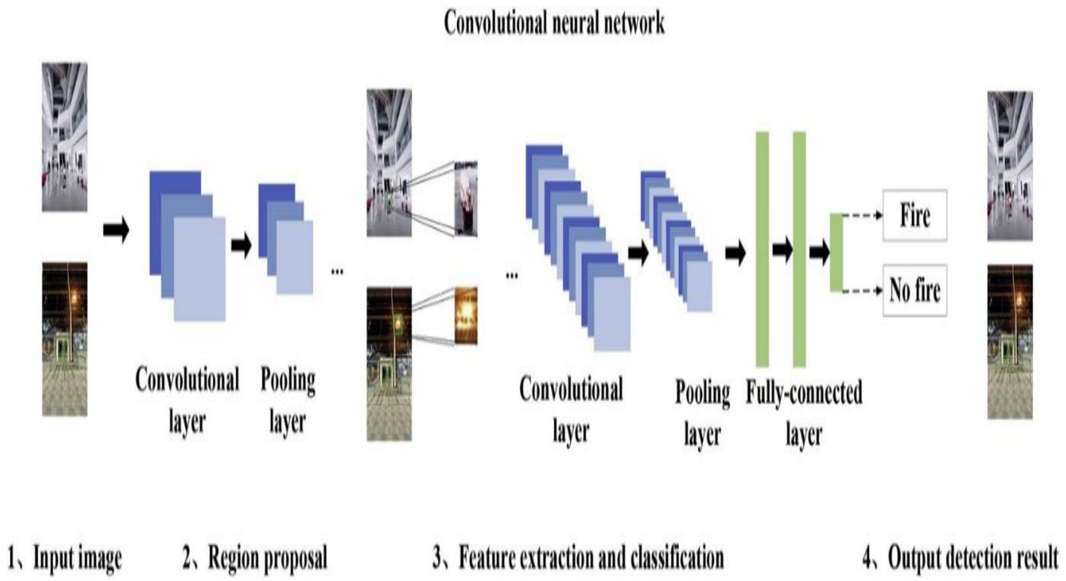

Figure 2: Algorithm flow chart for detecting fire in images using CNNs [33].

However, depending on the method of implementation, each CNN model differs, and as a result, performance varies. Due to their automatic learning of the unique features of smoke and flame, CNNs are the most recommended. A generic smoke and fire flame detection architecture utilizing CNN is shown in Figure 3 [9].

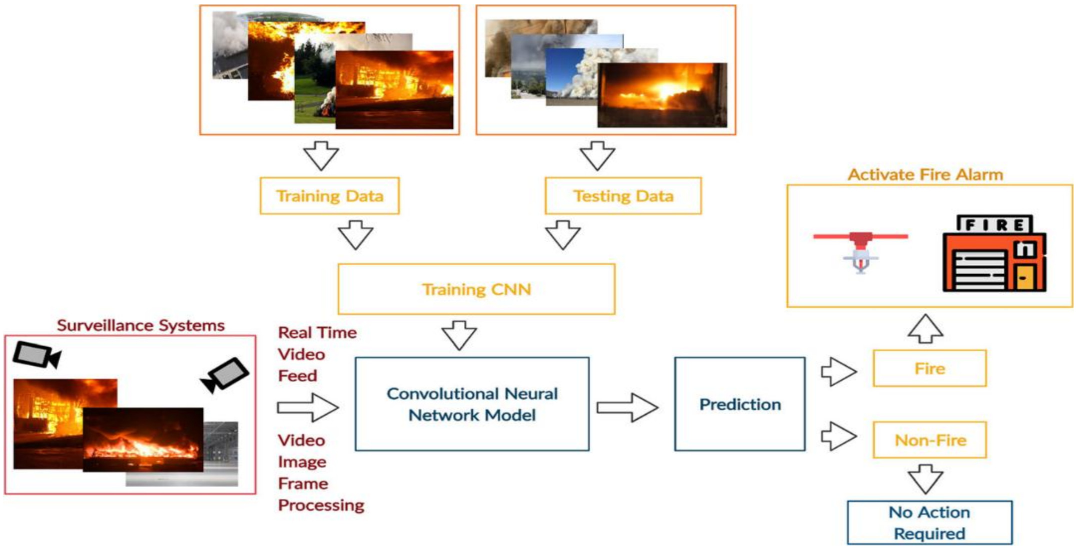

Figure 3: The basic structure of fire and smoke detection and alarm systems based on CNN [9].

5. Brief Comparison for Fire Detection Systems Research

This section gives a description of this survey's work. Table 1 gives a comparison of different fire detection system methods used and displays the selected dataset by various authors to train and test the system, then get results and accuracy, described by years, in ascending order.

Table 1: Comparison of Fire Detection Systems Research

Authors	Technique	Year	Dataset	Accuracy	Limitation
[18]	Fire detection system using VGG16 and Resnet50	2017	They assembled the dataset consisting of 651 images, which are very limited in size, allowing for testing generalization skills and efficacy. The training set consists of 549 images in total, including 59 images of fire and 490 images of non-fire.	A testing accuracy of more than 90% is attained by deep models.	The dataset contains extremely imbalanced and challenging-to-classify images.
[22]	Cost-effective Fire detection CNN architecture for surveillanc e videos	2018	There are 68457 total images utilized in the trials, of which 62690 frames are collected from the Foggia dataset (which has 31 videos covering various contexts, 14 videos of fire, and 17 more videos without fire), and the remaining from other sources, employing 80% of the data for testing and 20% of the entire dataset for training.	By performing the fine-tuning procedure for 10 epochs. They were able to reduce the false negative score to 1.5% and the false alarm rate to 0.054%, respectively, and increase the accuracy of the flame detection by up to 6%, from 88.41% to 94.43%.	The drawbacks of conventiona l hand engineering techniques
[38]	Deep Learning Fire Detection System for Surveillanc e Videos	2019	The combined use of the real data set and the generated dataset, totaling 23,842 images, was utilized as the data set and was separated into two sets: 80% for the training set and 20% for the test set.	Compared to the Single Shot MultiBox Detector (SSD), the true positive rate rose from 82.2% to 94.4%, the false positive rate rose from 17.8% to 5.6%, the true negative rate rose from 80.6% to 98.6%, and the false negative rate rose from 19.4% to 1.4%. True negative rates also increased from 80.6% to 98.6%.	The video surveillance system automaticall y switches to infrared mode at night, producing a black-and-white image that makes detection more challenging.
[39]	Image processing for feature extraction and SqueezeNet	2019	Obtaining 25,000 smoke images and 25,000 non-smoke images generated a dataset of smoke images. According to the 6:2:2 ratio, a training set, a validation set, and a test set were generated from	It achieved a test accuracy of 97.124%, and 89.41% of smoke detectors detected the smoke.	There are restrictions on the typical convolution al layer

	network was only used for smoke detection		the smoke image data set.		performance in SqueezeNet.
[40]	Fire detection in surveillance systems inspired by MobileNet	2019	A total of roughly 340 000 images were used, of which 20% were used for validation and 80% for training, respectively. A total of 36,000 images were used in the testing, with a 50:50 split between images with and without fire.	It achieved 95.44% accuracy.	The high computational cost of creating CNNs
[41]	Resnet50 architecture with ReLu using deep learning	2020	The dataset is split into train and test data with 80% and 20%, respectively, and the images are resized to 224x224 pixels.	The accuracy of the suggested model on the training set was 92.27%, while on the test set, it was 89.57%.	The limitations apply to light-sensitive objects.
[42]	The portable deep learning model for recognizing fires called KutralNet inspired by MobileNet V2	2020	They employed two datasets, the first of which comprises a training subset with 2425 images and a test subset with 871 images using FireNet as the model. The second collection has 6063 images altogether and is called the FiSmo dataset. In addition, 1968 images from a constrained subset of FiSmo were used, evenly split between the fire and no-fire labels. A completely fresh dataset is supplied for testing purposes, with 70% of the training dataset being used for training and 30% being used for validation. regards to the FiSmo dataset. The images are divided into two groups using an arbitrary split value of 80% for training and 20% for validation.	The model maintains great accuracy even as the number of parameters and flops is significantly reduced. In comparison to FireNet, one model offers 71% fewer parameters.	The model's computation complexity and size, the required computational resources, and the quantity of data needed for its training.
[43]	Real-time UAV Learning Strategy Based on YOLOv3	2020	On the desktop, the YOLOv3 model is first trained and put to the test. 64 images are used in each of the 57,000 phases that make up the training process.	The frame rate can increase to 30 FPS, and the testing results are close to 91%.	When network congestion occurs, the cloud computing model is not suitable to handle many video processing tasks.
[44]	A Single Shot MultiBox Detector in Real-Time Fire Detection for UAV	2020	They assembled the training dataset from various sources. Of the 31 fire and non-fire films in the dataset that Foggia provided, there are 1301 non-fire images and 1124 fire images in a portion of Sharma's collection, images from Google and Pixabay of fire accidents, and a portion of an image from four excellent fire videos. The final self-	In numerous real-time tests, the suggested algorithms reliably and automatically detected fire, achieving a mean average precision (mAP) of 92.7%	It is challenging to produce early and precise fire alerts because of the detection systems' limitations,

			labeled train dataset includes The bounding box information for each image's fire is included in the annotations of 1043 fire images. Each image is assigned to the class "fire," and all of the images in the dataset have this label.	with a detection velocity of 26 FPS.	which include missed detection, false alarms, and detection delays.
[45]	Single Stage Headless Context (SSHC) module and Receptive Field Block (RFB) module represented Yolov5's lightweight architecture	2021	They created a new large dataset that has 9462 high-quality images in all. Each image is taken from actual scenes, annotated, and reviewed using a reasonable and transparent standard to minimize annotation errors. The dataset has three classes: "fire," "smoke," and "other." Fire images are divided into three categories based on the magnitude of the flames: large, middle, and small, with 3357, 4722, and 349 images, respectively. 1034 further images contain luminous objects.	The suggested network achieves a smoke detection accuracy of 92.4% and a fire detection accuracy of 97.2%.	The Yolov5's restricted receptive fields and untargeted feature extraction capabilities.
[46]	Forest Fire Detection in Real-Time Framework Using Motion Feature Analysis and Color Probability Model	2022	Two training datasets make up the VisiFire system's dataset for classifying and segmenting fires. 30 100 × 100-pixel images of fire areas in varied situations made up the dataset for segmentation.	The suggested framework generated true positive rates of 89.97% and false negative rates of 10.03%.	If there is a lot of smoke or fog in the forest, it could lead the system to miss an invisible fire.

6. Conclusion

The best way to locate an existing fire and smoke in open areas and put it out before it spreads out of control is through early, precise detection of fire, flames, and smoke. For this specific goal, several CNN-based approaches and systems for identifying fire and/or smoke in images and videos have been developed. A brief examination of CNNs has been provided, which are crucial and significant deep learning frameworks.

This survey presents a thorough review of these CNNs, image processing methods, and intelligent surveillance systems, describing their approaches, datasets, and performances. The techniques and frameworks that have been covered are well-known works released starting in 2012. The fundamental conclusion that can be drawn is that the use of CNNs in smoke or fire detection in photos and videos has produced remarkably substantial high performances. There are issues and difficulties with these current procedures and systems. In light of this, CNNs' intuitive methods hold promise for enhancing early fire detection and control, as well as other detection-based fields of study, including object detection and identification.

7. Future Work

The risk that fires pose to human lives and financial assets can be significantly reduced by researchers creating new techniques for intelligent surveillance systems based on CNNs. Some possible ideas for improving the techniques include:

● Creating CNNs with whole new architectural designs that emphasize smoke and fire detection provides accurate detection results that are better than the current algorithms designed to be used in the smoke and fire detection process for open areas.

● Establishing cutting-edge deep learning and image processing methods in related regions for fire detection and increasing efforts to reduce the number of images in the dataset.

● Creating hybrid CNN focuses on several areas of fire and smoke detection, and it is not just about fires.

● Introducing advanced intelligent surveillance systems that increase the rate of true positives and reduce false alarms, in addition to lessening or limiting the quickly spreading fire damage [47], especially in open areas.

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