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ORIGINAL RESEARCH ARTICLE

TRADITIONAL SENSOR-BASED AND COMPUTER VISION-BASED FIRE DETECTION SYSTEMS: A REVIEW

A. Hassan and A. I. Audu*
Department of Computer Engineering, University of Maiduguri, Maiduguri, Nigeria
**Corresponding author's email address: Im324fairchild@yahoo.com*

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ABSTRACT

Fire emergency is one of the dominant disasters which is threatening human society, infrastructure, and the environment in the world. Fire disaster can lead to a great number of human casualties, loss of vast natural resources and serious infrastructural damage. To minimize these such catastrophic menace, protect and save human lives and infrastructure, substantial research efforts have been devoted to developing fire detection systems using different approaches. This paper discusses fire detection systems and summarizes the state-of–the-art achievements. A total number of 60 publications related to fire detection methods are extracted from IEEE and Google Scholar database and analysed. Different fire detection methods are reviewed, and their merits and shortcomings are highlighted. The literature review presented in this paper illustrates the advantages of computer vision-based fire detection approaches over the traditional sensor-based approaches which are characterised by limited detection range, transport delay, and high false alarm. In addition, it shows that the high hardware requirement and computational complexity remain the key drawbacks of the computer vision-based methods and most of the research works made no attempt to implement such methods on embedded hardware platform such as FPGA. Further research efforts are required to design, develop, and implement computer vision-based systems for fire detection on embedded hardware targets in an efficient and computationally less intensive manner.

1.0 Introduction

Fire outbreak is one of the leading hazards endangering human lives, properties and the environment around the world today. It causes huge number of death, massive economic loss and serious ecological problems (Asih et al., 2018; Huang et al., 2017; Khan et al., 2019; Singh and Sharma, 2017). In recent years, a great number of fire incidents were reported across Nigeria. For instance, in Kano State, Fire Service records shows that 134 human lives and 635-million-naira assets were lost due to fire outbreaks in the state between January 2021 to December 2021(Rabiu, 2022). A typical incidence was that a fire event reported at Sabon-Gari Market in Kano City, Nigeria in which properties and shops worth millions of Naira were lost and took more than 10 hours to be put out completely by the Kano State Fire Service team. Not less than 64 people, including eight fire fighters, were reported to have gotten different degrees of injuries from a petroleum tanker explosion at a filling station in Sharada area of Kano State On 23 May 2021 (Rabiu, 2022). In order to mitigate against such huge losses and save valuable human lives, accurate and timely fire detection systems are inevitable (Islam et al., 2015).

With advances in computing and electronics, many fire detection systems have been proposed in the last decades using different methodologies and approaches. Existing fire detection methods are: smoke detector, flame detector, heat detector, gas sensor (Cheong et al., 2011; Courbat et al., 2011; Fonollosa et al., 2016; Hoefer and Gutmacher, 2012; Krüll et al., 2012; Liu and Kim, 2003; Solórzano et al., 2022; Sowah et al., 2014; Wang et al., 2020) and computer vision (Asih et al., 2018; Chen et al., 2019; Filonenko and Danilo, 2018; Hossain et al., 2019; Huang et al., 2017; Jinlan et al., 2016; Kaabi et al., 2017; Monte et al., 2017; Rabiu, 2022; Russo et al., 2018; Santamaria-guerrero et al., 2018; Yuanbin, 2016). These methods have been classified into traditional sensor based and computer vision based methods (Chen et al., 2019).

This paper aims at reviewing existing methods proposed for fire detection and highlighting future research direction. The remaining part of this paper is organized as follows. Section 2 presents the traditional sensor based methods. Section 3 presents the computer vision based methods. Finally, a summary and future direction is presented in section 4.

2. Traditional Sensor-Based Fire Detection Systems

The conventional sensor based methods for fire detection measure ultraviolet or infrared radiation, heat, gas or particulate emissions generated by combustion (Wang et al., 2020). The operation principle of these methods is based on employing different physical parameters such as: light scattering, flame particles or air density fluctuation, ion capture by flame particles, smoke concentration to detect fire incidents (Chen et al., 2019; Vasiliev et al., 2017). However, the shortcomings of such methods include suffer from transport delay, conduction delay, and limited range detection. Additionally, these devices are not suitable for outdoor applications and can produce high false alarm rate (Khan et al., 2019; Rabiu, 2022). The operation principles, advantages and drawbacks of these methods are discussed in the subsequent section.

2.1 Thermal Detectors

Fire detection systems based on heat sensing are designed to activate when the ambient temperature or rate of rise of temperature exceeds a set point. These sensing devices are not good for early warning due to the fact that they have to be in very close contact with the fire to be activated. However, they are so easy and inexpensive and highly reliable in areas where other sensors such as smoke detectors have a high level of false alarms like kitchens. They are also best suited in areas of home where systems based on smoke sensing cannot perform effectively due to extreme temperatures (Li, 2011; Perilla et al., 2018).

Rate of rise (RoR) thermal sensing detectors, respond to emergency change or rise in ambient temperature from a normal baseline conditions. The set alarm criteria will be activated by any sudden increase in temperature. These kinds of thermal detectors can respond to a lower set conditions than if the set point were fixed (Li, 2011).

One of the innovative thermal detectors for fire detection applications is the distributed fibre-optic temperature sensor. The optical fibre sensor cable has a faster response in detecting fluctuations in temperature compared to traditional thermal detectors due to its low mass. It is also completely immune to all sorts of nuisance emissions. In the late 1980's, the distributed fibre optic temperature sensors using Rayleigh and Raman scattering were introduced. They have been employed in fire detection system for application areas with difficult ambient conditions, which include tunnels, underground railways and stations, conveyor lines, steal works and petroleum and chemical industries (Liu and Kim, 2003).

Distributed optic fibre sensor using Rayleigh scattering measure the temperature by detecting changes in the quantity of reflected light, during the time the fibre is micro-bent because of heating effect. The fibre optic sensors based on Rayleigh scattering are majorly employed in applications, which include road tunnels and underground installations (Liu and Kim,2003).

The distributed fibre optic sensing devices based on Raman scattering detects the change in temperature by measuring the ratio of stokes to anti-stokes back scattered intensity signals as a function of temperature (Liu and Kim, 2003). The Brillouin scattering based fibre optic device is one of the likely successors of both Rayleigh and Raman scattering systems for temperature sensing. The distributed optical fibre sensor using Brillouin scattering also has superior spatial and thermal resolutions in comparison with the Rayleigh and Raman scattering systems (Liu and Kim, 2003).

2.2 Smoke Detectors

Smoke is generated much earlier before other fire signatures during the phases of fire incident growth and development. The chance for successful fire suppression, escape and survivability can be maximized by initial rapid detection of smoke at very low levels by fire detection systems (Liu and Kim, 2003). Fire detection was performed mainly by visual inspection and confirmation by people. In an effort to develop a sensing device for toxic gases, a sensor that could detect smoke was accidently discovered by the Swiss chemist Walter Jaeger during the late 1930's, there by paving way for development of modern smoke sensing devices (Sowah et al., 2014). The first automatic smoke detector developed was based on the sensing of the ionization current using americium-241 as a radioactive source in 1940 (Fonollosa et al., 2016). Fire detection systems based on smoke detection are much new innovation and commonly used in residential and life safety application during the 1970's and 1980's. Fundamentally, there are two sensing approaches for smoke detection that are employed for commercially available fire detection devices. These approaches are photoelectric detectors that use light scattering and ionization detectors. Smoke detectors mimic human sense of smell and are designed to recognize fire incidents while in their smouldering or early flame phase. The great benefit of smoke detectors is their capability to detect fire while it is yet in its incipient level. They are most preferred method for life safety and high content value applications due to the fact that they provide added space for emergency team to respond and control the developing fire incident before dangerous damages to happen. Fire detection systems using smoke sensing elements have greater immunity to inadvertent alarms and they are normally more expensive to get installed but much more reliable with an extremely low chance of false alarm if properly chosen and designed (Fonollosa et al., 2016; Perilla et al., 2018).

Optical smoke sensing devices uses the light scattering nature of smoke particles to detect the presence of smoke during fire event. On the other hand, ionization smoke sensors are designed with an ionization chamber which contains a radioisotope, usually Americium. In the absence of smoke particles, the ionized air molecules within the chamber provide the passage of a small amount of electrical current between the charged electrodes in the chamber. The presence of smoke particles causes a drop in the current between the electrodes. The drop in current between the electrodes results in a fire warning being activated (Sowah et al., 2014). Standard fire detection systems rely on the sensing of backscattered light emitted by a Light Emitting Diode (LED) and reflected on smoke particles. However, such devices suffer from high response time, false alarm and have no capability to detect non-smoking fires (Courbat et al., 2011).

2.3 Flame Detectors

Flame detectors mimic the human sense of sight and represent one of the major kinds of automated fire detection approach. These methods are line of sight systems which operate on either infrared, ultraviolet or combination principle. Radiant energy which is in the 4,000 to 7,700 angstroms range is an indicator of a flaming condition. The fire sensing device based on flame detection identifies the fire signature and transmits a signal to the fire notification module. Not like thermal and smoke based fire detection methods, line of sight must exist between the flame detection device and the fire source to recognize emitted fire signatures. But the application of these methods is severely limited. The benefit of these flame detectors is that they are very reliable in a noisy environment. They mostly deployed in high value energy and transportation applications where other fire detection devices based on traditional sensors would suffer from spurious activities. They are also commonly used in locomotive and aircraft maintenance facilities, refineries and fuel loading stations, and mines (Li, 2011; Perilla et al., 2018).

Infrared detectors recognize fire incidents when a characteristic flame flicker generated by fire is received. The ultraviolet detectors identify fires when a flame emit an ultraviolet radiation and is detected. Fire detection devices based on flame recognition can be to deployed safeguard large areas and they have high response due to the fact they do not have to depend on smoke or heat generated by fire combustion. However, false alarm may be produced by radiation from other hostile sources which include welding, sunlight and tungsten lamps. Research and development effort have been made to mitigate against the nuisance alarms generated by infrared and ultraviolet detectors by introducing multi-wavelength radiation sensing and computational algorithm that determine object temperature, flame temperature, surface area and presence of a flame (Liu and Kim, 2003).

Optical flame detectors provide higher reliability, great long-term stability and rapid response to fire emergency compared to fire detection systems using smoke detectors. Flame detectors based on optical sensing devices operate on specific spectral ranges to record the incoming electromagnetic energy at the specified wavelengths which include infrared, visible and ultraviolet. Ultraviolet-only flame detection devices operate on wavelength shorter than 400nm. They detect flames at a great speed of 3-4ms because of the ultraviolet high energy radiation generated by fires and explosion incidents at the instance of their ignition. Ultraviolet and infrared detection devices compare the threshold signal in two spectral ranges and their ratio to each other to determine the reliability of the fire signal to minimize false alarms. However, commercially available ultraviolet flame detection devices are based on Geiger-Muller counter which is a quartz tube filled with an inert gas which conducts electric current when a photon of wavelength between 185 and 260 nm of a flame makes the gas to conduct temporarily (Cheong et al.,2011). This kind of flame detection system is really huge in size and expensive, operates at high voltage, has short lifetime and electronically interferes with other devices in close range. Hence, the lower voltage and compact semiconductor ultraviolet sensing device is usually the interesting device (Cheong et al., 2011).

Cheong et al. (2011) presented inexpensive and low-power wireless sensor node for ultraviolet detection of flame. The device employs the state-of –the-art nanotechnology based on semiconductor benefiting the advantage of low cost, compact size and light reliability. In addition, there is no external bias needed, minimizing power consumption and extending the device lifetime. There is also no interference with other devices as in ultraviolet flame sensing devices based on the Geiger-Muller counter.

2.4 Gas Sensors

Volatile chemicals are released normally in fire combustions before smoke particles are generated. Therefore, fire detection devices based on chemical gas sensors may have a faster response time compared to the devices based on smoke detectors which now dominate the market. The key hypothesis underpinning the development of fire detection based on gas sensor is the fact that gases and volatile are generated in many fire types before smoke is produced. The early release of gas creates the possibility to develop fire detection systems with shorter response time compared to method based on smoke detection (Fonollosa et al., 2016).

The first step in chemical gas sensor based method for fire detection starts with sensitivity analysis of different sensing technologies to relevant combustion products, usually carbon monoxide and carbon dioxide. However, sensor sensitivity to volatile gases produced in fire incidents determined by the feasibility of chemical sensing for fire identification, gas sensing devices also demonstrate high cross-sensitivity to water vapour and to great range of volatiles which are generated during many common daily activities. As a result, chemical gas-based systems for fire detection are vulnerable to false alarms (Fonollosa, et al., 2016). Therefore, sensor design for robust fire detection devices, have to extend beyond the mere analysis of sensor sensitivity to combustion products, and the examination of cross-sensitivity to interfering scenarios is necessary too (Fonollosa et al., 2016).

In order to address the drawbacks of cross-sensitivity of chemical sensing devices and provide robust fire detection systems, sensor fusion algorithms have been investigated in the literature.

The great concern with these algorithms is the good detection of fire while minimizing nuisance effects. Variety computational algorithms have been examined such as logic rules, neural network, probabilistic neural network, hierarchical linear discriminant analysis or k-nearest neighbours. However, yet further work is required to enhance detection time and nuisance rejection of fire alarms based on chemical sensing method (Fonollosa et al., 2016). Multi-sensor approach is motivated by the need for development of more robust fire detection system devoid of false alarms. This kind of approach uses more than one fire signature to detect fire events. Because of the robustness of multi-sensor based fire detection devices, recent research efforts on fire detection is hugely focused towards developing more robust algorithms and image processing methods based on the data obtained from sensors in order to minimize false alarms. These such kind of detectors which combine different type of sensors are seen as an effective method to minimize the shortcomings of systems employing individual sensors (Sowah et al., 2014; Wang et al., 2020).

Fonollosa et al. (2016) presented a multi-sensor system based on chemical sensing for fire detection. The system was integrated in a sensing chamber in which different fire types and interference were performed. The result obtained showed that the system is able to identify fire from non-fire situations, and activate the alarm faster than conventional fire detection systems based on smoke detection for some fire types. However, there is need to achieve a shorter response time and enhance the robustness of fire detection devices using chemical sensing.

In a development to increase the sensitivity of fire detection systems and reduce nuisance alarms, Sowah et al. (2014) presented the design and development of a multi-sensor fire detection and alarm system based on fuzzy logic. A microcontroller was used to process data obtained from a smoke sensor, temperature sensor and flame sensor using fuzzy logic algorithm to confirm fire status.

Díaz-Ramírez et al. (2012) proposed and evaluated two algorithms for forest fire detection. The algorithms are designed based on information fusion techniques. The first algorithm employs threshold method and nodes attached with temperature, humidity and light sensors. The second algorithm employs the Dempster-Shafer theory that has a basic assumption that the nodes use temperature and humidity sensors. Fire detection systems based on gas sensing are well-suited for fast fire detection since they have high sensitivity to the early release of volatiles. On the other hand, these systems have low specificity because they respond to volatile gases from non-fire sources. The use of pattern recognition algorithms can enhance the effectiveness of such gas sensor-based fire detection methods.

All works reviewed on traditional sensor-based fire detection methods are provided in Table 1.

Table 1: Summary of Traditional Sensor based Fire Detection Methods

Author(s) and Year	Technique Used	Contribution	Research Gap
Li, 2011; Perilla et al., 2018	Thermal sensing	Easy and inexpensive	Slow response, limited detection range
Liu & Kim, 2003	Thermal sensing	Insensitive to noise	Slow response, limited detection range
Fonollosa et al., 2016; Perilla et al., 2018	Smoke sensing	Ability to detect fire in its early stage	Slow response, high false alarm, limited detection range
Courbat et al., 2011	Smoke sensing	Capability to detect fire in its early stage	High response time, high false alarm, expensive, limited detection range
Cheong et al., 2011	Flame sensing	Inexpensive and insensitive to external interference	Limited detection range
Fonollosa et al., 2016	Gas sensing	Faster response compared to smoke detectors	Still the response time and robustness can be enhanced

3. Computer Vision Based Fire Detection Systems

Advances in computing and electronics in recent years have led to the rapid development of fire detection systems based on image processing and computer vision techniques. The computer vision based method employs surveillance camera to capture video image in real time and then input it into computing system to extract the fire image features and then apply a suitable machine learning or deep learning algorithm to detect fire in order to activate the alarm device. These Computer vision based methods for fire detection can address the limitations of the conventional sensor based methods and have the advantages of faster response, accurate detection and rich descriptive information (Chen et al., 2019). These computer vision-based systems for fire detection can be classified into hand-engineered feature-based methods or deep learning based methods (Chen et al., 2019).

3.1 Hand Crafted Features Based Methods

The hand-crafted feature based methods can be mainly distinguished into two classes based on the analysed features: colour based and motion based. The colour feature based methods are designed around the consideration that a fire flame which is assumed to be produced by common combustibles such as wood, plastic, paper, or others, can be uniquely characterized by its distinctive colour feature in such a way that the evaluation of the colour components in RGB (Red, Green, Blue), YUV (Luminance, Chrominance) or any other colour space is strongly robust to recognize the presence of flame. This basic idea motivates a number of recent methods (Foggia et al., 2015).

The introduction of the HSI (Hue, Saturation, and Intensity) colour space in great ways simplifies the definition of the rule for the designer by being better for providing a user focused approach way of describing colour. The major drawback of such colour based methods is that they are in particular sensitive to the fluctuation in scene brightness, hence leading to a greater level of false positive because of the shadows present or different tonalities of red. This limitation can be overcome by switching to a YUV colour space. To sum up, it is evidently clear that the methods based on colour feature information, despite the fact that being naturally simple to design, can be best suited for sterile environment only, where there is no moving object generally inside. The major shortcomings of such methods are about the number of false positives when deployed in usually populated areas. People wearing red clothes or red cars may be wrongly recognized as fire feature due to their dominant colour. Several studies have been proposed in the literature to address this problem (Foggia, et al., 2015).

All these studies begin with the assumption that a fire flame changes its shapes in continuous manner and the unstructured motion of red regions can make it possible to discriminate it from moving rigid object in the scene. For example, the physical features of the fire are employed to design a feature vector based on improved optical flow algorithm, which have capability to analyse in variety of ways both the temporal features of fire and its saturated flame. Dynamic features have been employed in a study, where a two-phase texture detection process have been proposed in the literature to enhance the speed of the segmentation phase, extremely useful to extract a broad class of shape-based features, making the detection of the fire in a good time possible. The wavelet transform has also been employed in some studies to segment accurately the dynamic behaviour of flame regions. It is observed that the methods using wavelet transform, compared to colour based methods, cannot be used on still images and generally require extremely high frame per second to ensure reasonable results, hence limiting their applicability. However, the major limitation of methods based on motion is that the performance enhancement is most of the times paid from different perspective. Several sensitive parameters need to be rightly configured for the application at hand in most cases. Secondly, the flame motion and shape depend to some extent on the burning material as well as on the geographic conditions (Foggia et al., 2015).

In recent years, several methods have been proposed based on computer vision algorithms employing hand engineered features to achieving robust fire detection using video images captured by surveillance cameras by combining the static and dynamic features of fire. For instance, (Foggia et al., 2015) proposed a fire detection using employing a combination of expert based on colour, shape and flame motion information. The method has been tested on a broad database to evaluate its performance in terms of sensitivity and specificity. Experiment results obtained show that the effectiveness of the approach.

An algorithm for forest fire smoke detection is proposed by Cai et al. (2016). The algorithm consists of three aspects: moving target segmentation, feature extraction and classification. Firstly, Visual Background Extractor (ViBE) is used for motion segmentation. Morphological operation is performed to connect concentrated but not linked regions. Then, the static and dynamic features of smoke are obtained based on colour histogram, energies of wavelet sub images, compactness and direction of moving target. Finally, the feature vector is classified using support vector machine. The algorithm has an accuracy rate of 92.7% but still the accuracy needs to be improved and tested on sufficient number of smoke video dataset to enhance its performance.

Shuai et al. (2016) proposed an algorithm for smoke detection in remote surveillance video based on fast self-tuning background subtraction method and judgement of smoke static and dynamic features. The proposed algorithm has two steps. First, extracting the moving smoke area using the fast self-tuning background subtraction algorithm proposed, which achieves better results compared to colour based and motion based segmentation approaches. Then, colour, shape and variance feature of smoke are employed to eliminate smoke-like features to guarantee the accuracy of the detection. The results obtained show that the algorithm could detect smoke regions in remote video surveillance in real-time, precise and reliable manner and it is robust to environmental change. However, the algorithm is not tested on large video dataset.

Shrivastava and Matlani (2016) proposed an efficient computer vision based algorithm for smoke detection using background subtraction and K-means segmentation. The algorithm is comprised of five steps: (i) Smoke video image is read (ii) The RGB colour space is transformed to L*a*b colour space to classify pixels as smoke or not. Spatial clustering and analysis is carried out on smoke colour pixels. (iii) Frame differencing method is employed to extract background from current frame to detect moving pixels. (iv). K-means method is used to segment colour features into three clusters based on Euclidean distance metric. (v) The results obtained from background subtraction and K-means segmentation are combined for final judgement. The result obtained demonstrates that the algorithm has a better performance compared to fuzzy c-means method. Nevertheless, the performance of the algorithm can be improved.

Wang et al. (2016) proposed an algorithm for fire smoke detection using optical flow approach and texture feature. The proposed algorithm consists of the following steps. (i) Firstly, bilateral filtering is employed to extract noises from poor video quality in image frames. Then, foreground regions are segmented by using Gauss mixture model and background subtraction method to remove static interference. (ii) Colour model used to segment region of interest. Median filter employed to remove isolated points and morphological processing to remove small isolated region to obtain a continuous target smoke area. (iii) Smoke texture features segmented using local binary pattern (LBP) and local binary pattern variance (LBPV) in region of interest. (iv) Motion feature in region of interest contour is extracted using optical flow approach based on image pyramid. (v) Finally, support vector machine is used to identify smoke based on the optical flow motion feature and LBP and LBPV texture feature. Simulation results reported illustrate that the algorithm is timely and accurate in fire smoke detection and robust to external environmental changes. The algorithm has also less computational complexity, fast computational speed but it is tested only five videos which are not sufficient enough.

A computer vision based smoke detection approach for intelligent surveillance system is proposed by Yuanbin (2016). The algorithm consists of the following steps. (i) Fuzzy logic is used to enhance image. (ii)Target smoke area is segmented using Gaussian Mixture Model (GMM). (iii) Static and dynamic features of smoke are extracted and fused. (vi) The segmented features are normalized and input into support vector machine algorithm for smoke classification. The algorithm is simple and achieves high detection rate and real-time performance. However, the algorithm could generate false alarm in a complex video environment and the processing speed need to be improved for deployment on embedded systems.

Gunawaardena et al. (2016) proposed a computer vision based algorithm for fire detection that can be compatible with the existing traditional sensor based devices is proposed to enhance the performance and robustness of the conventional system. The proposed video based fire alarming system consists of five steps. The system employs adaptive background subtraction to segment foreground moving region. The rule-based fire colour model is utilized to confirm whether the extracted foreground object is a fire colour feature. The fire pixel recognition is modelled using YCbCr colour space. Morphological operation is performed to remove isolated blocks from the segmented fire target regions and enhance the features by growing the missing pixels. The dynamic feature of the extracted target fire region is analysed in the temporal domain to extract the flame flicker to remove spurious fire-like colour feature or non-fire like objects. All these features are fused to form the fire detection system. An algorithm is developed to segment flame from fire video images. The proposed algorithm is computationally inexpensive, simple and can be integrated into existing security monitoring systems. It detects fire and flame successfully; however, it is affected by the scene illumination and tested on small dataset.

Jinlan et al. (2016) presented a method of fire and smoke detection using Surendra background and grey bitmap plane algorithm. Firstly, the dynamic background is modelled using Otsu adaptive threshold and Surendra background. Then, the moving target region is extracted by the continuous cumulative moving average of moving target region and the morphological processing algorithm. The smoke region is extracted using colour feature. Finally, the fire region is segmented using OHTA colour space and grey bitmap plane algorithm. The results obtained show that the proposed method can successfully recognize fire in moving vehicle scene, red plastic bag waving scene, red balloon fluttering scene, moving vehicle similar to fire colour. However, the algorithm is not compared with other recent methods and also not tested on sufficient dataset.

An algorithm for real-time fire detection based on AdaBoost, local binary pattern(LBP) and convolutional neural network in video sequence is proposed by Maksymiv et al. (2017). The proposed method has two main parts. First, region of interest (ROI) is extracted using AdaBoost and LBP algorithms. Combination of AdaBoost and LBP is fast but generates high false positive number. Convolutional neural network (CNN) architecture is employed to address this problem so as to make the algorithm better and reliable. Lastly, two support vector machines (SVM) classifiers provide a judgment on presence of fire or smoke in video sequences. The method has a reasonable execution time which means that it can perform in real-time at video rate. The experimental results obtained demonstrate that the method can achieve more than 95% detection rate. Nevertheless, this method has high false positive number in smoke and fog detection.

Wu et al. (2017) proposed a fire and smoke detection method based on adaptive threshold of feature and deep convolutional neural network in video images. The ViBE approach is employed to segment the background from the video image sequence and update the exact moving regions using frame-by-frame differences method. Dynamic and static features extracted are fused to detect fire and smoke region of interest. Deep learning is employed to detect static fire and smoke features based on Caffe model. Experiments illustrate that the proposed method achieves efficient fire and smoke detection. But the method is not tested on large dataset and deep learning models are generally computationally expensive.

An algorithm for smoke detection based on simplified descriptors of video information is proposed by Monte et al. (2017). Firstly, the descriptors of the scene on every frame are obtained. The inference processes of smoke presence are input by the descriptors and background estimation, which is updated with every frame. A group of classifiers perform the smoke inference process. The fusion outcomes of these classifiers provide a reliable detection. Simple Boolean logic combines the process outcomes, with minimum and maximum threshold values. The proposed approach is simple and efficient for deployment on computationally low embedded applications for real-time surveillance. Nevertheless, the algorithm does not take into consideration the variability of illumination and uncertainty of the environment.

Pritam and Dewan (2017) proposed fire detection system based on LUV colour space and hybrid transforms. Video captured are read and frame are segmented. All frames are analysed to confirm the presence of fire. Fire is detected by the presence of fire pixels in the image. Fire pixels are recognized using the features of LUV colour space and hybrid transforms. Edge detection algorithm is employed to extract the edges of the image when flame colour detects existence of fire. Image segmentation methods are employed to extract the fire region of interest from the background. The results reported show that the proposed system can achieve better performance. However, the system is not tested and compared with other approaches.

Vijayalakshmi and Muruganand (2017) proposed an effective smoke detection approach in video images for early fire emergency systems. The proposed algorithm uses fuzzy c-means clustering and background subtraction to segment smoke region of interest from moving regions. Result obtained show that the algorithm outperforms other algorithms and increase the accuracy smoke detection. However, the algorithm is not tested on large variety of dataset and the performance still can be improved because it is only based on motion segmentation.

Zhang et al. (2017) developed a method for smoke detection in video based dissipation function and ViBE. The proposed algorithm employs two key features of smoke to detect it. Visual background extractor (ViBE) is employed to segment moving objects in static scene. The atmospheric model is used to detect semi-transparent feature of smoke. The similarity between extracted regions and original background regions in the same position is computed using normalized cross correlation and the value of the original background is chosen from the frame that is nearest to the current frame. The blocks with high similarity are identified as smoke parts. Experiment results demonstrate that the algorithm can recognize fire and integrated into surveillance system. But the algorithm is not tested on sufficient dataset.

Huang et al. (2017) proposed an algorithm for video based smoke detection in low illumination indoor environment using support vector machine. The smoke region is extracted and then the area diffusion and main direction of movement of smoke region are selected as the dynamic features and texture is extracted as the static feature to recognize fire smoke in low-light indoor scene. Support vector machine is employed to design the classifier to realize smoke detection. Finally, the algorithm is tested under variety of conditions. The results obtained show the algorithm achieves high adaptability, high detection rate and good noise immunity. But the algorithm performs in only indoor environment and it is not tested on sufficient dataset.

An effective method for real-time fire detection based on video processing is proposed by Khan et al. (2018). The proposed method employs flame colour and spatial-temporal features to detect fire regions. Firstly, fire colour pixels are segmented using a set of improved rules based on RGB colour space. The foreground is segmented based on change in blue component trained using neural network. Lastly, the region of interest is extracted using growing area analysis. Experimental results illustrate that the proposed method outperforms other state of the art approaches and yields 97.7% detection accuracy. Nevertheless, the method is sensitive to variation in illumination and based on shallow features.

Yang et al. (2018) proposed a technique for video based smoke detection by combining Gaussian Mixture Model (GMM) and HSV colour model with the deep convolutional neural network. First, each frame is divided into 10-by-10 sub-images by the method. Secondly, Gaussian Mixture Model is employed to extract the motion region and later the sub-images block which contains the moving region is segmented. Then, the motion blocks segmented by the GMM is used to extract target smoke blocks successively using HSV colour feature analysis. Finally, the method confirms whether the bounding box detected by trained model is combined with target smoke block, or the bounding box does not intersect with one of the target smoke blocks, the bounding box will be segmented. The method has improved the detection accuracy and significantly reduced the false detection rate. However, the method is not tested on large dataset, and still the detection accuracy can be enhanced.

Zhao et al. (2018) proposed an effective method for smoke detection based on automatic vision system. The method employs an adaptive background subtraction technique to segment moving regions. Non-smoke regions are extracted out by employing colour feature and fuzzification. Regions that satisfy both the colour analysis and fuzzification criteria are classified as candidate smoke regions. The detected smoke regions are combined with symbolic objects around to confirm the nature of the smoke source using contextual object detection. The method precisely connects specific scenes with spatial and temporal domain statistical approaches to identify target objects. However, the method cannot perform well in complex video scenes.

Kaabi et al. (2018) proposed a novel approach for video based smoke detection based on machine learning approach to overcome forest wildfires. Firstly, the video is divided into frames for training with deep belief network. In addition, Gaussian Mixture Model is employed to segment candidate regions from the target smoke video to be trained by using Deep Belief Network. Logistic regression is used to classify on the output data. The approach is reported to achieve 95% detection rate. However, larger frame size can make the method to diverge and it is computationally expensive which makes it not feasible to be deployed on embedded systems.

A robust algorithm based on information on colour and shape was proposed by Rabiu (2022). The algorithm starts with loading video image database developed to detect presence or absence of fire in video frames. Background subtraction is used by this method to compare the current frame with the reference frame. When the outcome of the background subtraction is less than the set point, the frame is discarded and the next frame is checked. But if the difference is equal or greater than the set point, the frame is then subjected to colour and shape test. This is achieved by employing combined RGB colour space model and shape feature. The proposed algorithm was extremely robust in detecting fire compared to those algorithms based on colour or motion features.

3.2 Deep Learning Based Methods

The traditional hand engineered feature based methods do look to be great but do not seem to be the ideal choice to employ on image based tasks. Hence, these days deep learning based methods have achieved superior performance on computer vision tasks. In addition, deep learning based methods have a variety of applications such as object recognition and classification in videos, images and these days is also employed for real-time detection of activities, speech recognition and natural language processing. Current research on fire detection based on computer vision have proposed many approaches using deep neural networks such as CNN have achieved great results. Therefore, studies on fire detection using CNNs have been proposed by some researchers in order to improve the performance of the existing fire detection systems (Majid et al., 2022). For example, in Vinicius et al. (2021) a robust fire detection system based on two-dimensional convolutional neural network where an object tracker is integrated into an object detector with the aim of confirming if detected events show fire or smoke behaviour over time.

In the work of Saeed et al. (2020), a hybrid approach was presented that consists of an Adaboost MLP neural network model to forecast fire events. Subsequently, an Adaboost LBP model was developed to extract the region of interest (ROIs) and finally a convolutional neural network for fire detection with videos and images captured from installed surveillance camera.

Majid et al. (2022) presented an attention based convolutional neural network model for fire detection using real life images. An attention mechanism was also added to the model which achieved great improvement in the performance of data. The introduced neural network has demonstrated significantly great performance on the testing dataset having minimal false positive level.

In Aktas et al.(2019), the existing CNN based methods for fire detection in video sequences was extended by integrating Multiple Instance Learning (MIL). MIL ease the need for having accurate locations of fire patches in video frames, which are needed for patch level CNN training. Only frame level labels showing the presence of fire somewhere in a video frame are required instead. Thus, reducing substantially the annotation and training efforts. The proposed approach was tested on a new fire datasets developed by extending some of the recently used fire datasets with video sequences obtained from the web. Result obtained illustrated that the presented method enhances fire detection performance.

Muhammad et al. (2018) proposed a cost-effective CNN architecture for fire detection in surveillance videos. The model is inspired from Google Net architecture which is reasonably less computationally complex and suited for the intended task compared to other networks that have high computational cost such as Alex Net. Taking into consideration the nature of the target task and fire data, the model is fine tuned to achieve balance between efficiency and accuracy. Results obtained using benchmark fire datasets showed that the proposed model was effective and suited for fire detection based video images captured by cameras from surveillance systems in comparison to the state-of–the art methods.

In Xie et al. (2020), a method was proposed that employs the motion-flicker based dynamic features and deep static features for video based fire detection. First, the dynamic features are segmented by, analysing the differences in motion and flicker features between fire and non-fire objects in video scenes. Second, an adaptive lightweight convolutional neural network is proposed to segment the deep static features of fire. Finally, the dynamic and static features of fire are cascaded to develop a video based fire detection system with enhanced efficiency in terms of accuracy and run time.

Zhang et al. (2021) developed an effective asymmetric encoder-decoder U-shape architecture based on Squeeze Net, Attention U-Net and Squeeze Net performs most of the time as an extractor and a discriminator of forest fire. The model uses attention mechanism to extract useful features and suppress non-related features by embedding Attention Gate (AG) units in the skip connection of U-shape structure. Key features are highlighted through this way so that the proposed method may be great at forest fire extraction problems with a minimum set of parameters.

In the work of Mukhopadhyay et al. (2019), a model was developed that has the capability of forecasting fire event with a reasonably great accuracy. The model is based on the convolutional neural network architecture, Mobile Net. The developed model can be deployed on embedded computing devices in an easy manner due to the fact that it has small size and hence can also be employed as a robust stand-alone fire detection system.

Hao et al. (2019) proposed an algorithm based on convolutional neural network for video based flame detection. First, the video image is extracted RGB-HIS colour synthesis model and enhanced adaptive mixture Gaussian model. Then, the classifier is designed by learning a great number of fire dataset using the CNN designed. Then, the flame region of interest is extracted by the classifier criteria. The result obtained revealed that the proposed algorithm has high detection accuracy.

Tao et al. (2016) proposed an innovative method based convolutional neural network that can be trained end to end from raw image pixel values to classifier outputs and segment automatically features in a way to avoid the tedious image pre-processing stage of the hand-engineered feature based methods. Experiment results obtained showed the proposed method has high detection accuracy rates with low false alarm rates on the small dataset that clearly achieves greater performance compared to the existing methods.

In Yang Wang et al. (2019), presented a method for video based smoke detection that combines conventional smoke detection and a lightweight convolutional neural network. First, the smoke YUV colour space information is fused to minimize the smoke region of interest based on the VIBE algorithm. Secondly, the lightweight convolutional neural network is designed to segment the information on smoke image in an automatic manner. The training speed of the model is enhanced by using the transfer learning approach for deep learning. The proposed method achieves the real-time performance of smoke detection, guarantees the accuracy of smoke detection and minimizes the false positive level.

Son et al. (2018) proposed a method for fire detection based on deep learning. The deep learning networks employed are Alex Net, Google Net and VGG-16 in three manners. Image input that were captured by surveillance camera is classified into three different categories: normal, smoke and flame. Then, the network is trained to detect each corresponding category. The results obtained illustrate that all the three network models were able to recognize fire at over ninety percent detection accuracy.

In the work of Zeng et al. (2018), an enhanced object detection method based on deep convolutional neural network for fire detection was proposed. Firstly, the feature extractor is substituted in various neural network object detectors for faster R-CNN, Single Shot MultiBox Detector (SSD), Region based fully Convolutional Networks (R-FCN). Secondly, the MSCOCO dataset was used to optimize the parameters of the object algorithm. Lastly, the smoke detection dataset was used to perform the experiments. The proposed algorithm has achieved great results in terms of accuracy and computational speed compared with the existing smoke detection methods.

Shi et al. (2019) developed a method that combines dark channel image input and a relative precise CNN. The difference between the smoke and background could be greatly enhanced by the dark channel of an image. The comparatively concise CNN could be efficiently trained on an insufficient dataset. Results from the experiments performed show extensively that the proposed method achieved great performance when compared to other smoke detection methods.

In the work of Sadewa et al. (2019), an image base fire detection system was developed using CNN. The proposed system achieved an accuracy level of over ninety percent.

Table 2 provides a summary of works reviewed on computer vision based fire detection.

Table 2. Summary of Works reviewed on computer vision based fire detections.

Author(s) and Year	Algorithm	Dataset	Contribution	Research gap
Foggia et al. (2015).	Hand crafted features based on motion, colour and shape	fire video	Robust detection	High false alarm
Cai et al. (2016)	Static and dynamic features based on colour histogram, energies of wavelet sub images, compactness and direction of moving target	Smoke images	92.7% detection rate	High false alarm
Shuai et al. (2016)	Static and dynamic features based on motion, colour and shape	Smoke video	Real-time and reliable detection	Not tested on sufficient dataset
Shrivastava and Matlani (2016)	Background subtraction and K-means clustering	Smoke video	Good detection rate	High false alarm

Wang et al. (2016)	Optical flow motion and texture feature	Smoke video	Timely and accurate detection	Tested on small dataset
Yuanbin, (2016)	Static and dynamic features	Smoke video	Simple and real-time detection approach	High false alarm
Gunawaardena et al. (2016)	Motion and colour features, adaptive thresholding	Fire video	Simple and computationally inexpensive	Not robust to environmental changes
Jinlan et al. (2016)	Colour and motion features	Smoke video	Successful detection	Not tested on large dataset
Maksymiv et al. (2017)	Local binary pattern and convolutional neural network	Fire video	Real time fire detection	High false alarm
Wu et al. (2017)	Adaptive thresholding and deep CNN	Smoke and fire video	Effective detection	Computationally expensive
Monte et al. (2017)	Background estimation	Smoke video	Simple and efficient	Not robust enough
Pritam and Dewan (2017)	LUV colour space and hybrid transform	Fire video	Good detection rate	High false alarm
Vijayalakshmi and Muruganand (2017)	Fuzzy c-means clustering and background subtraction	Smoke video	Accurate detection	High false alarm
Zhang et al. (2017)	Visual background extractor and dissipation function	Smoke video	Good detection	Not tested on large dataset
Huang et al. (2017)	Support vector machine	Smoke video	High detection rate	Performs only in door environment

Khan et al. (2018)	Colour and spatial temporal features	Fire video	Good detection rate	Sensitive to illumination variation
Yang et al. (2018)	Gaussian mixture model, HSV colour model and deep CNN	Smoke video	Reasonable detection rate	Not tested on large dataset
Zhao et al. (2018)	Adaptive background subtraction	smoke	Good detection rate	Not robust to environmental changes
Kaabi et al. (2018)	Machine learning	Smoke video	good detection rate	Computationally expensive
Rabiu (2022)	Colour and shape information	Fire video	Robust and reliable	High false alarm
Saeed et al. (2020)	Adaboost MLP neural network model	Forest fire	Good detection	Computationally expensive
Majid et al. (2022)	Convolutional neural network	Fire video	Good detection	Computationally expensive
Aktas et al. (2019)	Convolutional neural network	Fire video	Good detection	Computationally expensive
Muhammad et al. (2018)	Convolutional neural network	Fire video	Effective detection	Computationally expensive
Xie et al. (2020)	Convolutional neural network	Fire video	Effective detection	High computational cost
Zhang et al. (2021)	Convolutional neural network	Forest fire	Effective detection	Not tested on large dataset
Mukhopadhyay et al. (2019)	Convolutional neural network	Fire video	Good detection	Not tested on large dataset
Hao et al. (2019)	Convolutional neural network	Fire video	High detection rate	High computational cost

Tao et al. (2016)	Convolutional neural network	Smoke video	High detection rate	High computational cost
Yang Wang et al.(2019)	Convolutional neural network	Smoke video	Good detection	Not tested on large dataset
Son et al. (2018)	Convolutional neural network	Fire video	High detection rate	Computationally expensive
Zeng et al. (2018),	Convolutional neural network	Fire video	High detection rate	High computational cost
Shi et al. (2019)	Convolutional neural network	Smoke image	High detection rate	Computationally inexpensive
Sadewa et al. (2019)	Convolutional neural network	Fire image	High detection rate	Computationally inexpensive

4. Conclusion

In this review paper, a survey of various available and proposed fire detection systems was performed. The two categories of fire detection systems were reviewed. The first category is the traditional sensor based methods which involve measuring the ultraviolet or infrared radiation, heat, gas or particulate emissions produced by fire combustion. The methods that belong to this category include thermal detectors, smoke detectors, flame detectors and gas sensors. These methods have a number of shortcomings which include transport delay, conduction delay, limited detection range, high false positive and do not provide rich information. In the second category, the computer vision based methods employ image processing and artificial intelligence techniques to detect fire in video images captured by surveillance systems. These systems can be broadly classified into handcrafted feature based and deep learning based methods. The hand crafted feature based methods tend to be time consuming and affected by environmental conditions while the deep learning based methods learn and extract dep features automatically which eliminate the need for hand feature engineering but they are limited by their high computational cost.

Based on this analysis, it can be concluded that each method has some merits and shortcomings. For example, the sensor based methods are suitable for indoor application but not appropriate for outdoor environment. It also suffer from transport delay and high false alarm. The computer vision based methods using hand crafted features are affected by the complexity of scene and environmental factors. This problem is addressed by the deep learning based methods but such methods are, however, computationally expensive which restricts their applicability for deployment on real-time embedded computing systems. We observe that the recent advances in vision-based fire detection are driven by CNN. This development can be due to the fact CNN achieves superior performance in various computer vision tasks. But the trade-off is between accuracy, model size and computational speed.

Finally, it is evidently clear that great amount of academic research efforts has been invested in computer vision-based approaches for fire detection to address the limitations of the sensor-based systems. But many of these methods have not been implemented on hardware platforms such as FPGA. Computational complexity and high hardware requirement are the major shortcomings of the computer-based approaches. Therefore, more research work is required to design, develop, and implement such systems on hardware targets in a computationally efficient manner.

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