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Video Flame and Smoke Based Fire Detection Algorithms: A Literature Review

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Abstract. This review is focused on video flame and smoke based fire detection algorithms for both indoor and outdoor environments. It analyzes and discusses them in a taxonomical manner for the last two decades. These are mainly based on handcraft features with or without classifiers and deep learning approaches. The separate treatment is provided for detecting flames and smoke. Their static and dynamic characteristics are elaborated for the handcraft feature approach. The blending of the obtained features from these characteristics is the focus of most of the research and these concepts are analyzed critically. A fusion of both visible and thermal images leading to multi-fusion and multimodal approaches have conversed. It is a step towards obtaining accurate detection results and how the handcraft feature approach tackles the problems of flame and smoke detection, as well as their weaknesses are discussed which are still not solved. Some of these weaknesses can be tackled by developing a technology based on artificial intelligence named deep-learning. Its taxonomical literature study with a focus on the flame and smoke detection is presented. The strengths and weaknesses of this approach are discussed with possible solutions. The latest trend in literature which focuses on the hybrid approach utilizing both handcraft feature, and deep learning approaches is discussed. This approach aims to minimize the weaknesses still present in the current systems.

Keywords: Fire detection, Video flame and smoke detection, Sensor

1. Introduction

Fire is one of the key factors that is accountable for life, property and economic losses. The International Association of Fire and Rescue Services (CTIF) reported 23,535 structure fire incidents in eighteen selected cities of the world in the year 2017 and 6581 fire casualties in selected forty-four cities of the world during 4 years (2013–2017) [1]. Electrical fire is the major reason for the fire throughout the world. The National Fire Protection Association (NFPA) reported the short

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circuit as an important cause of the electrical fire and it is responsible for 14% of the total fire casualties during 4 years (2012–2016) in the USA [2].

Another major fire losses are due to forest fires, tunnel fires, etc. Forest fires lead to major environmental losses that take several decades to repair. The advancement in sensor-based technologies is playing an important role in early detection of the fire to minimize the losses. The earlier sensing technologies were primarily based on particle activated 'point sensors'. These were based on heat, gas, flame, smoke and some other important fire characteristics [3]. They activate when particles reach the sensor body from the fire source, which causes a certain delay in their responses. They work very well for flame and smoke detection in small rooms in a building, but these are not suitable for large and open spaces. Because particles have to traverse a more path to reach the sensor. The fire flames and smoke has certain static and dynamic features such as color and motion respectively. The point sensors do not utilize these important features to detect fire [4]. The task of firefighting becomes easier if the information of flame and smoke location, their severity, height, growth, direction, etc. are known. Such multidimensional information is not possible with point sensors [5]. But for smaller space locations, these are the low-cost options for detecting smoke and flames and these can be used for multisensor systems in a complementing mode.

Vision-based fire flame and smoke detection systems (VFSDS) overcome most of the problems of point sensor-based smoke and flame detection systems. There are mainly three categories of vision-based smoke and flame detection systems and these are centered on patch, blob and pixel-level methods. The pixel-level methods utilize color, flicker, etc. as pixel features and make them faster but easily biased. Blob level methods show better performances as compared to pixel level methods but their classifiers are difficult to train and the reason is the different fire blob shapes. The patch level algorithms show better performance as compared to the above two, but the problem is many outliers results and it affects their accuracy [6].

The VFSDS utilizes the detection of reflected and emitted light by an object to find its details. Here the objects of focus are fire flames and smoke. The fire flames and smoke have entirely different behavior, and algorithms have to be designed keeping this into consideration. Some of the algorithms work in parallel for their simultaneous detection. The camera acts as a volume sensor for detecting fire flames and smoke as an image. Since the speed of light is very high, the camera captures the fire flame and smoke information through image frames in a negligible amount of time and that is the potential advantage of the visual-based technique. The visual-based fire detection techniques can be categorized according to: (i) the flame and/or smoke, (ii) visible range, infrared range or multimodal (i.e. using both visible and infrared) [7], or according to (iii) fire location, (iv) rule (with or without classifier) or deep learning-based flame or smoke detection. No single technique is suitable for all different fire locations and situations.

The present article review the ongoing research work and future directions in fire flame and smoke detection algorithms of all the categories mentioned above with their strengths and weaknesses.

The remainder paper organization is in the following manner. Section 2 shows an elaboration of handcraft rules and classifiers based fire flame and smoke detection and multisensor and multifusion approach for flame and smoke detection. Section 3 explains deep learning-centered fire smoke and flame detection. In Sect. 4, the conclusions are discussed with the strengths, limitations and future directions in video-based fire smoke and flame detection algorithms.

2. Handcraft Rules and Classifiers Based Fire Flame and Smoke Detection

Fire is characterized by its flames and smoke, and these are the important candidates to check its presence. But due to the different appearance and behavior, these are treated as separate problems. Smoke appears before flames, so it is a better characteristic for early detection of fire, but it is difficult to detect as compared to flames [8–10].

2.1. Smoke Detection

Smoke is a combination of gases, airborne solid, and liquid particulates produced during the burning phase of fire [11]. The smoke's color, location, height, optical density are used to get a clue about the fire. The color of smoke is blackish near the fire and its speed is high. For regions farther away, it is slow in speed and lighter in color. The distant smoke, as in the case of a forest fire, moves very slowly and it is a challenge to detect it. The color of smoke is also related to the fire's stage, but color based smoke detection is not fully reliable because gray or black color of smoke is common for non-smoke pixels of other objects [12, 13]. Apart from color, its shape [14], shade, motion, and density are also unpredictable due to its fluid characteristics [15] and it is difficult to detect. Dynamic textures also play an important role in smoke detection [8], [12]. Most of the time, smoke blurs images and the features extracted from it become unreliable. An important feature of smoke is its low saturation of color [15]. Some significant exceptions of smoke detection are swinging bags, fog, moving persons, driving cars at night and some important characteristics are smooth streamline, fixed source, low frequency, right-leaning, and vertical horizontal ratio [16]. The smoke tends to progress rather backtrack and it develops in different ways [17]. In its starting phase, the smoke slowly smooth image edges [18]. These are the few problems related to smoke detection and researchers are working in these areas to overcome them.

The important static features related to smoke are color, wavelet, texture, hog, and irregularity. The dynamic features are motion direction, change in direction, and speed [19]. Researchers used these features to detect smoke. Earlier research was focused on very few of these, but false alarms rates were higher. So more and more features get extracted from the images, but combining all of the extracted features was a problem and it leads to a solution that was based on machine learning.

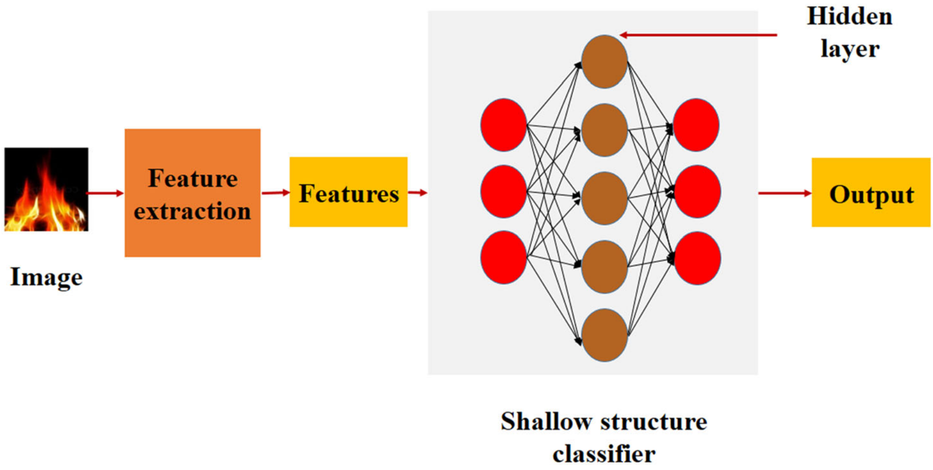

Figure 1. A generalized shallow structure classifier based model for fire detection.

Figure 1 shows a generalized shallow structure classifier based model to detect fire by extracting features from an image. Here, the layers are shallower i.e. not deeper. Gomez-Rodriguez et al. [20] used wavelet decomposition and optical flow method for smoke detection of wildfires. The algorithm is useful for extracting many smoke features but the drawback is the high computational cost of this approach.

Fujiwara and Terada [21] proposed fractal encoding ideas to extract smoke regions from the image. It is based on the self-similarity property of smoke. Self-similarity is the parts repetition of a pattern within itself. They used K-means methods in their algorithm. This algorithm alone cannot be used to detect smoke and it is costly in terms of computation. Toreyin et al. [18] presented a five-step algorithm for detecting smoke. These are moving pixels detection, the spatial wavelet transform to detect a decrease in high-frequency content at the edges, a decrease in U and V chrominance channels, temporal wavelet transform based flicker analysis, convexity check by shape analysis of moving region. Chen et al. [22] utilized motion and color rules for smoke detection. They assumed that smoke has nearly the same R, G, B values. So light and dark gray colors of smoke can better be represented with intensity components of HIS color space. For smoke dynamics, they focused on disorder and growth property of the fire. The clouds or shadows create false alarms, particularly for smoke detection in open space. It is because the static characteristics like gray color and dynamic characteristics like their movement resembles smoke. So a color based smoke detection alone is not a robust technique.

Celik et al. [23] utilized motion and color approaches for both smoke and flame detection. They used statistical analysis and assumed that smoke is gray with different illumination levels. Xu and Xu [24] used both static and dynamic features of smoke for its detection. The extracted features like disorder, growth, self-similarity, flicker, and wavelet energy are utilized in the form of joint feature vector. After the normalization, they train the BP (Back Propagation) neural network to classify smoke and non-smoke pixels. It was one of the earlier works that open a path for artificial intelligence-based smoke detection. It is a promising approach, but the results are not shown quantitatively.

Yang et al. [25] suggested the importance of smoke features like the variation in unevenness in density distribution and smoke contour irregularity. For the integration of features, they used a SVM (support vector machine), which classifies smoke and non-smoke pixels. Piccinini et al. [26] proposed background suppression and smoke detection modules. The focused features are energy changes in the wavelet model and smoke color model. The obtained features are classified using the Bayesian approach.

Gubbi et al. [27] proposed the detection of smoke based on wavelet and support vector machine classifier. A total of 60 features extracted and used to train the classifier. The algorithm is slow due to a large feature vector dimension. Yu et al. [28] used texture as the feature for smoke detection and it is based on GLCM (gray level co-occurrence matrices). The neural network is utilized to classify smoke and non-smoke pixels. Although the results are promising according to authors, there is need of testing on a large dataset. Toreyin [29] developed an algorithm to detect smoke in a forest location. The algorithm uses human judgment for updating the decision. Its four sub algorithms are the use of adaptive background subtraction to detect slow-moving objects, use of YUV color space for gray as a smoke color, use of HMM (hidden Markov models) for detecting rising regions, RGB angle between background and image for shadows. Fuzzy decisions of the sub algorithms are joined using the LMS method. Verstockt et al. [30] proposed an algorithm to detect the smoke with chromaticity feature that uses a back-step correction. The five steps of the algorithm are the sub-blocking, the background subtraction, the energy analysis, the disorder analysis of boundary, the clean-up post-processing. The technique provides good results for real-time smoke detection, yet the fixed threshold usage and non-possibility of smoke localization are the problems of this approach. Krstinic et al. [31] evaluated a relationship between different color space transformations and the smoke segmentation algorithm. According to their findings, HSI and the derivatives, as well as RGB color spaces, are good choices with Bayes classifier. Their algorithms can be a part of different algorithms as a preprocessing stage. Kim and Wang [32] proposed a method to detect smoke that is based on the block-based approach. As a first step, it is ensured that whether the camera is stationary or not. In the second step, the connected component analysis is used for the detection of areas that have changed in the present frame for the background image and to locate ROI (regions of interest). Then they used k-temporal information of shape and color from extracted ROI to verify the smoke presence. There is a need for testing of the algorithm using a large dataset. Han and Lee [33] proposed a smoke detection algorithm for tunnel environment using motion feature and used motion history image and invariant moment methods.

Zhou et al. [34] used quaternionic wavelet features to detect fire flames and smoke. According to them, the candidate smoke regions have the characteristics of moving in a vertically upward direction. The five texture descriptors like an angular second moment, entropy, contrast, image pixel correlation and inverse different moment with average candidate smoke region trains SVM classifier. According to them, the results are good, but their method is computationally costly. Ma et al. [35] proposed smoke detection using Kalman filtering and Gaussian color model. Offline samples are used to train the Gaussian color model and Kalman filtering with MHI (moving image history) analysis is used to detect the moving object, in this case, the smoke. Chengjiang et al. [36] proposed transmission as a feature to detect smoke and an airlight-albedo ambiguity model is used. According to their findings, the method is effective for both light and dense smoke but it has limitations to detect grayish-white smoke. The quantitative results are not provided.

Kwak et al. [37] used spatiotemporal features and pattern classification techniques to detect smoke during wildfires. Thresholding is used with two consecutive frames for movement detection. Then the smoke candidate blocks are clustered using morphological closing. Due to the generation of large feature vectors, the applicability of the present approach for real-time smoke detection is difficult. Habigoglu et al. [38] used spatiotemporal correlation descriptors for smoke based wildfire detection. The SVM classifier is trained from these descriptors to detect the presence of smoke. Some more details of their approach are given in the flame detection subsection. Yuan [39] used LBP and LBPV pyramids histogram sequence for smoke detection. The feature vectors are obtained and used to train a neural network classifier for classifying smoke and non-smoke pixels. Truong and Jong-Myon [40] proposed a four-step smoke detection algorithm. The moving regions are segmented using an approximate median method and used for making cluster candidate smoke areas using fuzzy- C means. They used temporal and spatial features of smoke to extract parameters like area randomness, surface roughness, and motion vector. Then the extracted parameters are utilized to train the SVM classifier for smoke detection.

Yuan [41] used a double mapping framework for extracting smoke features based on partition. Adaboost classifier is used for selecting shape invariant features. Lee et al. [42] proposed smoke detection using spatial and temporal examination with a block processing approach. A combination of GMM (Gaussian mixture model) background subtraction and temporal difference technique is used to detect the candidate smoke regions. Then energy and normalized RGB color-oriented features are extracted in temporal, spatial and spatiotemporal wavelet domains and fed to an SVM classifier. It leads to a spatiotemporal descriptor for every candidate block. Then hierarchical k-means clusters are applied to the descriptors and a visual vocabulary is built with developing fast bag-of-words. The HSV color space with thresholding is used to localize smoke content. Avgerinakis et al. [43] proposed an algorithm to localize smoke. According to them, the approach is suitable under challenging conditions like other moving objects and blowing wind. The motion information is obtained from background and foreground separation. Then HOF (histograms of oriented optical flow) and HOG (histograms of oriented gradients) are constructed for motion and appearance information. Then averaging takes place for temporal smoothing. Vidal-Callega and Agammenoni [44] proposed an unsupervised smoke detection technique that is based on the BOW (bag of words) paradigm. This approach classifies objects as well as creates a codebook. Their approach does not need extraction of ROIs, segmentation, or motion estimation. This probabilistic approach also provides information regarding the amount of smoke present in a region. But, a test on a large dataset, with different background conditions is required. Tian et al. [45] used a linear combination of background and smoke components and constructed a blended image model for obtaining a smoke component. They devised an algorithm to solve smoke opacity and smoke component with given input and background image to detect smoke. Gunay et al. [46] developed EADF (Entropy-functional based online adaptive decision fusion) framework for video-based wildfire detection. Its sub algorithms are slow object detection, smoke like colored section detection, wavelet transform based section levelness detection, shadow detection with elimination, and classification based on covariance matrix. The ADF (adaptive decision fusion) method is used to combine the decisions obtained from the separate sub algorithms. An oracle is also used to monitor and verify the decisions of the combined algorithm.

Labati et al. [47] proposed algorithms for smoke detection and simulation under varying environmental conditions of wildfire. The computational intelligence approach is used for smoke detection and the lattice Boltzmann method is used for simulation. The synthetic and real smoke frames under varying environmental conditions are useful for creating big datasets for wildfires. Yu et al. [48] proposed a method to detect both flames and smoke. They used two parameters for foreground image accumulation to distinguish flames with smoke. The optical flow technique is used to detect smoke. Junzhou and Yong [49] proposed methods based on textures for detecting smoke. The texture features are evaluated using the HEP (histogram of equivalent patterns) framework. The space–time features of smoke are described using BIFD (Block-based Inter-frame difference) and improvised LBP-TOP (Local binary pattern from three orthogonal planes). The smoke history image is used to reduce false alarms and SVM is used as a classifier. Ho [50] used a LASER based arrangement for smoke detection. The LASER beam after reflecting from the field of view is analyzed for scattering and diffusing characteristics of the smoke region. The diffused and scattered light signal are chosen as the feature vectors which are fed to the SVM classifier. According to them, it is difficult to capture smoke in videos using an IR camera due to high levels of background noise. They have used a smoke sensor (HS-135) for verification and comparison of their method for detecting the smoke. According to the findings, their arrangement successfully detected true smoke signal whereas the smoke sensor was unable to detect it. The unstable behavior of the wavelength of LASER due to temperature and power supply is a problem of this arrangement. This approach is suitable for the ranges that match the range of the LASER. So for large ranges like in the forests, this approach is not applicable.

Yuan et al. [15] proposed a smoke detection method based on both static and dynamic characteristics. In this approach, the extended Haar-like and statistical features are extracted from the saturation and intensity components of RGB images. These features are fed to a dual-threshold Adaboost algorithm with a staircase searching technique to classify smoke and non-smoke images. Further validation of smoke is done by dynamic analysis. Zhao et al. [51] proposed a forest fire smoke detection method using spatiotemporal and dynamic texture features. The segmentation and Kalman filtering are used to obtain the candidate smoke regions. Then divisions in small blocks and extraction of spatiotemporal energy of each block take place. The motion of the centroid of the segmented region computes the flutter direction angle in this approach. The dynamic texture features are defined using LBMP (local binary motion patterns) and the Adaboost algorithm is used to detect smoke. Ye et al. [52] used a dynamic texture descriptor with a surfacelet transform and HMT (hidden Markov tree) model to detect smoke. The image frames sequence is considered as multidimensional volumetric data in this approach. The temporal and spatial coefficients information is taken into one model. The joint probability density is obtained from the above results and the SVM classifier is trained to judge each block. Qureshi et al. [53] proposed parallel sub algorithms for smoke and flame. For the smoke sub algorithm, the steps are background subtraction with static background model, the chromatic color model for smoke and thresholding, morphological image processing, the region of interest localization, turbulence analysis, and thresholding.

Yuanbin [54] used both static and dynamic features for smoke detection. They employed fuzzy logic for image enhancement. The next step is the candidate image target detection. The Gaussian mixture model is used to extract candidate smoke areas. After determining the SVM hyperparameters, the SVM model is established and fed with the characteristics vectors for smoke detection. Shiping et al. [55] proposed an algorithm to detect both smoke and flames in open space. Adaptive background subtraction is used to detect movement and optical flow-based movement estimation is used to detect random motion behavior. Spatial and temporal wavelet analysis, color segmentation using YCbCr color space and Weber contrast analysis is used for moving blob classification. Zhiqiang et al. [12] proposed a method to detect wildfire smoke, aimed at long distances. They extracted local extremal smoke regions using a MSER (maximally stable extremal region) detection method. The reported cumulate region approach is insensitive to image shaking and suitable for camera placements on towers which often shakes and creates disturbances.

Wang et al. [56] used the shape, color, and dynamic features to detect smoke. According to their observations, the general shape of smoke plumes is conical and their algorithm is based on this feature for extracting candidate smoke regions. Another sub-algorithm mentioned is based on texture filtering. Dimitropoulos et al. [57] introduced a higher-order linear dynamical system (h-LDS) descriptor and its application in video-based fire detection. They have used a combination of particle swarm optimization approach and multidimensional dynamic texture analysis with spatiotemporal smoke modeling to increase the classification accuracy.

Xuehui et al. [19] used static and dynamic features of smoke and after extracting them, smoke detection is performed using the Robust Adaboost algorithm. Alamgir et al. [8] proposed a method to detect smoke that is based on local and global texture properties got by Local Binary Co-occurrence patterns meant for

RGB color space. They used a co-occurrence encoding scheme and LBP (Local binary patterns) which is rotation invariant. The LBP and their variants are texture descriptors and these are insensitive to illumination changes and image rotation. The Fuzzy C-Means (FCM) algorithm to produce optional clustering is used to extract the features which are fed to the SVM classifier.

An overall analysis is required after going through the smoke detection techniques of nearly the last two decades. The techniques based on the pattern analysis of smoke are having high computational cost. The color cue is not a good indicator of smoke, but due to its lower computational needs, it can be used in sub algorithms as a preprocessing qualifier for other algorithms. Most of the techniques focused on spatial and temporal features and some of them on spectral features. The flickering is not a prominent feature of smoke, so its use can be avoided in algorithms to reduce the computational burden. From the results of several research works, it becomes clear that the disorder and growth features are a good indicator of smoke. The algorithms in most of the works focused on smoke detection problems, but a few focused on smoke localization problems. Habiboglu et al. [38] approach is one of the few that allows the use of non-stationary cameras. Most of the techniques used stationary cameras because otherwise, motion detection will become a difficult task. But for longer distances like forest areas, the stationary camera is not sufficient to detect the smoke because when there are sufficient pixels in the camera view, vast damage already takes place. It requires cameras mounted on UAVs to detect smoke regions early. In other words, there is a requirement of movable cameras to detect smoke. There is also a scope of improvement in the present smoke datasets for various fire locations. Various rendering techniques are is use and new techniques like GANs (Generative Adversarial Networks) are going to improve the current smoke datasets soon. Some of the techniques seem promising in terms of accurate results but computational costs are still high and make difficult real-time smoke detection and need improvement. The block-level approaches are giving improved results. For the classifier based approaches, the final decision is based on the optimum weights of feature vectors used to train the classifiers. There are some algorithms for it, yet a scope of improvement is there so that the number of false positives will reduce. The number of false positives also reduces when some other indicator of fire known as the flame is detected early. Although the starting of fire is with smoke, in some cases the density of smoke is high whereas in some cases density is very low and it depends on many factors like burning fuel, environmental conditions, etc. Therefore the detection of fire by flames is a better option and flames have certain distinct features as compared to smoke.

2.2. Flame Detection

The fuel and oxidant exothermic reactions create flames, which have various colors [10]. Apart from that its shape and contour changes with time and it has a flickering, motion as well as dynamic texture feature. Although the flames have distinct color features that separate it from its background, yet there are some problems like fire similar color objects in the backgrounds. Then there are questions related to the choice of the suitable color model. Similar to smoke, the flame shape, contour, movements, and growth features are also unpredictable and do not follow ordinary rules of object detection. Researchers focused on these issues and tried to provide solutions for them.

Liu and Ahuja [58] presented spectral, temporal and spatial models of fire regions. According to them, the color probability density of the fire pixels is related to spectral features. The spatial arrangement is related to the spatial features and the shape of the fire area is related to the Fourier coefficients of the spatial frequency content of the area contour. Temporal change of Fourier coefficients is used as temporal features of fire. For fire classification, they have used an SVM classifier with RBF kernel. Chen et al. [59] used both chromatic and dynamic analysis to detect fire flames. For chromatic analysis, they provided three rules relating to R, G, B, S (Saturation) and threshold of R and S values. To distinguish real fire from fire color like objects, the dynamic analysis is performed and it uses disorder and growth characteristics of fire.

Horng et al. [60] used the HIS color model for real-time flame detection and they also estimated the burning degree of the flames. Dedeoglu et al. [61] proposed an algorithm using color and temporal variation information. The temporal wavelet transform is used for flicker determination and spatial wavelet transform is used to determine color changes in moving regions. Toreyin et al. [62] suggested a flame detected method using color, motion, and flickering features. The RGB color model rules are used for color feature, the background estimation method is used for motion estimation and the three-state Markov model is used in spatial and temporal manner to detect the flame flickers. But their algorithms are computationally rigorous and less flexible in case of sudden illumination changes because of the use of fixed thresholds for image's energy.

Marbach et al. [63] proposed a real-time fire detection algorithm using temporal features of fire intensity. Temporal accumulation of the time derivative of images is used for the extraction of candidate fire regions. They have used two features in their algorithm. The first one is the flickering frequency range of fire flames which is nearly 1–10 Hz and the other one is the very high luminance levels for the fire flame regions. The YUV color space is used due to its representations in terms of luminance and chrominance levels.

Celik et al. [23] proposed a fuzzy logic-based fire detection method using a generic YCbCr color model. The YCbCr color space is used for separating luminance from chrominance and fuzzy logic replaced the heuristic rules. The statistically derived chrominance model is used to discriminate fire and nonfire color objects.

The features used by Borges and Izquierdo [64] for fire detection in newscast content are color, skewness, roughness, area change and variance using Bayes classifier for the decision between fire and non-fire images. Horng and Peng [65] proposed a flame detection method using the HSI color model. Zhang et al. [66] used wavelets for detecting fire pixels and FFT (Fast Fourier Transforms) for describing the fire area and applied these two concepts for forest fire detection.

True [67] used color and motion-based approach for fire detection. Spatial clustering on fire pixels and dynamic texture analysis is performed. They used a multilayered perceptron to classify fire and non-fire pixels. According to them, fire detection by this approach can be done on movable platforms like planes and robots. Qi and Ebert [68] observed that the variation in green pixels is more as compared to red and blue pixels during the fire. Gunay et al. [69] used a hidden Markov model for fire pixel detection. The pixels' flicker is detected by temporal wavelet analysis and the nonuniform texture of the flames is detected by spatial wavelet analysis. Wavelet analysis of contours is done to detect the irregular shape of fire. The output decisions of the algorithms are combined in a linear manner using the set of weights updated with the LMS (Least Mean Square) approach when the ground-truth value is obtained. A proper choice of learning rate parameter is needed so that there is a convergence of the update of weights. Gunay et al. [70] detected the wildfire at night using video-based techniques. They have used a visible PTZ (Pan-tilt-zoom) camera for the detection of smoke at daytime and flames during nighttime for wildfires. The proposed sub algorithms are the detection of slowly moving objects, detection of bright regions, detection of the objects in the cyclic motion, interpretation of region movement. They used an adaptive active fusion approach to combine the decisions obtained from sub algorithms. Han and Lee [33] proposed a flame detection algorithm for tunnel environment using color information. The steps of flame detection algorithm are pixel by pixel AND operation, dilation, erosion, etc. Ko et al. [71] used motion and color cues for flame detection. They have made a luminance map to remove nonfire pixels and created a temporal fire model with wavelet coefficients and apply to SVM classifier using the RBF (radial basis function) kernel.

Zhu et al. [72] proposed a hidden Markov model-based fire detection system. According to them, a reduction of data redundancy takes place from state transition between fire and nonfire combined with the motion information. Chen et al. [73] used a multifeature fusion approach for flame detection in videos. They have used the temporal and spatial characteristics of flames like flame movement, color cue, and flame flickering. The Gaussian mixture model method is used for moving foreground object extraction. The flame color filtering algorithm is applied after detecting the moving object as fire or nonfire. The flame flicker detection is performed by statistical frequency counting. Celik [4] proposed a color and motion feature-based fire detection system. For color related features, the author used CIE L*a*b* color space because of its unvarying property. Jiang and Wang [74] used adaptive Canny edge algorithm and flame geometric features for flame detection. They have used a luminance map to remove the nonfire pixels. Ko et al. [75] used a background and color based model for fire detection. According to the changes in the pixel values of fire, the probabilistic models are generated and applied to Bayesian networks for fire detection. Zhou et al. [76] presented flame and smoke detection using quaternionic wavelet features. They compared flame classification accuracies for different color spaces such as RGB, HIS, YCbCr, and LAB. According to their results, it becomes evident that using different color spaces is equally reasonable if the training is in the same color space. To analyze local spatial, spectral and temporal characteristics of fire quaternion, Gabor wavelets are made. The color, turbulence, and contour cues are treated in total for the filtering process.

Habiboglu et al. [38] proposed a covariance matrix based fire flame detection method. As a first step, they have converted the video into spatiotemporal blocks, then the extracted covariance-based features are fed to the SVM classifier for decision. The main feature of their approach is the non-use of background subtraction method for moving region and therefore non-stationary cameras can be used. The other main feature is that the feature classification is done only at the blocks' temporal boundary instead of each frame. Yu-Chiang and Wei-Cheng [77] proposed a fire detection method combining a statistical fire color model and sequential pattern mining. The steps of their method are the collection and pre-processing of fire images, extracting the rules of a sequential pattern of flame regions and combining a statistical color model and mined rules for detecting the fire. Ko et al. [78] used color models for flame detection and background subtraction for moving region detection. The probability density functions are produced for intensity changes, motion alignment and wavelet energy applied to fuzzy finite automata. Rossi et al. [79] presented an instrumentation system using stereovision in an outdoor environment and give a quantitative characterization of fire fronts. For it, they have used visible pre-calibrated cameras and obtained volume, surface area, heading direction and length of 3D fire front information. According to them, it is difficult to perfectly locate and match salient points by a vision system due to the dynamic fire characteristics. They have used a two-level fire segmentation technique. A fire regions global segmentation from the unstructured scene is done in the first level and the fire image is segmented in multiple inner areas of homogeneous colors in the second level. The K-means clustering algorithm is used for segmentation. Zhao et al. [80] used static and dynamic characteristics of fire to detect forest fire. As an initial step, the possible flame region is segmented from a Gaussian mixture model which is obtained by a 3D point cloud of sample fire pixels. A total of eleven static fire features are obtained which trains SVM classifiers and provides a fire decision.

Yunyang et al. [81] proposed a method to extract the flame contour features based on flame area threshold. The idea behind their approach is based on the fact that burning flame contours are similar to each other irrespective of their continuous jitter. But contour information is not sufficient alone and other features are required to correctly detect fire flames. Qiu et al. [82] suggested that flame edge detection is a preliminary step that reduces the processing time and filters out the unwanted background noise from an image. They examined several earlier edge detection methods. According to them, the fragmentation is a problem seen after edge extraction. They detected coarse and superfluous edges in the flame image and then identify flame principal edges and removed the irrelevant ones. Dimitropoulos et al. [83] presented an algorithm for spatiotemporal flame features like contour irregularity, color probability, spatial energy, flicker and spatiotemporal energy. They tested and compared different background subtraction algorithms and estimated fire propagation using a 3D visualization tool. Wang and Zhou [84] used the threshold of the area as the key feature for flame detection. As a first step adaptive threshold is used for segmenting the image. Then the knowledge of set theory is used for the extraction of object contour. For the final judgment step, the features like color and spread are used.

Mueller et al. [85] focused motion features for fire detection. These features are based on motion estimators. They designed two optical flow methods for detecting the fire. Rong et al. [16] proposed an algorithm to detect the fire based on motion, pattern and color features of fire. The algorithm is composed of a rule-based color model and C-GICA (cumulative geometrical independent component analysis) model without a static background for motion detection. Wang et al. [86] proposed a fire flame detection method in which the flame color probability is calculated using Gaussian distribution modeled in YCbCr color space. The probability of motion is calculated by background image dynamically updated with an approximate median method. Then the motion and color probabilities are multiplied and thresholds are used to binary masks. Each frame feature vector extraction is done to determine the candidate flame regions.

Lascio et al. [87] proposed a method to detect the fire for both indoor as well as outdoor environments. The approach is based on both motion and color-based features with giving more weight to motion features. They have used YUV color space because it is more effective as compared to RGB color space in separating luminance with chrominance. For motion detection, SIFT (Scale-invariant feature transform) tracker is used because fire shows disordered movement as compared to other objects. The main feature of their technique is the proper combination of color and movement information using an MES (multi-expert system) classifier. Ko et al. [88] proposed a fire detection method in which they have used a stereo camera to calculate the fire distance and the reconstruction of the fire front 3D surface. They have used a generic color and background difference models. Then GMFs (Gaussian membership functions) are generated for size, shape and motion changes of fire. To verify the real-time fire, the obtained three GMFs are applied to the fuzzy logic. Schroder et al. [89] proposed a deflagration detection method using a two-stage algorithm. In the first stage of the algorithm, chromatic and dynamic intensity features are used to identify fire pixels. In the second stage of the algorithm, the evaluation of temporal expansion of the counted pixels takes place by the use of SEP (spatial expansion parameter). They have used fuzzy classification for each stage. Stadler et al. [90] investigated five different pixel intensity flickering features based on the methods presented in earlier research works and compared them based on flame and nonflame classification rates. According to them, the flame flickering is the explicit visual characteristics of flames and they flicker in height, size, and brightness. Wong and Fong [91] focused on segmenting the flame images, their recognition, predication, and tracking. They used multi-threshold algorithms of earlier methods like Otsu's method and Rayleigh distribution analysis method to segment flame images. After segmenting, they used pool fire images centroid analysis. Zhang [92] proposed a probabilistic model for color-based fire detection and it generates candidate fire regions. They used motion features for fire detection, which are appropriate for characterizing flame flickering in the final decision phase.

Chino et al. [93] considered the combination of color and dynamic texture to be more useful as compared to other combinations for fire detection. Foggia et al. [94] proposed a fire flame detection approach based on shape variation, color and motion and their combining with a multi-expert system and weighted voting. The motivation of using a multiexpert approach is due to the difficulties of managing high dimensional feature vectors obtained from color and motion characteristics of fire. They proposed a descriptor to represent motion and used the bag-of-words approach. Dimitropoulos et al. [95] proposed a real-time video-based flame detection algorithm. They used various spatiotemporal features and dynamic texture analysis for the temporal evolution of pixels intensities in the candidate image block. Qureshi et al. [53] proposed parallel sub algorithms for flame and smoke. For the flame sub algorithm, the steps are thresholding, morphological image processing, the region of interest localization, growth rate computing and thresholding, optical flow rate based flow rate calculation.

Rui et al. [96] presented a multi-feature approach for fire detection for less than 50 m range. They focused on chromatic, dynamic texture and contour features of fire. The GMHI (gradient motion history image) is used to extract the moving regions and the K-means algorithm is used to check the colors of moving fire pixels. The flickering frequency check is performed by the motion history image information. Then LBP features are extracted and used to train the SVM classifier. Then, the fractal dimension analysis of contours is performed. The combined outputs of SVM and analysis of contours provide a decision about the fire. Toulouse et al. [97] used twenty-nine different rules and two of their own to detect fire. They showed experimentally that Phillips et al. [98], Rossi et al. [79] and two of their methods are efficient to detect fire as compared to other methods. They proposed two different ways to combine the rules and according to them, the machine learning technology based on logistic regression performs better. Kong et al. [99] used logistic regression and temporal smoothing for fire flame detection. The color component ratio is used to find out the candidate fire region, the background subtraction is used to find the motion cue of fire flames, and the logistic regression is used for size, motion, and color-related information. They used distribution and Chroma ratio (Cb/Cr) to differentiate fire flames, fire like objects and the background. According to them, the temporal smoothing reduces false alarms.

Han [100] suggested a fire detection method using motion and color features. For motion features, they have used the Gaussian mixture model using background subtraction and for color feature detection, they have used a combination of RGB, HSI and YUV color spaces. Gong et al. [101] used color and motion cues for fire detection. As an initial step, they combined frame difference detection and RGB color model to screen nonmoving and nonfire pixels respectively. Then they take spatial and area variability, boundary complexity and shape-changing properties into consideration to determine the characteristics of flames. They proposed a flame centroid stabilization algorithm that is centered on spatiotemporal relation.

After analyzing the findings, some conclusions come out. The literature showed that all three characteristic features such as spectral, spatial and temporal are utilized. The main advantage of the color-based approach is the low computational cost and hence processing at large frame rates and real-time fire detection. RGB color space has the drawback that it is sensitive to brightness changes and false positives generate due to shadows and different red tonalities. This drawback can be overcome by using YUV color space. It is used in most of the works due to its luminance and chrominance distinguishing capabilities. Color-based methods are suitable where things are almost stationary and fire color matching objects do not move in fire like disordered manner and these are suitable for designing the pre-processing sub algorithms to be validated by other sub algorithms. Due to the drawbacks of a color-based approach, the focus also goes towards the shape change and disordered movement of fire. The flickering is one of the prominent features of flames, but the detection range up to which the flickers are observable is limited. The nonstationary camera-based approaches are also very few and not robust enough. Similar to smoke, there is a need for better algorithms to optimally combine the feature vectors for the classifier. The approaches based on multiexpert systems seem promising and are in improving stage. The block-level based detection techniques are showing improved performance as compared to pixel level techniques. The dynamic texture techniques are showing improved results but these are high in computational cost. Some of the works are there that focus a simultaneous detection of both smoke and flames using parallel algorithms and this will reduce the number of false positives. The techniques that can successfully detect flames both daytime and nighttime are very few. There is a difference in spatial and temporal characteristics for daytimes and nighttime fires. There is a need is to overcome these drawbacks by improving the existing techniques. For it, the researchers are focusing on multisensor and multifusion approaches for detecting the smoke and flames.

2.3. Multisensor and Multifusion Approach for Flame and Smoke Detection

Fire flame and smoke detection are based on several of its visual characteristics and most of them are discussed in the previous section. Still, there are some more cues that indicate the fire and one of the cues is the temperature of the fire object. If the object is not very far away, then its thermal image can be captured. The infrared cameras measure the thermal radiation emitted by the object and researchers are using the fusion of information of both infrared and visible images for better detection accuracies. There are some problems associated with infrared-based fire detection and these are their higher costs, disturbances due to nonfire hot objects, disturbances due to obstructions due to cloud covers in open space, etc. Specific limitations of them are infrared blocking, thermal reflections, and thermal distance problems. Researchers focused on these issues and tried to find solutions for them.

Arrue et al. [102] proposed a multisensor based approach for forest fire detection. They used IR cameras and meteorological sensors with a geographical information database. The high-resolution IR cameras can detect fires in a range from 1 m to 20 km. ANNs (Artificial neural networks) are used for classification and their output goes to a fuzzy decision function. They suggest the strategies to combat the false signal producing sources like the car, the Sun radiation etc. According to them, there is more need for low orbit satellites to detect smoke and fire. The multisensor approach reduces false alarms.

Bosch et al. [103] proposed a forest fire detection system based on infrared image processing. The presented algorithm is the fusion of detectors that focuses on the fire features like persistence and growth, as these are the potential features that differentiate the fire from the other objects. Bosch et al. [104] analyzed that the reason for the false alarms is the lesser weight given to the geometrical and spatial fire characteristics. Some factors responsible for creating false alarms are wind, precipitation and cloud cover and they affect the temperature. So a true thermal image cannot be obtained from the fire scene and the other reason for a false alarm in the presence of hot nonfire objects. The three steps of their proposed approach are getting the thermal images, segmenting the region of interest and distinguishing the object (e.g. fire) using feature extraction. The final step is achieved by plotting different graphs after calculating characteristics from each chosen pair. The objects of interest mentioned in the paper are the people, vehicles, and fire and the background is termed as noise. The descriptors they mentioned are the intensity, orientation, and signatures. They focused to distinguish between vehicles, fire, and people and gave a strategy for it. They analyzed the frequency curve and found that intensity remains almost constant for people whereas it increases in the case of fire. In this way, they differentiated between people and fire. The fire has random orientation whereas for other objects like people and vehicles does not show this behavior. The fire shows a random signature due to its varying shape. The problem of smoke detection during the night was discussed by different researchers (Liu et al. [105], Toreyin [29], Gunay et al. [70], and Verstockt et al. [106]). They suggested the use of an infrared camera because it is sensitive to the thermal image. Verstockt et al. [107] proposed a flame detection method using spatial, geometric and temporal features and these are obtained using LWIR (Long Wave Infrared) thermal images. A discussion is there for some applications of LWIR like hot spots detection and to look through the smoke. They focused on localization and propagation problems. According to them, their technique can be a viable alternative or it can complement the traditional sensors. In this paper, the authors explored the fusion possibilities of visible and infrared technologies for fire detection. Their proposed LWIR based flame detection technique consists of histogram-based hot object segmentation and using a set of features. After combining principal orientation disorder, bounding box disorder, turbulence variance, and histogram roughness probabilities, the combined probability provide a decision about the fire. Verstockt et al. [108] proposed a multi-view fire localization framework. In this framework, there is a merger of single view results of different cameras, using the homographic projection technique. The projection is performed on multiple vertical and horizontal planes to slices the scene. They named the crossing of the slices as FireCube. At these crossings, a 3D grid of virtual sensor points gets created. They used this grid with temporal and spatial 3D filters. Then they analyzed the fire growth, localization as well as smoke propagation.

Verstockt et al. [109] expanded their earlier works and focused on both flame and smoke. They provided the state of the art for visible and infrared fire detection methods. They proposed a multi-sensor for both smoke and flames using a multimodal approach of fire detection. The important feature of their approach is fire localization in three dimensions, its growth rate, and size can be obtained. The smoke detection problem is tackled by visual images and it is achieved by observing a continual decrease in the coverage area. This decrease shows a disorder property that is utilized in earlier research works also in a successful manner. Dios et al. [110] tackled the forest fire detection problem by using both visible and infrared cameras placed on ground stations and mounted on UAS (unmanned aerial systems). They obtained location, shape, height, spread rate information of fire. The authors address an important issue of using complementarities of infrared and visible sensing technologies. The geolocation technique is also used in its approach. The statistical data fusion approach is used to combine the information obtained from different cameras. The advantage of their approach is that there is no need to focus on a certain area for the possibility of fire. Their approach overcomes the limitation of PTZ and fixed camera approach because these require a direct view of the fire origin point. Bosch et al. [111] and Bosch et al. [112] expanded their earlier works by including more features such as remote monitoring of the locations and the communication between the sensors and the control stations.

Verstockt et al. [113] used a multimodal approach for detecting flames and smoke for open spaces like car parking. In this approach, they have used a TOF (time-of-flight) camera for flame detection. It consists of IR (infrared) LEDs and a sensor. The IR LEDs transmit a frequency modulated IR signal which falls on the object and then reflects. The reflected signal is captured by the sensor on the camera. The time lag in the process gives the depth information of the pixel. At the same time, the camera also calculates the reflected IR signal's strength which provides the amplitude information. In this way, these cameras can provide a 3D image data output. In this work, the amplitude, depth, and visual information fusion take place. Won-Ho [114] proposed a block-level instead of a pixel-level approach to detect flames using infrared images. This approach also evaluates the temporal motion behavior of flames and the advantage is that the system can be implemented on an embedded platform due to the lesser computational needs.

After reviewing different works in the area of a multisensor based approach, certain conclusions come out. Color cameras are of lesser cost as compared to infrared cameras, but the former ones have limitations under heavy fog and no light conditions. So under challenging environments, the information fusion of both camera images is a requirement. The change in environmental conditions causes a change in motion, shape, transparency, patterns, and colors of smoke that is why traditional methods of using visual images only are not sufficient to reduce the number of false alarms. The manufacturers are hopeful that the cost of IR cameras will go down soon. As a lower-cost alternative of IR cameras, the TOF cameras are also in use. These are not sensitive to light changes or shadows and it is because TOF cameras use their IR signal. The post-processing time lowers and the shape and location information is obtained by the depth map. The depth map information is profitable for indoor applications. The drawbacks associated with these are the low spatial resolution, measurement artifacts and need for active illumination.

The disturbance from the other IR sources can also be eliminated based on the fact that the variation pattern of intensity behavior is different for fire and other non-IR emitting sources. Literature also shows that the range of detection by these approaches is also satisfactory and is in kilometers. The multisensor, multifusion and multimodal approaches are also suitable for night-time fire detection. The use of UAV deployed multisensor fire detection systems need to develop and there use in mountainous areas having steep slopes is very much required. Because in steep slope areas, the fire spread is quicker. The issues like finding the correct location, size, the growth and the direction of fire and smoke are also important and by the multisensor approach, they can be solved easily.

After discussing the handcrafted features with or without classifiers and multisensor-multifusion-multimodal approaches it is clear that the multidimensional problem of fire flame and smoke detection can be performed satisfactorily. But still, there is a scope of improvement because of the need for early detection and lower false positives. There is also a lack of robustness in some of the algorithms and the careful selection and weight of features is a critical task requiring great human expertise. Table 1 compare some of the algorithms on the basis of detection rate and false rate. In some of the cases, averages of these rates are taken because the rates are mentioned for individual fire (or nonfire) or smoke (or nonsmoke) video clips. These results are obtained using different datasets under different environmental conditions, so these cannot be compared directly to each other. In some of the references, there is a comparison of these rates with rates of few algorithms from earlier references. A good algorithm should have fire or smoke detection rate above 90% and false alarm rate below 5%. References [23, 33, 34, 37, 39, 95, 96, 101, 107, 113] comes under these criteria. Ref. [95] shows good detection and false rates for detecting the flames. And references [37] and [39] shows promising results for detecting the smoke. One more important parameter is the response time taken by these algorithms. Some of the references mention it quantitatively, but it is missing in most of the references.

To overcome these issues, there is a need for an approach that can complement the existing approaches discussed up to now. The potential approach that is showing improved results for video-based flame and smoke detection is based on one of the current artificial intelligence techniques, named as deep learning.

3. Deep Learning-Based Fire Flame and Smoke Detection

The conventional machine learning approach is difficult to process the data in the raw format. It requires a great amount of expertise for designing a feature extractor that will transform this data into a feature vector [115]. The deep learning approach removes this difficulty. The deep learning techniques are gaining momentum for detecting fire flames and smoke. Presently these techniques are in the developing stages and there are also certain limitations and problems associated with them. Some of them are the requirement of long training time, a need of rich and diverse dataset according to the fire scene, a choice between transfer learning and scratch based model selection, deployability on embedded platforms, difficult to use the temporal cues, their dependence on mainly lower-level cues, hard localization as compared to handcraft based approach and a lack of control

Table 1
Smoke/Flame Detection and False Rates of Handcraft Rule and Classifier Based Algorithms

Ref.	[23]	[25]	[28]	[33]	[34]	[37]	[38]	[39]	[40]	[41]	[95]	[96]	[101]	[107]	[113]
S/F	F	S	S	F	F	S	S	S	S	S	F	F	F	F	F
DR (%)	99	80.06	65	96.92	96.9 (SVM) 96.7 (Adaboost)	93.2	71.74	95.34	89.50	83.50	99.17	97.02	95.29	>90	92.75
FR (%)	4.5	22.81	2.35	4.3	4.6 (SVM) 8.86 (Adaboost)	2.2	1.34	2.325	3.4	0.1	0.0	0.0	3.09	1.2	0.0

S Smoke, *F* Fire flame, *Ref.* References, *DR* Detection rate, *FR* False rate

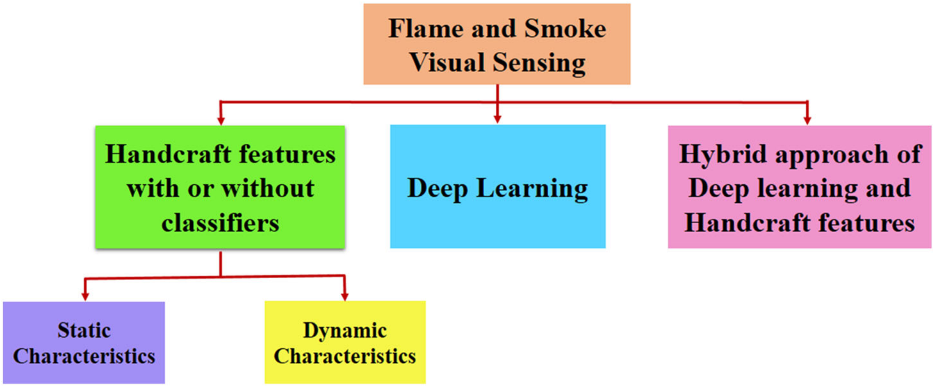

Figure 2. Flame and Smoke detection techniques: Classification.

over internal processes. The literature shows that these issues are in focus and the researchers are aiming at them.

Figure 2 shows a classification of flame and smoke detection techniques. It is required to get an insight into deep learning before going to the problem of flame and smoke detection by deep learning techniques.

3.1. An Insight into Deep Learning

Deep learning applications exist in areas like speech recognition and detection, face and object detection, robotics and natural language processing. For two-dimensional data like images, a CNN (convolutional neural network), is a suitable choice. They require less amount of data pre-processing and consist of deeper layers.

Figure 3 shows a generalized form of deep neural network model to detect fire. The layers filter the feature of the input image by the convolution process. For

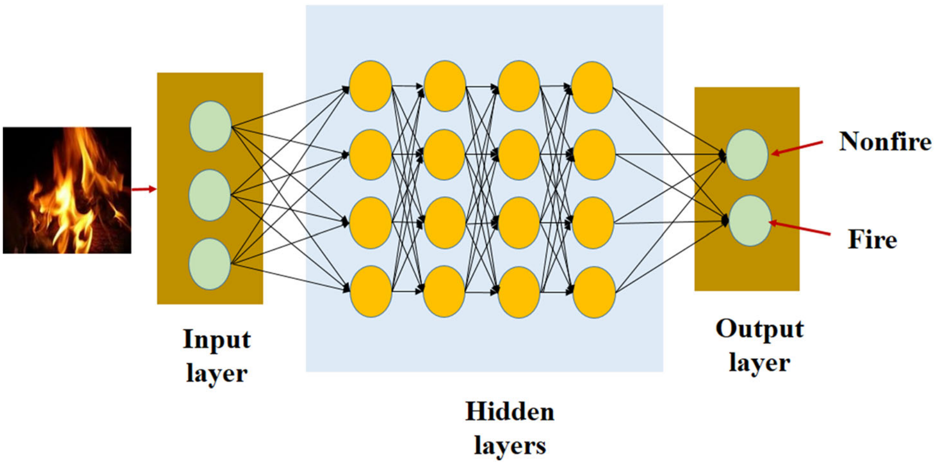

Figure 3. A generalized deep neural network model for fire detection.

dimensional reduction, the subsampling process takes place after input layers. Then the data passes through the activation function and these tasks repeat a particular number of times.

Gonzalez [116] provided an insight into the CNNs architecture with an example showing the process of training for the classification of handwritten numerals. Willis [117] discussed the advances going on in deep learning to recognize an image. In deep learning, tasks like classifications, regression, auto-encoding, and clustering are performed with the use of multi-neuron, multi-layered neural networks. The prime categories of deep learning are unsupervised, supervised, and reinforcement learning [118]. The nature of the input data decides the choice of learning to be used. Deng [119] discussed current deep learning algorithms and architectures under discriminative, generative, and hybrid categories. For discriminative type, a discussion is there for DSNs (deep stacking networks) and recurrent neural networks. There is a discussion of DNNs (deep neural networks) which are trained with DBNs (deep belief networks) for hybrid types, and deep autoencoders description for generative type.

3.2. The Dataset

The dataset is a significant part of deep learning applications. Good results are obtained from a diverse nature dataset. For fire detection applications, there is a lack of good datasets consisting of a large collection of images of high dimensionality. A linear increase in dimensionality causes an exponential increase in the learning complexity [120]. The data consists of both spatial and temporal dimensions to be captured by a deep learning algorithm. The present datasets consist of both images and videos in different pixel sizes. For the training of a model, videos are converted into a set of images and resized according to the model.

Since fire has a range of colors varying from blue to red with various backgrounds, a universal dataset must have a diverse range of color images. And the fire color depends on the material which is burning and several other factors. Smoke which is also an indicator of the burning of material has Grey, white or black colors. The place or location where fire detection is to be performed also plays an important role. It may be an industry, nuclear power plant, building, home, or a forest. To fulfill the distribution of image features of such vast application areas would require a very big and diverse dataset. Large training times are required even with GPUs. There is a requirement of place-specific datasets like industrial fire datasets, residential/commercial building fire datasets, and forest fire datasets, etc.

Toulouse et al. [121] developed the Corsican fire database for wildland fire with images in both visible and near IR range and it is in evolving mode due to contributors from different parts of the world. They provided annotations about images and their environments. The annotation of images is in terms of descriptors which will assist the users to select images according to their specific research purposes. Such type of properly annotated datasets is also required for other application areas like industries, buildings, tunnels, car-parking, etc. Some of the other important datasets are FIRESENSE [122], MIVIA [123], and Multiview video fire analysis RABOT2012 [124], etc.

The proper class labeling of the images is also important for the preparation of the dataset. The most basic division would be fire and nonfire images. Other divisions can be flame, smoke, and nonfire images. Classes may further be subdivided like low flames, medium flames, violent flames, low smoke, medium smoke, dense smoke, and nonfire images. The low, medium and high subdivisions are based on the segregation of images based on the percentage of flame or smoke pixels in the total image pixels. There may be further subdivisions like flame and nonsmoke, smoke and nonflame, flame and smoke, nonfire in a dataset or based on the colors of the flame. The more the classes, the more information about fire detection can be obtained.

The camera which is capturing the real-time images of the place of detection has different environmental settings as compared to the camera from which the dataset has been created. The factors may be the different lighting conditions, angles, etc. To match the dataset to fulfill these conditions, the dataset augmentation is performed. Several transformations can be performed on each image and these are angle, brightness, color changes, blending of images with different backgrounds, etc. It will extend the distribution of image features of the dataset. Pinto et al. [125] suggested that synthetic images can be generated to prepare the dataset. It takes care of the real world variation effects in images. Mopuri and Babu [126] showed experimentally that if object proposals are passed to CNNs, then the robustness of deep learning model increases and images acquire less memory footprint.

3.3. Flame Detection

The deep learning model based on fire flames and smoke detection is the present focus of research. Different models developed from scratch or transfer learning are in use.

Figure 4 shows a generalized fire detection system based on deep learning model. Initially, images are captured by the camera and resized according to a trained deep learning model. Classification results are in terms of fire or nonfire classes. In the case of fire class result, local analyzer processes and transfers this information to different subunits like fire suppression, alarm, evacuation path display, and an information gateway.

The process and steps of detecting flame or smoke remains almost same with deep learning approach, in contrast to their detection using handcraft feature or classifier based approach. This subsection is focused on the flame detection through deep learning approach. Polednik [127] used deep CNNs with a Caffe framework for fire detection in images and videos. They recorded several static scenes using a camera and modeled the fire artificially. They have used Blender, a 3D modeling tool to create fire animation and created composite fire images using a nonfire background and modeled fire. Most of the models are not robust with geometrical transformations like rotation, translation, and scaling of images. Zhang et al. [128] proposed a vision-based method for forest fire detection that

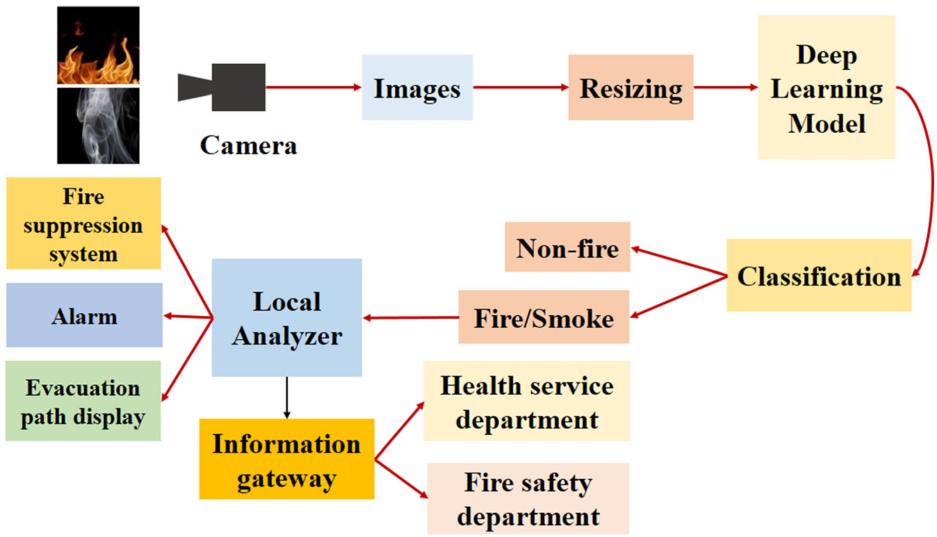

Figure 4. Generalized deep learning-based fire detection system.

can work with non-stationary cameras also. So, it can be mounted on UAVs for forest fire detection. They also proposed a fire detection benchmark dataset. They have collected fire sequences from previous literature and with their dataset made patch wise annotations. They also compared their work with Habiboglu et al. [38] that used covariance descriptors and also suitable for non-stationary cameras. Habiboglu et al. [38] approach needed a careful design of handcrafted features. Zhang et al. [128] also focused on the fire localization problem, for it, they manually annotated present fire patches with bounding boxes of a certain dimension. The authors used a smaller dataset in this work because manual annotation is a time-consuming task. Their future task is to increase this dataset with lower-dimensional patches and to automate the process. The main goal of their approach is to detect the fire at the patch level. Kim et al. [129] proposed a forest fire detection system from UAVs, with an optical sensor. They focused on good labeling of dataset images which leads to improved detection accuracy. They have also used data augmentation techniques to increase the dataset.

Gonzalez et al. [130] used CNNs for fire detection with UAVs (unmanned aerial vehicles). The proposed approach used by them consists of simple feature extraction with FCN AlexNet. They integrated two CNN models. The first model is based on AlexNet and it targets shape and texture features. It has a strong fire region finding capability but it loses resolution. The second model which is a convolution sequence does not reduce image dimension and it targets color and texture features. It is adequate for fire detection but false positives are high. In this way, the positive features of both models get fused. The proposed future task is the use of multisensors integrated with the present system and mounting on

UAVs. Huttner et al. [131] proposed a deep learning-based video fire detection system using Google's Inception V3 and checked its performance using different optimizers, reduction functions, learning rates and convergence time. They used the TensorFlow framework and according to them, the best accuracy is achieved with Adam optimizer.

Muhammad et al. [6] proposed a CNN based video fire detection system, inspired by GoogLeNet architecture. The model is fine-tuned according to the fire detection problem to increase accuracy and efficiency. The reasons they give for choosing GoogLeNet are its good classification accuracy, suitability to implement on FPGAs and a small-sized model. Muhammad et al. [132] proposed indoor and outdoor fire detection methods for surveillance videos using fine-tuned CNNs. They proposed a priority-based mechanism for camera nodes and used CNNs and IoMT (Internet of multimedia things) for disaster management. They proposed a dynamic channel selection algorithm for higher priority cameras using cognitive radio networks. They used a model inspired by AlexNet architecture with some modifications according to the fire detection task handling. The employed cooperative SS algorithm is used for multisensor systems. The Foggia's and Chino's dataset is used and according to them, Foggia's dataset is challenging. For future research works, they proposed lightweight CNNs for the reduction of model size. Shen et al. [133] used optimized YOLO (You Only Look Once) deep learning model for flame detection and the training is done by TensorFlow. The YOLO uses the full image in place of regional proposals for training and testing and it could reach 45 fps. They also used the data augmentation technique for enhancing the dataset. Zhao et al. [134] proposed a UAV (Unmanned Aerial Vehicle) deployed visible camera-based forest fire detection system. The detection and localization of the fire become difficult due to the motion of the UAV. To tackle this problem, they proposed a saliency detection method. It is used to locate the core fire areas and after that extracting the fire regions into several fire images. The main attraction of their techniques is that it prevents feature losses due to the resizing of the images. They proposed a DCNN architecture and named it as Fire-Net for fire classification tasks. In future tasks, they proposed to use an IR sensor to validate the classification results.

Aslan et al. [135] proposed a video-based flame detection using DCGANs (Deep Convolutional Generative Adversarial Neural Networks). They proposed a two-stage DCGAN training and it uses spatiotemporal flame features. Real spatiotemporal images are used to train DCGAN and separate training of discriminator that uses temporal flame images without the generator. The DCNNs do not utilize the temporal features of flame and this is their major drawback. This work utilizes the temporal features of flames which are related to their flickering. But one point must also be considered that flickering of flames is not visible after a certain distance of the fire scene from the camera. Therefore the range of detection is limited. They obtained temporal slices off images and process them using DCNN. They used a densely connected layer followed by five transposed convolutional layers for generator and five convolutional layers with a densely connected layer for the discriminator. They train DCGAN with flame data, a noise vector, and nonflame data. It is different from a conventional CNN fire detection approach. The major drawback of using the CNNs for fire detection is that these have high memory and computational needs. Muhammad et al. [136] used a computationally efficient CNN architecture which is inspired by SqueezeNet architecture for detecting and localizing the fire. This approach is different as compared to other deep learning approaches in terms of the use of small kernels with no dense and fully connected layers. They focused on a trade-off between fire detection accuracy and efficiency. The AlexNet architecture with the transfer learning strategy is used. They fine-tuned the model having the same architecture to the SqueezeNet model and reduced its size from 238 MB to 3 MB. In this way, the computational efficiency and the possibility to deploy them on the embedded platform also increased. They used the feature map selecting the algorithm to choose feature maps from trained CNN convolutional layers that are more sensitive for fire regions. In this way, a better segmentation is achieved as compared to traditional handicraft feature-based methods. This segmentation information can further be used to know the fire growth rate. One more thing on which they focused is the identification of the object on fire. It means the system can differentiate whether the fire is in the house, car, forest, etc. This information will be helpful for the fire-fighters. The fire localization problem is also focused and its algorithm consists of two sub algorithms. The first algorithm provided a feature map selection for localization. Then the obtained 8, 26 and 32 feature maps are used in the second algorithm. Kim and Lee [137] used faster R-CNN for fire and nonfire regions of interests focusing on spatial features. Then LSTM accumulates the obtained features in the bounding boxes of different successive frames and provides the classification results in a short time. Then a majority voting is done after combining the obtained short term decisions. They calculated flame and smoke areas for the analysis of temporal changes to predict the dynamic fire feature with the final fire output decision.

3.4. Smoke With/Without Flame Detection

Some of the researchers detected smoke or both flames and smoke using deep learning approach. Yin et al. [138] proposed a deep normalization and DCNN for detecting the smoke. The model which they have used consists of 14 layers and the main difference as compared to traditional DCNNs is that they used normalization and convolution layers instead of convolutional layers. The normalization and convolutional process make the convergence faster. The data augmentation is used to overcome the overfitting. Zeng et al. [139] proposed R-CNN, SSD, and R-FCN for detecting the smoke. TensorFlow is used to build object detectors. They have used Inception V2, Inception ResNet V2, ResNet V2 and MobileNet for comparison testing. The MSCOCO smoke dataset is used in the present work. The experimental results they obtained, shows that for the SSD and R-FCN training speed. The SSD with MobileNet is fastest in terms of iteration and detection speeds, but it is lower in terms of accuracy. The Faster R-CNN with Inception ResNetV2 is best in terms of accuracy but it is slowest. Xu et al. [140] proposed a video-based smoke detection system using a single-shot multi-box detector and DCNN (deep convolutional neural networks). The main limitation of smoke detection is the lack of sufficient images for training. They used synthetic smoke images and used adversarial strategy and domain adaptation. It is helpful to bridge the gap between real and synthetic images. The available smoke samples are limited in scale and diversity for training detectors, they applied synthetic smoke samples with annotations of boundary box to the detection task. For synthesizing smoke samples, they have used renderer Mitsuba and it uses media rendering algorithms to render smoke. The domain adaptation is used in the state of the art detector SSD and MSCNN. Xu et al. [141] proposed a video-based smoke detection using the concepts of deep saliency networks. In these methods, the most important objects are highlighted with pixel and object level salient CNNs and these extract a smoke saliency map.

Wu et al. [142] used a fusion-based approach, to extract both static and dynamic features. They have used deep learning to extract static features of fire and smoke using the Caffe model. The ViBe method is utilized to extract the background from video and motion areas updated from frame differences. They have used the adaptive weighted direction algorithm. The frame image is divided into 16 by 16 grids and smoke and fire occurrence time are recorded. All the cues are combined and to achieve the final detection. The forest fire detection is a challenging problem and an integration of both traditional (handcrafted) and deep learning techniques can tackle it in a better manner. The adaptive method is used for fire localization. The traditional feature-based algorithm includes degree of irregularity and sum of weighted direction values. Zhang et al. [143] used faster CNN for the detection of smoke and flames in the forest. They generated synthetic smoke images with the help of real and synthetic smoke images with forest background. The simulative smoke approach improved the results and it is verified by their experiments. They observed that there is a vast variation in the green pixel values as compared to the red and blue pixels in the forest environment. Namozov et al. [144] used the deep learning approach for fire and smoke detection. They have used adaptive piecewise linear units instead of ReLU or tangent function. They have created their dataset and used conventional and latest data augmentation techniques such as GANs (Generative Adversarial Networks). The label preserving transformations is the commonly used data augmentation technique. The GANs algorithm is used to estimate generative models based on the min–max rule. Cycle GANs transfers images from one setting to another e.g. different seasons images can be generated using only one season image and it increases a data diversity in image data. In particular, they have used cycle-consistent adversarial networks for the unpaired image to image translation. They include different seasons in images, then for every daytime image, they converted it into night-time image. The CNN model is inspired by VGGNet and used adaptive piecewise linear activation (APL) function in convolutional layers. The fire localization task will be in their future list of task.

Although CNNs can automatically capture the smoke/flame features from an image frame, they are hard to capture the motion information for any two successive frames. Maksymiv et al. [145] used a combined traditional and DCNN based approach for flame and smoke detection. They have used the HSV color model for flame and smoke segmentation and the method of frame subtraction is used for motion detection. The morphological operations like dilation and erosion are used to remove the noise problem due to frame differencing. Hu et al. [146] used the temporal cue in a two-stream CNN and opening a new path for hybrid techniques. They focused on smoke detection. This technique will provide combined features of handcraft rule and deep learning approaches. They proposed a two-stream (spatiotemporal stream) CNN that extracts appearance and motion features at the same time. After that, an enhanced architecture is used for real-time smoke detection. The architecture of their proposed method is different as compared to other conventional DCNN approaches in terms of some final layers. The strategy which they followed is based on multitask learning. Here in the one path of the final layers, they have used fully connected layers and a softmax classifier to detect the smoke presence and in the other path, they have used four deconvolutional layers for motion detection based on optical flow estimation. A quantitative comparison is also there with some traditional handcrafted approaches and some CNN based approaches. The processing speed seems also reasonable at fps 196. Gaohua et al. [147] tackled the smoke detection and localization problem by developing a joint framework of RCNN and 3D CNN. The RCNN uses the static spatial information to locate the smoke region and 3D CNN is used to detect the smoke with spatial and temporal features.

Table 2 provides a feature-based summary of some of the current research papers on deep learning-based fire detection. It is important that the detection rates and false rates provided in the table cannot be used to compare different reference works. Because of the datasets, environmental conditions, etc. are different for each of them. Comparing the results of Tables 1 and 2, it is clear that most of the deep learning algorithms shows very low false rates as compared to handcraft feature and classifier based algorithms. The literature survey of deep learning-based video flame and smoke detection algorithms (VFSDA) shows that developments are going and improvements are still required to tackle the associated problems. The problem of long training time is overcome by the use of fast GPUs, using such datasets that have lesser but diverse images. Because most of the benchmark datasets contain videos in which different frames differ very less in diversity. More work is required for both flame and smoke dataset creation. The GANs (Generative adversarial networks) are playing an important role to enhance the diversity of datasets. The transfer learning approach speeds up the model creation but for developing smaller models that can be deployed on embedded platforms, the scratch based models are preferred. These problems are addressed and tried to be solved by Jadon et al. [151] and a few others. Jadon et al. [151] focused on performance and model size issues. They used a scratch based model design approach and named the model as FireNet. According to them, the model can be deployed on embedded platforms like Raspberry Pi. They targeted both smoke and fire and used a smoke sensor for validating the results. They introduced a shallow neural network and used a small but diverse training fire dataset.

The localization problem which is harder for CNNs to deal is solved by Zhang et al. [128] and Muhammad et al. [136]. To tackle the problem of lack of control over internal processes, there must be interpretability and information visualization. Choo and Liu [152] provided a review of visual analytics and discussed the

Table 2
Features of Current Deep Learning Based Fire Detection Algorithms

Fire/smoke or Both	Network	Accuracy/detection rate (%)	False rate (%)	Future work proposed	References
Fire	CNN (GoogLeNet)	94.43	0.054	Reducing false alarm	[6]
Fire	Deep CNN (Inspired from CaffeNet)	100 (128 by 128 size image)	24	Bigger dataset	[127]
		84 (256 by 256 size image)	5		
Fire	CNN (AlexNet)	84.8	1.2	Data augmentation, deployment on UAVs	[128]
Fire	CNN (AlexNet)	94.39	9.07	Model size reduction	[132]
Smoke	Deep normalization and CNN (14 layers)	97.52	0.6	Use of GANs	[138]
Both	CNN (12 layers)	96.18	0.33	Inclusion of fire location features	[144]
Smoke	Spatio-temporal stream ConvNet + Optical flow + SVM	97	3.5	Better motion feature extraction	[146]
Smoke	RCNN + 3D CNN	95.23	0.39	***	[147]
Smoke	CNN (AlexNet)	99.40	0.44	***	[148]
Smoke	CNN (9 layers)	99.76	0.003191	***	[149]
Both	CNN (Inspired from AlexNet)	98.10 (Fire) 96.58 (Smoke)	0.21 (Fire) 1.478 (Smoke)	3D CNN, Bigger dataset	[150]
Fire	CNN (14 layers)	93.91	1.95	Develop more diverse dataset	[151]

***No significant future work is proposed research gaps. Zeiler et al. [153] proposed a visualization technique that provides an understanding of intermediate layers of deep convolutional networks. Their technique uses a deconvolutional network of multiple layers and finally get input pixel space from feature activations.

Some review articles related to video-based flame and smoke detection also worth mentioning here. Verstockt et al. [30] provided insight into video-based flame and smoke detection techniques. They also proposed a block-based smoke detection algorithm. Cetin et al. [154] discussed in detail the developments in the field of flame and smoke detection techniques. They suggested the use of a multi-modal system to improve the detection results. Li et al. [9] reviewed the video-based flame and smoke techniques in a detailed manner. Ojo and Oladosu [155] focused on the review of smoke detection techniques critically and analytically.

Alkhatib [156] provided insight and a review of forest fire detection techniques. After these works, many new developments have taken place in video-based flame and smoke detection techniques. There is also a need to include the deep learning-based video flame and smoke detection techniques and to show how these can complement the earlier techniques based on handcrafted features. In the above-mentioned articles, deep learning-based smoke and flame detection algorithms are not treated, mainly because the deep learning-based works started maturing after the year 2015. The present article is targeted at filling this gap.

4. Conclusions

This section summarizes the current scenario in video-based flame and smoke detection algorithms. The prime requirement is real-time early fire detection with lesser false outputs. After reviewing the literature, some conclusions are drawn out. The presence of fire is indicated by its flames and smoke. The smoke comes first so a focus is on detecting it at an initial stage and then confirming it with flames.

The earlier techniques focused on handcraft feature based video flame and smoke detection. These are classified into with and without classifier-based methods. The static and dynamic characteristics of both flames and smoke are mainly focused. These characteristics features are used in the literature to obtain the decision about flames and smoke. Most of the works revolve around a careful blend of these features. Some of them are good cues of fire but may require computationally rigorous algorithms while some are opposite. There is a need for using such cues at an initial stage that have less computationally demanding sub algorithms and at the same time minimizes the burden of computational demand of other sub algorithms. A general behavior is that the detection accuracy and computational efficiency have an inverse relationship and a trade-off is required between these two. The treatment of smoke and flame also differs because they have different prominent features. The behavior of flame and smoke also depends on their distance from the camera, background, day or night time and many such factors. The multimodal techniques are promising in this regard. The role of the camera is also important and the techniques which allow both stationary and non-stationary cameras are having generalized location applicability. Very few handcraft-feature based techniques allow a non-stationary camera. It is restricting the use of VFSDA in robots or UAVs. Then the issues of combining the feature vectors to train the classifier are discussed. The use of too many features creates the problem of computationally demanding algorithms. A careful selection of features to achieve the optimal solution is required. The multiexpert approach is giving promising results in combining the feature vectors.

The current techniques for VFSDA are focusing on the use of deep learning as a complementing approach for a handcraft feature-based approach. Some initial works used DCNN (Deep Convolutional Neural Networks) alone to detect flames and smoke. But it is hard to detect the strong temporal cues of fire mainly based on lower level cues like color, edges or textures by CNNs. So hybrid approaches are developing that are utilizing both handcrafted as well as DCNNs features in their algorithms and the other approach is the use of 3D CNNs. Another focus area that needs improvement is the rich and diverse dataset creation for both flames and smoke according to different fire indoor or outdoor environments. A dataset consisting of images from electrical sparks is also required because it is one of the important causes of indoor fires and a cause of many casualties. A camera trained from these images can detect it and possibly minimize the damage. Similarly, for other locations like tunnels, car parking, industrial and forest environments separate flame and smoke datasets need to be prepared for better detection results. Generative Adversarial Networks (GANs) can play a major role in creating such datasets.

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