A Survey of Deep Learning Methods for Vision-Based Fire Detection and Localization

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***Abstract*—Undetected fires have caused significant damage globally, highlighting the importance of a reliable fire detection system. However, current smoke and fire detectors have proven to be inadequate due to system inefficiencies. To address this issue, a surveillance camera-based vision-based fire detection system with a high detection rate and low fault warning rate has been proposed. This system utilizes live video data analysis for real-time fire detection and incorporates edge detection and thresholding approaches to recognize fire attributes. The model identifies harmful flames based on their color, velocity, form, and texture, and employs color models such as HSV to increase detection accuracy. Deep learning methods like YOLO and transfer learning, as well as IoT technologies, can be incorporated to improve fire detection both indoors and outdoors. This paper presents a comprehensive literature review on various approaches for the detection and localization of fires in indoor and outdoor environments. The paper highlights the strengths and limitations of each approach. It also discusses the challenges and future research directions in this field to identify opportunities for advancing the state-of-the-art in vision-based fire detection and localization.**

Keywords*—Fire Detection, Computer Vision, HSV, Deep Learning, CNN, YOLO, Transfer Learning.

I. Introduction

One of man's greatest achievements is widely considered to be the capacity to produce fire, yet fire is a fickle companion that, when unregulated, may wreak enormous destruction. From ancient history, fires have devastated entire cities, leaving a trail in their wake. By using scientific and technological concepts, fire prevention seeks to protect people, property, and the environment from a disastrous fire. Humans have understood from the dawn of time that early fire detection aids in fire control. The history of fire detection is long and illustrious, and considering past advancements enables house and business owners, as well as fire protection security companies, to better protect against current fire hazards and to develop revolutionary strategies from detecting fire and preventing it in the future. Prior to the discovery of electricity, communities had to deal with flames. The first occurrences of fire protection are attributed to the terrible fires that started in Rome under the Roman Empire. As a response, Emperor Neron enacted regulations mandating the use of fire-resistant materials when renovating buildings [1].

The establishment of fire prevention laws was documented for the second time in 1666, following the Great Fire of London, which burnt more than 80% of the city. The London fire inspired the development of the earliest firefighting apparatus, such as hand pumps and water distribution systems known as fire hydrants [2]. Over the last century and up to the present day, there has been significant progress in detecting fire, from the development of smoke and flame sensors to the use of surveillance cameras equipped with artificial intelligence.

Nowadays, the majority of buildings are equipped with fire alarm systems and smoke sensors, which are commonly used for fire detection. These systems operate based on the principle that smoke, resulting from a fire, rises and activates the installed smoke sensors primarily on the ceilings of rooms. Alternatively, they may use a group of considerations such as temperature, humidity, and others. Once activated, the sensors then activate the fire suppression systems and fire alarm. Although this technique is generally reliable, it suffers from a natural delay as smoke takes time to rise and reach the sensor. Unfortunately, this lag can often lead to the rapid and uncontrollable spread of fire. To address this issue, one approach is to leverage image and video data from surveillance systems. In images or videos, fire is typically categorized by its moving yellow or orange flames. Smoke, on the other hand, is characterized by a mixture of black, grey, and white clouds. Smoke emerges when materials are burned by fire, which can occur due to various causes such as chemical reactions, electrical sparks, arson, and more. As smoke is generally denser than clean air, it rise up swiftly, propelled by the intensity of the fire [3].

The advancement of computer vision technology has played a significant role in the growing interest in intelligent fire detection among both academics and businesses. By relying on vision sensor-based techniques, several benefits can be achieved, including reduced response time, improved detection probability, and the ability to cover large areas, such as open environments, more effectively. Vision sensors provide valuable information concerning the direction, size, and growth of both smoke and fire [4]. Furthermore, it is possible to upgrade current surveillance systems in several settings, such as public areas and factories, at a relatively low cost. This upgrade enables the early detection of fires, as well as the identification of flames and smoke, through the utilization of video processing and machine vision techniques [5].

This paper conducts an extensive literature review of current research on vision-based systems that detect and localize fires. The review encompasses diverse methods and approaches proposed in existing literature, such as color-based, motion-based, deep learning-based, transfer learning and internet of things methods. Additionally, it investigates the limitations and challenges associated with these techniques and provides suggestions for future research directions in this field.

II. Literature review

In this section, several research initiatives are discussed that focus on developing fire detection systems using different methodologies and algorithms.

A. Computer Vision using Colour Features

Many of the studies attempted to use fire's color and motion characteristics for fire detection. Jubeena Maheen and Aneesh R. [6] proposed a model, as represented in Figure 1, that uses the color correlogram feature to differentiate the fire zone from the video frame.

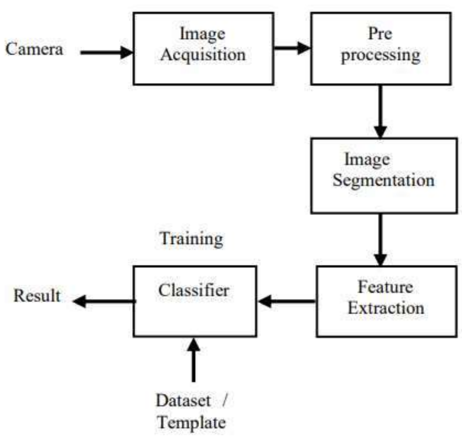

Figure 1. Illustration of the Fire Zone Detection Model [4].

Dzemil Dzigal et al. [7] established a novel approach for detection of fires in forest, shown in Figure 2, that combines several fixed and ambiguous picture segmentation parameters. With the use of appropriate picture processing techniques, it is possible to identify the distinctive color of a forest fire, especially during the late times of summer and spring, as the fire shade is easily distinguishable from the surrounding green background.

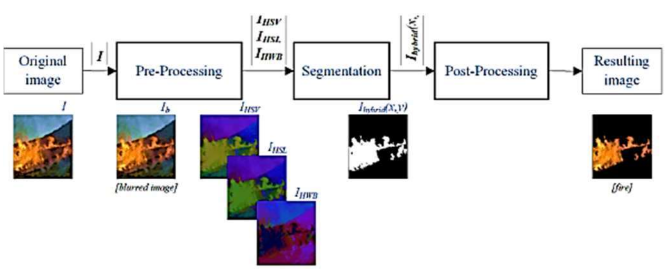

Figure 2. Forest Fire Detection block diagram [5].

Yakun Xie et al. [8] anticipated a new technique for early fire detection based on the reflection of firelight properties in enclosed indoor situations. Lida Huang et al. [9] developed a novel Wavelet-CNN approach that extracts spectral information from images using the 2D Haar transform and feeds it into CNNs at various layer levels, utilizing conventional spectral analysis techniques in fire image detection. Dedy Riyadi and Siti Aisyah [10] proposed a system that detects flames that applies segmentation, filtering techniques, and image enhancement utilizing LabVIEW's Vision Assistant. The system can identify flames using HSV color filtering, based on intensity and color patterns. Ankit Jain and Abhishek Srivastava [11] proposed a framework for detecting fire that can monitor personal spaces while safeguarding the privacy of the occupants. A near infrared camera is used to capture images, ensuring the privacy of the individuals within the space. An innovative approach that considers both the geographical and temporal characteristics of fire is employed to effectively identify fires.

Sneha Wilson et al. [12] proposed a vision-based video surveillance system linked with a fire detection system that has low fault alert rates and high detection rates. The system can analyze feeds from live video to detect fire in real-time. To identify dangerous fires, it analyzes the color, velocity, shape, and texture of the flames. The system utilizes color models like HSV and YCbCr for higher detection accuracy for both outdoor and indoor scenes. DongHyun Kim and WonSun Ruy [13] recommended employing mixed channel data (RGB-IR) as a fire detection image-based system that could be deployed on ships. The combined channel data is expected to merge the advantages of the visible spectrum from the RGB data with the infrared spectrum from the IR data, as illustrated in Figure 3.

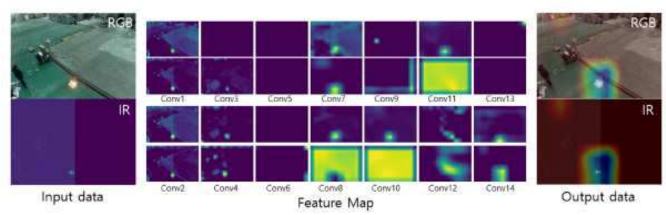

Figure 3. Feature Map of a Model for Detecting Fire Using Grad-Cam (Fire is Predicted) [11].

B. Deep learining

Deep learning models have several advantages over manually coded models. Deep learning systems automatically learn a variety of properties from training data. As a result, deep learning models become more trustworthy and efficient. The richness or diversity of labelled data has a significant impact on the accuracy of a deep learning model. In today's world, rich data may be quickly obtained, cleansed, and labelled over the Internet.

Muhammad Khan et al. [14] proposed a solution by using convolutional neural networks CNNs to process camera photos and detecting the presence of smoke and wildfire. Another study by Jefferson Almeida et al. [15] used a CNN model for detecting wildfires in RGB photos. Viet Nguyen et al. [16] introduced a novel technique for detecting smoke using a camera, a deep convolutional neural network is used.

Meanwhile, Rahul Diwate et al. [17] created a less complex CNN model using AlexNet and GoogleNet architecture as inspiration. On the other hand, Ngonidzashe Mwedzi et al. [18] suggested a model that enhances the home fire alarms performance and reduce false alarm scenarios by using of modern image processing and classification techniques. Dewi Lestari et al. [19] presented a different approach that uses CCTV cameras to identify fire hotspots. Artificial intelligence and other technologies were employed to evaluate CCTV data, to identify fire hotspots on CCTV footage, using YOLO approach. Kewei Wang et al. [20] developed a novel technique to detect fire in infrared (IR) video surveillance bas.ed on support vector machine (SVM) and CNN. Meanwhile, Pu Li and Wangda Zhao [21] presented a novel technique for image fire detection based on object recognition using strong CNN models, including YOLOv3, SSD, R-FCN, and Faster-RCNN. Alternatively, James Pincott et al. [22] developed a solution that recognizes interior fire and smoke dependent on eyesight. They used models that already exist based on the SSD MobileNet V2 and the Faster R-CNN Inception V2 models. Sergio Saponara et al. [23] [24] use the YOLOv2 to show live detection for smoke and fire using video for anti-fire surveillance systems. They also proposed a detection method using Region Convolutional Neural Networks (R-CNN) to quantify smoke and fire characteristics in constrained interior or outdoor video surveillance environments. The application scenario includes a signal and a fixed camera for each scene that works in the visible spectral range and is integrated into a surveillance CCTV system.

A. Q. Nguyen et al. [25] suggested developing a real-time solution for using unmanned aerial vehicles for detecting fire by integrating alarm systems and optical detection for monitoring wide areas. The device includes telemetry modules, localization, a flight controller, a cheap camera, and a portable computer. Parth Mehta et al. [26] used the YOLOv3 algorithm to release a deep learning model that evaluates video frames in real-time to detect irregularities and generate notifications for the appropriate authorities.

Meanwhile, Ravi Sha and Tapas Guha [27] proposed a solution that uses security cameras as the primary instrument for detecting smoke. The recommended strategy consists of two main stages. Optical flow is used in the first stage for detecting movement between sequential frames. Smoke is detected in the stage two using a deep CNN in moving locations. Alternatively, Moin Ahmed et al. [28] proposed a variant of CNNs inspired by GoogleNet for detecting fire in binary settings. Their network performs better while being less expensive and less complex, making it easier to interact with embedded devices like CCTV security cameras to identify fires before they spread and help the emergency services. Sudhakar K et al. [29] suggested a model for low-cost fire detection infrastructure using CNN architecture inspired by GoogleNet, which is more suitable for challenge than other expensive networks like AlexNet and has a lower processing complexity. Dilanga Abeyrathna et al. [30] developed a two-module, multi-stage system that obtain anomalous area recommendations using a convolutional autoencoder module and select region recommendations using a CNN classifier. The recommended strategy is good for a live fire detection system. which uses security cameras. G.Sathyakala et al. [31] elaborated a solution that alert a distant fire station and detect fire using computer vision technologies. This warning includes a video and an emergency message to help the emergency services determine how many people are in the room. In their study, they detected fires with OpenCV and a Raspberry Pi, sent a brief video to a fire alarm control unit outside the building, and issued alarms within the building, and. Alexander Filonenko and Kang-Hyun Jo [32] developed a fire flame detection algorithm that is appropriate for contemporary surveillance systems without requiring changes to the settings. The algorithm generates every color and shape characteristic using internal images and combines parallel computing on the graphics processing unit and central processing unit cores to reduce processing time. Detection is resistant to camera jitter and rotation because it does not rely on background erasure.

Al.maamoon Rasool Abdali et al. [33] have introduced a deep learning model that detects real-time fire. This model incorporates a Long Short-Term Memory (LSTM) network for temporal relation learning and a CNN for spatial feature extraction. Their focus during the development was to achieve an optimal balance between overall generality, accuracy, and fast response time. Through extensive testing on an extended dataset, this proposed model achieved an impressive accuracy of 95.39% while processing 120 frames per second.

C. Transfer Learining

Transfer learning refers to the application of a model that was previously learned to a new problem. Its ability to train deep neural networks using small amounts of data has made it popular in deep learning and beneficial in data science, as real-world examples often lack the millions of labeled data points required to train complex models.

Abdul Bari et al. [34] observed that transfer learning was used to utilize Deep Learning models that used the ImageNet Dataset for training. For transfer learning and in-between comparison, they used pre-trained InceptionV3 and MobileNetV2 models. Saima Majid et al. [35] proposed an architecture based on transfer learning for detecting fire that utilizes cutting-edge CNNs trained on real-world fire breakout photographs.

Mijanur Rahman et al. [36] used 14 different types of atypical images to develop a more complex ResNet-50 model to learn atypical patterns. The proposed system uses the input from real-time video, separates video frames, and feeds the data directly to the well-trained CNN model. After examining each frame to identify abnormalities, the model generates an ordered list of categorized frames, along with the type of expected abnormality and its likelihood. When there is a change in the output frame label, a warning notification is generated, and an alarm is activated. If there is a normal label on frames, no warning is generated.

D. Internet of Things (IoT)

Nikhil Komalapati et al. [37] presented a fire detection system that modifies the Arduino IDE to sound an alarm, send to a Telegram account a warning message, and track the ESP32's internet movements as a notice on any mobile device to prevent people from accessing the fire area during emergencies. The movement of a warning message across a Telegram account can be used to develop a Telegram bot for an ESP32 with PIR sensors attached. Temperature detection in fire sensors can trigger an alarm through the Telegram channel.

Abdullah Altowaijri et al. [38] developed a system that detects fire maintains a high level of accuracy while respecting the privacy of the surroundings. The suggested solution uses the cloud to detect fires, but instead of sharing the actual video collected by the IoT device, it sends characteristics derived from it. The fire detection technique uses binary video descriptors and CNN. While CNN is used for classification, extracting features is done using video descriptors.

III. DataSets

Studies discussed above are concerned with early fire detection, with different tactics but the same purpose. Many studies attempt to recognize fire using the color and motion aspects of flames, while others employ machine learning approaches such as transfer learning. Many authors use deep learning approaches such as CNN and RNN because the richness or diversity of labelled data strongly influences the accuracy of a deep learning model.

Detecting objects demands a large number of images in the dataset. The dataset is used for training, testing, and validation. With the availability of abundant and easily accessible data on the internet, obtaining, cleaning, and labeling the data has become convenient. There are several datasets available specifically for fire detection:

- *The Foggia Dataset* contains 9521 images for fire and smoke detection, split into 6659 images for training, 1903 images for validation, and 959 images for testing [39].
- *The Furg Fire Dataset* contains fire movies with frame-by-frame annotations, to test detection algorithms for non-stationary fire. The enhancement of fully autonomous firefighting robots is accelerated by the collection of videos from hand-held, robot-mounted, and drone-mounted cameras [40].
- *The Corsican Fire DataSet (CFDS)* currently includes 500 pictures collected only in the visible range, 100 pairs of images acquired simultaneously in the visual and near-infrared ranges, and five sets of image pairs acquired concurrently in the near-infrared and visual ranges [41].
- *The Wildfire Images Dataset* has been specifically compiled to address the issue of detecting forest fires. All the images in the dataset have three color channels and a resolution of 250 × 250 pixels. The dataset is designed for binary classification, where the goal is to distinguish between images that depict forest fires and those that do not. It is balanced, with a total of 1900 images, evenly distributed between the two classes. To facilitate training and testing, the dataset has been divided into an 80:20 ratio [42].
- *The Intel Image Classification Dataset* comprises approximately 25,000 images, each measuring 150 by 150 pixels. The images are categorized into six distinct groups [43].
- *The Fire and Smoke Dataset* was compiled by DataCluster Labs. The collection contains over 7000 original images of fire and smoke, sourced from over 400 urban and rural areas through crowdsourcing. Each image has undergone manual review and verification by computer vision experts at DataCluster Labs, making this a particularly challenging dataset [44].
- *The Fire-Flame-Dataset* was created with the aim of training machine learning models to accurately identify images depicting fire, smoke, and those that do not depict either. The dataset comprises approximately 3000 images, categorized into three classes: neutral, smoke, and fire. Each class includes 1000 images, with 900 allocated for training and 100 for testing purposes [45].
- *The Fire 2018 Dataset* contains 755 outdoor images depicting fires, some of which also feature dense smoke, and 244 images of natural scenery, such as lakes, trees, foggy forests, forests, grass, roads, rivers, waterfalls, animals, and people, with no instances of fire present [46].
- *The Internet Movie Firearm Database (IMFDB)* was established in May 2007 by "Bunni" with the primary objective of identifying firearms used in Hollywood movies. Initially, the database only featured a small number of movies, such as Pulp Fiction, Platoon, and The Matrix. Over time, the site expanded to include other forms of media. By June 2007, the database started listing shows from the television, and it has since grown to encompass anime and video games. As of June 2012, the IMFDB has significantly expanded, with a total of 686 video games, 1,925 TV shows, 6,445 films, and 423 anime films and series listed in its database [47].
- *The URG dataset* has been constructed using genuine network traffic and the latest known attacks. The data was obtained from various NetFlow v9 collectors located at strategic points throughout the network of a Spanish Internet Service Provider. The dataset consists of two categories of data separated into weekly intervals: a calibration dataset and a test dataset [48].
- *FireNet* includes an annotated dataset consisting of a total of 502 images, divided into two sets. The training set and the validation set has 412 images, and 90 images [49].
- *The BoWFire Dataset* comprises two sets of images: the training set and the test set. The training set contains 240 images, each measuring 50 by 50 pixels in resolution. Of these, 80 images have been classified as fire images, while the remaining 160 images are considered non-fire images. It should be noted that the non-fire images may contain yellow or red objects. The test set comprises 226 images of

various resolutions, categorized into two groups: 119 fire images and 107 images that do not contain fire. The fire images depict various emergency scenarios, including industrial fires, riots, building fires, and car accidents. The remaining images represent emergency situations that do not feature visible fires, as well as images that contain fire-like regions such as yellow or red objects or sunsets [50].

IV. COMPARITIVE ANALYSIS FOR FIRE DETECTION METHODS

In this section, an analysis and summary of the fire detection techniques developed using different datasets, including those mentioned earlier, will be presented. Moreover, a comparative evaluation of recently introduced fire detection algorithms is provided in Table 1

TABLE 1. COMPARITIVE ANALYSIS OF THE DIFFERENT METHODS FOR FIRE DETECTION.

Year	Basic methodology	Model	Dataset	Methodology	Accuracy
2019 [6]	Image processing	This study presents a model that uses the color correlogram feature to differentiate the fire zone from the video frame.	Fire 2018 [43]	Machine learning algorithm is implemented to train the feature vector. With the naïve bayes classifier the algorithm consistently produces fair results. The suggested color correlogram-based automated fire and flame detection algorithm has been proven to be robust and effective.	96.97 %
2019 [7]	Image processing	Image segmentation in this study is done by combining several predetermined and fuzzy criteria	Corsican Fire DataSet1 (CFDS) [38]	In this study, a method is suggested that utilizes multiple predefined and variable image segmentation parameters. By employing suitable image processing techniques, it becomes feasible to recognize the unique color of a forest fire, particularly during late spring and summer when it is easier to distinguish the fire color, which is affected by the surrounding trees and vegetation.	97.7%
2022 [8]	Image processing	Early indoor stopped fire detection-based fire light reflection characteristics	Customed Dataset	The method proposed is based on the reflective properties of firelight and is specifically designed for early detection of fires in confined interior spaces.	92.80%
2019 [10]	Image processing	The camera is used as an image scanner sensor to identify a flame color or shape	NA	This paper presents a flame detection system for images that utilizes image enhancement, segmentation, and filtering techniques through LabVIEW's Vision Assistant. By utilizing color patterns and intensity, the system can identify flames through HSV color filtering.	98%.
2020 [14]	Deep learning	CNN	wildfire images database [39]	In this paper, the authors propose a solution that utilizes CNNs to process camera photos and detect the presence of smoke and wildfires. The results indicate that CNNs are highly effective for image recognition tasks.	97.9%
2021 [17]	Deep learning	Lower complex CNN	Fug from Kaggle [37]	To propose a solution, the authors developed a CNN model inspired by the AlexNet and GoogleNet architectures. This approach improves the precision of fire detection and reduces the occurrence of false alarms.	93%
2019 [19]	Deep learning	YOLO	CCTV videos	The proposed model employs CCTV cameras to detect fire hotspots. The system utilizes various technologies, including artificial intelligence, to analyze CCTV data. To identify fire hotspots in CCTV footage, the authors propose using the YOLO approach.	90%
2018 [21]	Deep learning	A 9-layer CNN named IRCNN	Customed Dataset	The authors developed a unique approach based on CNNs and SVMs to detect fire in infrared (IR) video surveillance.	98.82%
2020 [23]	Deep learning	Object detection CNN models	Customed Dataset	The authors combined advanced CNN models for object recognition, including Faster-RCNN, R-FCN, YOLOv3, and SSD, to develop a novel approach for detecting fires in photos.	83.7%
2020 [26]	Deep learning	CNN	IMFDB [44], UGR [45], and FireNet [46]	In this study, a deep learning model based on the YOLOv3 algorithm examines video frames in real-time to detect anomalies and alert the relevant authorities.	89.3%, 82.6% and 86.5%
2018 [31]	Computer vision	detection method using OpenCV and Raspberry Pi	NA	A fire detection system is proposed that utilizes computer vision technologies to alert a remote fire station. The system sends a warning message containing a video and an emergency message, and the fire station's rescue squad dispatches rescues based on the number of persons displayed in the footage. The system employs an OpenCV-based fire detection approach through a Raspberry Pi.	NA

2021 [34]	Deep Learning	Transfer learning	BoWFire [47], Foggia's dataset [36]	In this study, Transfer Learning was employed to develop a deep learning model using the ImageNet Dataset. For transfer learning and comparison purposes, the authors utilized pre-trained InceptionV3 and MobileNetV2 models.	88% and 87%
2022 [35]	Deep learning	CNN	Wildfires Dataset [39], Fire and Smoke Dataset [41],Smoke Dataset [42], Fire Detection Dataset [46]	The authors proposed a novel transfer learning-based architecture for fire detection, utilizing CCNNs that have been trained on real-world photos of fire breakouts. High values for these parameters demonstrate that the model was generated efficiently and accurately. The resulting model surpassed the performance of most recent solutions to this problem.	95.40%
2021 [36]	Deep learning	Fine-tuned ResNet-50 model	Customed Dataset	In this study, the authors proposed a more sophisticated ResNet-50 model, which was trained on 14 different types of anomalous photos to learn anomalous patterns. The proposed system takes live video as input, dividing it into frames and feeding the data into the trained CNN model. If the output frame label changes, a warning message is created, and an alarm is triggered. No alert is sent when frames are designated as normal.	79.69% for classification and 100% for detection
2021 [37]	IOT	IoT based fire alarm scheme	NA	In this study, the authors developed a detection system using the Arduino Integrated Development Environment (IDE) that triggers an alert in emergency situations, sends a warning message to a Telegram account, and tracks the internet movements of the ESP32 (a microcontroller that can be programmed using the Arduino IDE) as a notice on any mobile device. The authors also utilized the movement of a warning message through the Telegram application to build a Telegram bot for the ESP32 with Passive Infrared (PIR) sensor connection.	NA
2021 [38]	Deep learning	CNN	Foggia dataset [36]	The proposed solution utilizes the cloud to detect fires. Instead of sharing the actual video collected by the IoT device, the system sends derived characteristics. The fire detection technique is based on Convolutional Neural Networks (CNNs) and binary video descriptors.	97.5%

V. Future Work

In order to further improve the fire detection system, several areas of future work can be recommended. Firstly, the accuracy of fire detection could be enhanced by reducing false alarms and improving detection rates. One potential approach could be to explore the use of additional features or attributes to refine the fire detection model. Additionally, the system's real-time detection capabilities could be improved by optimizing its performance to detect fires even faster, possibly through the implementation of more advanced algorithms or hardware optimizations. Another important area of future research is evaluating the scalability of the system. While the current system is effective at detecting fires, it is unclear how well it would perform at scale in larger environments. Therefore, future work could aim to optimize the system's performance to handle large amounts of data and ensure that it can be deployed in a variety of settings.

VI. Conclusion

Fire is one of the most catastrophic natural calamities, claiming lives and destroying property all over the world. As a result, developing a reliable and trustworthy system for early fire detection is vital. Early fire detection improves survival chances. This paper has presented a comprehensive review of vision-based fire detection and localization techniques. It is presented that detection of flames using HSV color filtering involves analyzing intensity and color patterns. While the program is capable of distinguishing between real and fake flames, its accuracy is limited due to the identification of certain pixels from light sources as flames throughout the segmentation process. The most accurate detection of flames occurs when the light source is turned off. The IRCNN architecture achieves the highest level of performance on the IR flame dataset, with F1 score, recall, and precision reaching 98.70%, 98.58%, and 98.82%, respectively. Furthermore, an evaluation of computation time across the SVM classifier and multiple layers revealed that the total computation time is determined by the input image size, with the convolutional layers consuming the majority of the time. Additionally, this algorithm has the capability to classify a minimum of twenty IR images per second, indicating the potential for real-time fire detection using regular IR surveillance cameras.

Through an analysis of various publications, it has become evident that the use of deep learning approaches and computer vision has revolutionized the fire detection field. The applications of these techniques are vast and can be applied to a wide range of environments, including indoor and outdoor settings. There is still possibility for enhancement in terms of detection accuracy, real-time capabilities, and scalability of the system. The identified areas of future research could allow the enhancement of more efficient and effective fire detection systems. Overall, this review provides a comprehensive overview of the state-of-the-art in vision-based fire detection and localization and highlights the potential for further advancements in this field.

VII. References

[1] EPS Security, "A brief history of fire alarm systems," EPS Security, https://www.epssecurity.com/news/eps-news/a-brief-history-of-fire-alarm-systems/ (accessed Jul. 10, 2023).

[2] M. Bistrović, D. Kezić, and D. Komorčec, "Historical development of Fire Detection System Technology on ships," NAŠE MORE: znanstveni časopis za more i pomorstvo, https://hrcak.srce.hr/112621 (accessed Jul. 10, 2023).

[3] Geetha, S., Abhishek, C.S. & Akshayanat, C.S. Machine Vision Based Fire Detection Techniques: A Survey. Fire Technol 57, 591–623 (2021). https://doi.org/10.1007/s10694-020-01064-z

[4] Bu, F., & Gharajeh, M. S. (2019). Intelligent and vision-based fire detection systems: A survey. Image and Vision Computing, 91, 103803. https://doi.org/10.1016/j.imavis.2019.08.007

[5] M. Shakhnoza, U. Sabina, M. Sevara, and Y.-I. Cho, "Novel Video Surveillance-Based Fire and Smoke Classification Using Attentional Feature Map in Capsule Networks," *Sensors*, vol. 22, no. 1, p. 98, Dec. 2021, doi: 10.3390/s22010098.

[6] J. B. Maheen and R. P. Aneesh, "Machine Learning Algorithm for Fire Detection using Color Correlogram," *2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT)*, Kannur, India, 2019, pp. 1411-1418, doi: 10.1109/ICICICT46008.2019.8993246.

[7] D. Dzigal, A. Akagic, E. Buza, A. Brdjanin and N. Dardagan, "Forest Fire Detection based on Color Spaces Combination," *2019 11th International Conference on Electrical and Electronics Engineering (ELECO)*, Bursa, Turkey, 2019, pp. 595-599, doi: 10.23919/ELECO47770.2019.8990608.

[8] Y. Xie *et al.*, "Early indoor occluded fire detection based on firelight reflection characteristics," *Fire Safety Journal*, vol. 128, p. 103542, 2022. doi:10.1016/j.firesaf.2022.103542.

[9] L. Huang, G. Liu, Y. Wang, H. Yuan, and T. Chen, "Fire detection in video surveillances using convolutional neural networks and wavelet transform," *Engineering Applications of Artificial Intelligence*, vol. 110, p. 104737, 2022. doi:10.1016/j.engappai.2022.104737.

[10] D. S. Riyadi and S. Aisyah, "Vision Based Flame Detection System For Surveillance Camera," *2018 International Conference on Applied Engineering (ICAE)*, Batam, Indonesia, 2018, pp. 1-6, doi: 10.1109/INCAE.2018.8579405.

[11] A. Jain and A. Srivastava, "Privacy-Preserving Efficient Fire Detection System for Indoor Surveillance," in *IEEE Transactions on Industrial Informatics*, vol. 18, no. 5, pp. 3043-3054, May 2022, doi: 10.1109/TII.2021.3110576.

[12] S. Wilson, S. P. Varghese, G. A. Nikhil, I. Manolekshmi and P. G. Raji, "A Comprehensive Study on Fire Detection," *2018 Conference on Emerging Devices and Smart Systems (ICEDSS)*, Tiruchengode, India, 2018, pp. 242-246, doi: 10.1109/ICEDSS.2018.8544329.

[13] D. Kim and W. Ruy, "CNN-based fire detection method on autonomous ships using composite channels composed of RGB and IR data," *International Journal of Naval Architecture and Ocean Engineering*, vol. 14, p. 100489, 2022. doi:10.1016/j.ijnaoe.2022.100489

[14] M. S. Khan, R. Patil and S. Ali Haider, "Application of Convolutional Neural Networks For Wild Fire Detection," *2020 SoutheastCon*, Raleigh, NC, USA, 2020, pp. 1-5, doi: 10.1109/SoutheastCon44009.2020.9368283.

[15] S. K, A. T, V. J and N. S, "A Novel Lightweight CNN Model for Real-Time Video Fire Smoke Detection," *2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2022, pp. 1056-1060, doi: 10.1109/ICICCS53718.2022.9788293.

[16] V. T. Nguyen, C. H. Quach and M. T. Pham, "Video Smoke Detection For Surveillance Cameras Based On Deep Learning In Indoor Environment," *2020 4th International Conference on Recent Advances in Signal Processing, Telecommunications & Computing (SigTelCom)*, Hanoi, Vietnam, 2020, pp. 82-86, doi: 10.1109/SigTelCom49868.2020.9199056.

[17] R. B. Diwate, L. V. Patil, M. R. Khodaskar, and N. P. Kulkarni, "Lower complex CNN model for fire detection in surveillance videos," *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*, 2021. doi:10.1109/esci50559.2021.9396851.

[18] N. A. Mwedzi, N. I. Nwulu, and S. L. Gbadamosi, "Machine learning applications for fire detection in a residential building," *2019 IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS)*, 2019. doi:10.1109/icetas48360.2019.9117318

[19] D. P. Lestari *et al.*, "Fire hotspots detection system on CCTV videos using you only look once (YOLO) method and Tiny Yolo model for high buildings evacuation," *2019 2nd International Conference of Computer and Informatics Engineering (IC2IE)*, 2019. doi:10.1109/ic2ie47452.2019.8940842

[20] K. Wang *et al.*, "Fire detection in infrared video surveillance based on convolutional neural network and SVM," *2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP)*, 2018. doi:10.1109/siprocess.2018.8600510.

[21] P. Li and W. Zhao, "Image fire detection algorithms based on Convolutional Neural Networks," *Case Studies in Thermal Engineering*, vol. 19, p. 100625, 2020. doi:10.1016/j.csite.2020.100625

[22] J. Pincott, P. W. Tien, S. Wei, and J. K. Calautit, "Indoor fire detection utilizing computer vision-based strategies," Journal of Building Engineering, vol. 61, p. 105154, 2022. doi:10.1016/j.jobe.2022.105154.

[23] S. Saponara, A. Elhanashi, and A. Gagliardi, "Real-time video fire/smoke detection based on CNN in Antifire Surveillance Systems," Journal of Real-Time Image Processing, vol. 18, no. 3, pp. 889–900, 2020. doi:10.1007/s11554-020-01044-0.

[24] S. Saponara, A. Elhanashi, and A. Gagliardi, "Exploiting R-CNN for video smoke/fire sensing in antifire surveillance indoor and outdoor systems for Smart Cities," 2020 IEEE International Conference on Smart Computing (SMARTCOMP), 2020. doi:10.1109/smartcomp50058.2020.00083.

[25] A. Q. Nguyen, H. T. Nguyen, V. C. Tran, H. X. Pham, and J. Pestana, "A visual real-time fire detection using single shot MultiBox detector for UAV-based fire surveillance," 2020 IEEE Eighth International Conference on Communications and Electronics (ICCE), 2021. doi:10.1109/icce48956.2021.9352080.

[26] P. Mehta, A. Kumar, and S. Bhattacharjee, "Fire and gun violence based anomaly detection system using Deep Neural Networks," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020. doi:10.1109/icesc48915.2020.9155625.

[27] R. Sha and T. Guha, "Detection of smoking in inside the office using Deep Learning for CCTV camera," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), 2022. doi:10.1109/icses55317.2022.9914319.

[28] M. Ahmed, A. Gupta, M. Goel, and S. Kumar, "Optimized convolutional neural network model for fire detection in surveillance videos," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022. doi:10.1109/iciccs53718.2022.9788301.

[29] S. K, A. T, V. J, and N. S, "A novel lightweight CNN model for real-time video fire smoke detection," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022. doi:10.1109/iciccs53718.2022.9788293.

[30] D. Abeyrathna, P.-C. Huang, and X. Zhong, "Anomaly proposal-based fire detection for cyber-physical systems," 2019 International Conference on Computational Science and Computational Intelligence (CSCI), 2019. doi:10.1109/csci49370.2019.00226.

[31] G. Sathyakala, V. Kirthika, and B. Aishwarya, “Computer Vision based fire detection with a video alert system,” 2018 International Conference on Communication and Signal Processing (ICCSP), 2018. doi:10.1109/iccsp.2018.8524216.

[32] A. Filonenko and K.-H. Jo, “Fast fire flame detection on videos using AdaBoost and Parallel Processing,” 2018 IEEE Industrial Cyber-Physical Systems (ICPS), 2018. doi:10.1109/icphys.2018.8390782.

[33] A. M. Rasool Abdali and R. F. Ghani, "Robust Real-Time Fire Detector Using CNN And LSTM," *2019 IEEE Student Conference on Research and Development (SCOReD)*, Bandar Seri Iskandar, Malaysia, 2019, pp. 204-207, doi: 10.1109/SCORED.2019.8896246.

[34] A. Bari, T. Saini, and A. Kumar, “Fire detection using deep transfer learning on surveillance videos,” 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 2021. doi:10.1109/icicv50876.2021.9388485.

[35] S. Majid et al., “Attention based CNN model for fire detection and localization in real-world images,” Expert Systems with Applications, vol. 189, p. 116114, 2022. doi:10.1016/j.eswa.2021.116114.

[36] Md. M. Rahman, Mst. S. Afrin, Md. Atikuzzaman, and M. A. Rahaman, “Real-time anomaly detection and classification from surveillance cameras using Deep Neural Network,” 2021 3rd International Conference on Sustainable Technologies for Industry 4.0 (STI), 2021. doi:10.1109/sti53101.2021.9732584.

[37] N. Komalapati, V. C. Yarra, L. A. Kancharla, and T. N. Shankar, “Smart fire detection and surveillance system using IOT,” 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), 2021. doi:10.1109/icais50930.2021.9395841.

[38] A. H. Altowaijri, M. S. Alfaifi, T. A. Alshawi, A. B. Ibrahim, and S. A. Alshebeili, “A privacy-preserving IOT-based fire detector,” IEEE Access, vol. 9, pp. 51393–51402, 2021. doi:10.1109/access.2021.3069588.

[39] “Foggia-11-19-MAP98 object detection dataset by fire detection,” Roboflow, https://universe.roboflow.com/fire-detection-uoeha/foggia-11-19-map98 (accessed Jul. 10, 2023).

[40] C. R. Steffens, R. N. Rodrigues, and S. S. Botelho, “An unconstrained dataset for non-stationary video based fire detection,” 2015 12th Latin American Robotics Symposium and 2015 3rd Brazilian Symposium on Robotics (LARS-SBR), 2015. doi:10.1109/lars-sbr.2015.10'

[41] C. F. Database, “A Propos,” Corsican Fire Database, https://cfdb.univ-corse.fr/ (accessed Jul. 10, 2023).

[42] “1.88 million US wildfires,” Kaggle, https://www.kaggle.com/datasets/rtatman/188-million-us-wildfires (accessed Jul. 10, 2023).

[43] P. Bansal, “Intel Image Classification,” Kaggle, https://www.kaggle.com/datasets/puneet6060/intel-image-classification (accessed Jul. 10, 2023).

[44] Carlo, “Fire_and_smoke.zip,” Kaggle, https://www.kaggle.com/datasets/carlo946/fire-and-smokezip (accessed Jul. 10, 2023).

[45] DeepQuestAI, “DeepQuestAI/fire-smoke-dataset: An image dataset for training fire and frame detection AI,” GitHub, https://github.com/DeepQuestAI/Fire-Smoke-Dataset (accessed Jul. 10, 2023).

[46] A. Saied, “Fire dataset,” Kaggle, https://www.kaggle.com/datasets/phylake1337/fire-dataset (accessed Jul. 10, 2023).

[47] EPS Security, “A brief history of fire alarm systems,” EPS Security, https://www.epssecurity.com/news/eps-news/a-brief-history-of-fire-alarm-systems/ (accessed Jul. 10, 2023).

[48] Author links open overlay panelGabriel Maciá-Fernández a et al., “UGR’16: A new dataset for the evaluation of cyclostationarity-based network IDSS,” Computers & Security, https://www.sciencedirect.com/science/article/pii/S0167404817302353 (accessed Jul. 10, 2023).

[49] FireNet, https://www.firenet.xyz/ (accessed Jul. 10, 2023).

[50] Bitbucket, https://bitbucket.org/gbdi/bowfire-dataset/src/master/ (accessed Jul. 10, 2023).