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Automatic Fire Detection, based on early recognition using deep features

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ABSTRACT

Automatic fire detection has the potential to provide a 24/7 monitoring system for various environments at a relatively low cost. Fire detectors are one of the most reliable ways to detect fire. Once a fire is detected, the system may perform different functions, including alarming the protection system, discharging the fire extinguisher system, or activating the fire sprinkler system. It depends mainly on smoke detector sensors which may not provide reliable results based on different environmental factors. With the help of computer vision, a fire detection system can automatically notify the occupants of a building and emergency services of a fire while it is still in its initial stages. Also, for outdoor environments, such a fire detection system can automatically monitor a large area and alert the appropriate channels at the first sign of a fire. Deep learning techniques have been proven effective in various computer vision tasks. This paper presents a Deep learning method for fire detection that ensures quicker response time and better management of fire incidents which help identify fires early, improving response times and potentially reducing damage. Experiments show promising results of the proposed method compared to the state-of-the-art.

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1. Introduction

Fire detection at first sign is critically important for several reasons, each contributing to the overall safety and security of individuals, properties, and the environment. For environmental Impact [1], early detection helps control fires before they release significant amounts of toxic smoke and pollutants into the atmosphere. Such systems are crucial in preventing widespread environmental destruction. Fire detection systems also, provide early warnings, allowing people to evacuate buildings safely before a fire spreads. This can significantly reduce casualties and injuries during fire incidents. By detecting fires early, fire detection systems can help minimize damage, especially in valuable assets such as museums, libraries, and other places with irreplaceable items. Efficient fire detection allows fire services to allocate resources more effectively, ensuring quicker response times and better management of fire incidents. Also, fire detection systems can alert fire services promptly, enabling them to respond quickly and with appropriate resources, which enhances their safety and effectiveness in firefighting operations.

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Fire detection systems are vital components of modern safety infrastructure. They play a crucial role in protecting lives, properties, and the environment, ensuring operational continuity, and complying with legal and safety standards. Once a fire is detected, the system may perform different functions that help in containing the fire. It depends mainly on smoke detector sensors which may not provide reliable results based on different environmental factors. Automatic fire detection based on computer vision can be an effective tool for fire surveillance. Due to a variety of problems, including an overwhelming number of video screens to monitor, human-based monitoring does not support an effective monitoring system. According to [2], most people's attention drops below an acceptable level after only 20 minutes of observing video surveillance screens. Using computer vision technology provides the potential for a 24/7 monitoring system for various environments at a relatively low cost. With the help of computer vision, a fire detection system can automatically notify the occupants of a building and emergency services of a fire while it is still in its initial stages. Also, for outdoor environments, such a fire detection system can automatically monitor a large area and alert the appropriate channels at the first sign of a fire.

Deep learning techniques have been proven effective in various computer vision tasks. Applying deep features for fire detection can help identify fires early, improving response times and potentially reducing damage. Feature extraction is one of the major problems in computer vision in video surveillance [3]. A significant amount of raw data is needed to represent them. The raw data can be downsized into more manageable sets for processing by using a feature extraction technique. Various methods tackle the problem, handcrafted features and deep learning are two approaches presented for feature extraction. The handcrafted features-based approach provides a way to visualize and analyze features. Still, the feature representation has wide-ranging features that increase computational complexity [3].

The deep learning-based approach extracts features automatically, with no human interaction. The self-learning representations of a deep learning model omit the manual feature extraction stage and work directly with the raw data which provides an end-to-end problem solution. This paper aims to present a method for fire detection that ensures quicker response time and better management of fire incidents. We present an effective system for automatic fire detection based on early recognition using deep features. The proposed method consists of different phases, the primary input to the system is videos including fire and non-fire frames. The model depends on two benchmark datasets [4] and [5]. To improve the model's generalization capabilities a preprocessing step is adopted where resizing, normalizing, and augmenting the images. After that, we fine-tune a pre-trained model on a large dataset like ImageNet to be able to detect fire. Finally, a fine-tuned pre-trained model is used to extract deep features from the images. These features capture distinctive patterns related to fires. Experimental results demonstrate that the proposed method performs favourably against state-of-the-art approaches.

The structure of this paper is as follows: Section 2 includes a literature review of some prior work relevant to the current study. Section 3 describes the proposed approach, whereas Sections 4 and 5 present the results of the experimental work and the conclusion, respectively.

2. Literature review

Automatic fire detection systems offer comprehensive, reliable, and immediate fire protection, enhancing safety, compliance, and operational efficiency. Their ability to provide 24/7 monitoring, integrate with suppression systems, and offer precise and rapid response makes them indispensable in modern fire safety strategies. Many facilities already have surveillance cameras installed, integrating fire detection capabilities into these systems can be a cost-effective way to enhance fire safety without needing entirely new infrastructure.

Several approaches have been proposed in the literature, varying between handcrafted features and deep learning models. In [6], they detect fire through extracting smoke regions from the image based on the self-similarity property of smoke. Their idea was based on extracting smoke regions by noticing the features of smoke regions in the code produced by the fractal encoding of an image.

In [7], proposes an efficient CNN architecture by using smaller convolutional kernels, and fully connected layers, to minimize the computational requirements. In [8], proposed a fire detection method based on the multi-feature fusion of flame motion and color using spatiotemporal relations. Then a support vector machine classifier was used for feature analysis. Li et al. [9] present image fire detection algorithm based on the advanced object detection CNN models of YOLO v3. In [10] a deep learning model has been presented that is able to detect small active fires robustly. On the other hand, [11] proposed a smart fire detection system based on the YOLOv8 algorithm, which consists of the application layer, fog layer, cloud layer, and IoT layer to collect and process data in real-time. In [12] , the authors proposed a hybrid-deep network model incorporating traditional methods with a transfer learning method to gain benefits of both models and improve the detection result. [13] presents a surveillance system developed for the early detection of forest fires. Different deep models were examined for forest fire detection, where the CNN-RCNN network obtained the best results.

3. Proposed work

This paper aims to present a method for fire detection that ensures quicker response time and better management of fire incidents. The detection rate depends on the quality of the features generated from the data set, while computational cost is affected by its length, [14]. The self-learning representations of a deep learning model omit the manual feature extraction stage and work directly with the raw data. As a result, a learned features method is utilized. The learned features are obtained after training a deep-learning model for classification. Training a deep learning model requires lots of training data, powerful GPUs, and memory space to achieve optimal performance. Training a deep-learning model from scratch is challenging. As a result, a pre-trained model of a similar problem expedites the training process. It is known as the transfer learning method. It involves modifying the last fully connected layer to represent the new classes and the remaining layers of the architecture extract features for the new related problem. For fire detection, two CNN architectures are used: the ResNet model [15] and the GoogleNet model [16], which are shown to be more robust than other models [17]. The Resnet50 model main component depend on the default model input data which is a 3-channel image of 224 × 224 pixels. The Resnet50 model [15] consists of 50 layers; 48 convolution layers, a max-pooling layer, and an average pooling layer to reduce the dimension of the feature map followed by a fully connected layer using the SoftMax activation function. The max pooling layer selects the maximum element of the feature map covered by a filter. In contrast, the average pooling layer computes the average of the features presented in the region of the feature map. In the GoogleNet model [16], the main idea was a wider network rather than a deeper one as the network with many deep layers might face the problem of overfitting. Its architecture can run on individual devices with low computational resources as it has filters with multiple sizes that can operate on the same level called a dimension-reduced inception module. The GoogleNet model consists of 9 inception modules of 3 different sizes of filters (1x1, 3x3, 5x5) to perform convolution on the input along with 3 x 3 max pooling. The outputs are concatenated and sent to the next inception module.

The learned features results of the GoogleNet model of 22 layers deep compared to the ResNet model of 50 layers deep, both of which were pre-trained on the ImageNet dataset. Figure 1 represents the learned features model, where the input frames are resized to 224 × 224 pixels to fit the model input, and the models were trained for 35 epochs using SoftMax as the activation function, cross entropy as the loss function, and Adam as the optimizer.

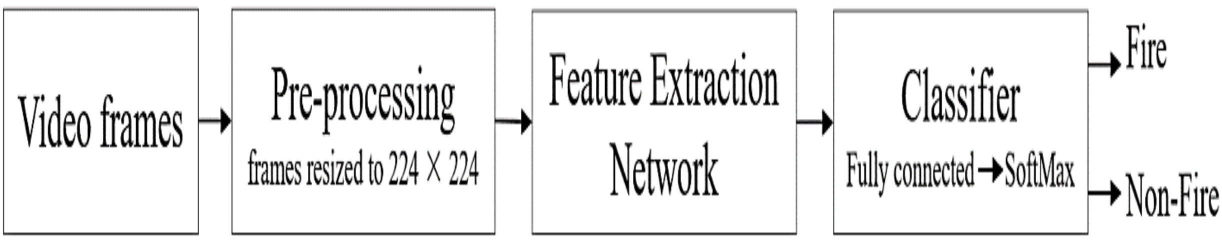

Figure 1. The Learned feature model.

4. Result and discussion

This section clarifies the results of the proposed method and a comparison with the literature. But firstly, we need to clarify the benchmark datasets used for assessing and comparing the performance of the proposed approach. Therefore, two benchmark datasets: Outdoor-fire images and non-fire images are used for fire detection task as shown in Figure 2.

Figure 2. shows a representative example from the dataset where the right column shows a negative sample of fire images, and the left column shows positive samples of fire images

In 2018 [4], a team of four produced a dataset to develop a model to discriminate between fire and non-fire photos in binary classification challenges. The data is divided into two folders: fire images, which comprise 755 outdoor-fire images, some with thick smoke, and non-fire images, which contain 244 nature images such as forest, tree, grass, river, people, foggy woodland, lake, animal, road, and waterfall. In 2019 [5], Atulya Kumar constructed a dataset of around 1000 still images, consisting of flame, smoke, and normal images. The dataset images are split equally into fire and normal images. Each dataset is divided into two sections, 70% is dedicated for training, and 30% is for testing. The model is calibrated using training data, and its performance is measured using test data.

For performance evaluation of the results, classification accuracy (ACC), F1 score, precision (Pr), and true-positive rate (TPR) are the parameters of assessment. To obtain evaluation parameters, we count true-positive (TP), false-positive (FP), true-negative (TN), and false-negative (FN) results to summarize the prediction's success. The TP is fire images, and the prediction result is fire images. FP is the non-fire images, and the prediction result is fire images. TN is the non-fire images, and the prediction result is non-fire images. FN is fire images, and the prediction result is non-fire images. The ACC, F1-score, Pr, and TPR were calculated using Equations (1)– (4), respectively.

$$ACC = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{1}$$

$$F1 = \frac{2*TP}{(2*TP+FN+FP)} \quad (2)$$

$$Pr = \frac{TP}{(TP+FP)} \quad (3)$$

$$TPR = \frac{TP}{(TP+FN)} \quad (4)$$

The learning rate is critical; if it is too high, the best possible outcome is missed, and if it is too low, too many iterations will be required. Therefore, several learning rates are examined for achieving reliable results from the model where the best accuracy is obtained with the 1E-05 learning rate of both models for the two benchmark datasets as shown Table 1. Following the result analysis of the proposed methods, Table 2 shows a comparison between the proposed method with the state-of-the-art methodologies based on detection accuracy. The evaluation of the results indicates that the proposed method achieved reliable accuracy. Also, illustrate the effectiveness of the learned features results of the ResNet model of 50 layers deep compared to the GoogleNet model of 22 layers deep.

Table 1. Feature performance evaluation metrics.

	Dataset1				Dataset2			
	ACC	F1	Pr	TPR	ACC	F1	Pr	TPR
GoogleNet	95.2%	0.925	0.925	0.918	97.6%	0.973	0.974	0.976
Resnet50	97.3%	0.963	0.965	0.962	98.3%	0.988	0.983	0.992

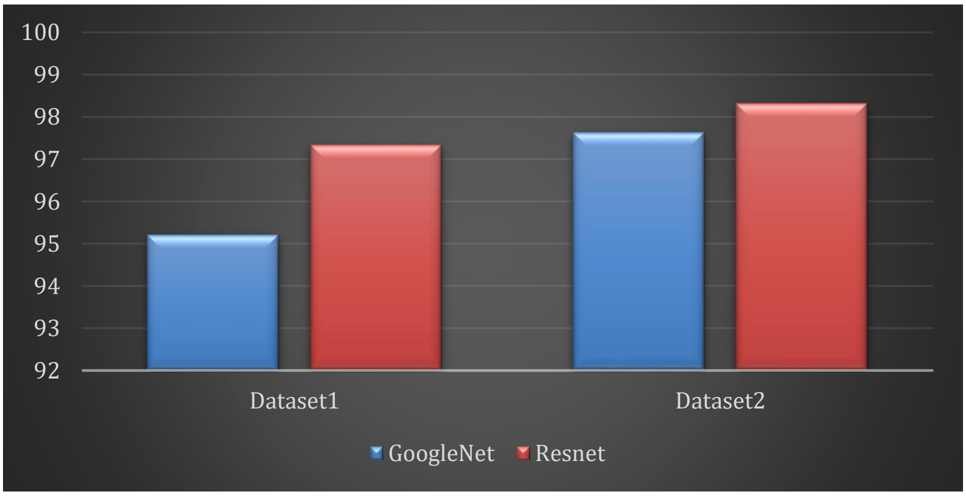

Figure 3. Models' accuracy results.

Table 2. Accuracy comparison of the proposed model with state-of-the-art methodologies.

Author	Method	Acc
Muhammad, K., Ahmad, J., Lv, Z., Bellavista, P., Y, & Baik, S. W., 2018 [7]	SqueezeNet	94.5%
Gong, F., et al., 2019 [8]	SVM	95.29%
Li, P. & Zhao, W, 2020 [9]	YOLO v3	83.7%
Seydi, S. T., Saeidi, V., Kalantar, B., Ueda, N., & Halin, A. A., 2022 [10]	Fire-net	97.35%
Talaat, F. M. & ZainEldin, H., 2023 [11]	YOLO v8	97.1%
Shamta, I. & Demir, B. E., 2024 [13]	CNN-RCNN	96%
Proposed approach	GoogleNet	95.2%
Proposed approach	Resnet50	98.3%

5. Conclusion

Using computer vision technology for fire detection presents numerous advantages over traditional methods, leveraging advanced image processing and machine learning techniques to enhance fire safety. Computer vision technology significantly enhances fire detection by providing early, accurate, comprehensive monitoring. Its ability to integrate with existing systems, reduce false alarms, and provide valuable insights makes it a powerful tool in modern fire safety and prevention strategies. The proposed model can identify early signs of fire even before traditional smoke or heat detectors, by analyzing video feeds to detect visual signs of fire, such as smoke, flames, and heat distortion, allowing for quicker responses and a more comprehensive detection mechanism. Also, it provides real-time surveillance and fire detection across multiple locations, accessible from a centralized monitoring center. From the results shown, ResNet model has a higher performance than the GoogleNet model for both datasets, The two models obtain better results on dataset 2 compared to dataset1, that's due to dataset1 doesn't have an equal number of samples.

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