

# Deep Learning Based Fire Detection System

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**Abstract:** The fundamental necessity of a fire alarm system is to report the occurrence of fire at the earliest. With the advent of computer vision this has become more advanced and reliable. A prerequisite of a Fire Detection System is the detection of fire conditions as early as possible, to provide enough time for Automated Systems/Fire personnel for effective counter actions. Conventional fire detection systems detect and forecasts fire by using by-products of combustible such as smoke, flame, temperature which takes a significant time to develop the required level to trigger heat sensors and smoke sensors. All these situations motivated us to think of a new method of fire detection which uses the technique of computer vision. Computer vision based fire detection systems overcome these limitations since it detects the combustible instead of it are by products. Furthermore, it detects through a camera, which is a volume sensor and covers a wide range from a single camera. The primary objective of this computer vision based fire detection system is to detect the fire, which is done by the method of deep learning, and produce warning alarms if the fire is detected. All of the above clues are combining to form a more efficient fire detection system compared to the conventional systems.

**Keywords:** Conventional fire detection systems, Convolutional neural network, Computer vision.

## I. INTRODUCTION

Fire detection is crucial for safeguarding human life and property. Conventional techniques for fire detection rely on smoke and other by-products of fire for detection. They detect the presence of particles generated by smoke and fire by ionization. This has its own limitations because many factors cannot be assessed such as origin of fire, intensity, direction of smoke propagation, size of fire, growth rate of fire etc.

Another major drawback of conventional systems is that it can only cover small areas because the sensors should be in close proximity to the fire for detection. To get over such limitations video fire detection systems are used.

With the advent of computer vision and image processing, vision based fire detection techniques are widely used in recent times. This technique provides numerous advantages over the conventional system such as quicker response and wider coverage area. Many algorithms are available for smoke and fire detection. These algorithms use convolution neural networks which give way better accuracy in detection than the conventional methods of detection.

The research in this area was started since the nineties. There are several video-based fire and flame detection algorithms in the literature. Most of these algorithms focus on the color and the shape characteristics together combined to the temporal behavior of flame and smoke. For successful detection of fire, certain features must be identified by the system. This can be done using certain feature extractors for identifying the fire.

Deep learning algorithms can learn the useful features for fire detection from a video source. Convolutional neural networks are a branch of deep learning that can extract topological properties from an image.

Therefore, in our approach we use convolutional neural networks to train the system for intelligently detecting fire. This is done by training the system on a very diverse dataset of fire and non-fire images. This can successfully improve the accuracy of detection. This method will hopefully improve the accuracy of detection than the existing vision based models.

## II. RELEVANT WORK

Various methods have been developed for detecting fire from videos and images. This Section includes a description of some

of the important works done in the area of fire detection from images and videos using computer vision and neural networks.

Sebastien Frizzi et.al [1] proposes a convolutional neural network (CNN) for identifying fire in videos. Convolutional neural network are shown to perform very well in the area of object classification. Within the same architecture the network has the ability to perform feature extraction and classification, notifies that using CNN to detect fire in videos is very promising.

A new approach based on deep convolutional neural networks is proposed [2] to improve smoke detection accuracy which can be trained end to end from raw pixel values to classifier outputs and automatically extract features from images. Smoke detection from visual scenes is an event used in many occasions because of its remarkable advantages such as fast response, non-contact and wide detection area. But it is still challenging to recognize smoke accurately from visual scenes due to its large variations in color, texture and shapes. The traditional smoke detection or classification methods extract features manually from input images and then train a classifier to classification, which is often blindness, cumbersome and complex. Especially in the larger image dataset, the performance of traditional algorithms declines relatively fast. To improve smoke detection accuracy, a new approach based on CNN's is proposed, which can be trained end to end from raw pixel values to classifier outputs and automatically extract features that avoids the complex pre-processing of images. Experiments show that this method achieves high detection rates with low false alarm rates on the small dataset and reaches the state-of-the-art level on the large dataset that obviously outperform the existing methods.

In paper [3] adaptive background subtraction to detect foreground moving objects the proposed video fire-detection system is used and then verified by the rule based fire color model to determine whether the detected foreground object is a fire or not.

Paper [4] focuses on the challenge related to the actual deployment of the vision system. The background subtraction is performed in a windowed way for improved accuracy, an attentive mechanism is employed to focus a computationally expensive frequency analysis of potential fire regions, interaction with a people detection and tracking system is inclined so as to enable model-based false alarms rejection, a new color-based model of fires appearance as well as a new wavelet-based model of fires frequency signature are proposed.

Binary hashing and block-wise histogram is discussed in this paper [5] by Tsung-Han Chan et.al. Basic data processing components cascaded principal components (PCA), PCA is employed to learn multistage filter banks in this proposed architecture. It done with two simple variations to the PCANet, called the RandNet and LDANet. The PCANet shares same topology that of the above data set but their cascaded filters are either selected randomly or learned from LDA. They have also tested these basic networks extensively on many

benchmark visual datasets for different tasks, such as LFW for face verification. MNIST for handwritten digits recognition, Multiple, Extended Yale B, AR, FERET datasets for face. The potential of the PCANet serving as a simple but highly competitive baseline for texture classification and object recognition can be demonstrated using additional experiments on other public datasets.

Computer vision based systems which utilize digital camera technology and image/video processing techniques play a very promising role to effectively augment or even replace conventional fire detection systems. In [6], a computer vision based fire detection system employs three major stages: (1) moving object segmentation, (2) fire pixel detection, and (3) analysis of the candidate regions containing fire pixels detected in the first two stages. Most of the works on fire pixel detection in color video sequences are rule-based. Instead of using the rule-based color model uses a mixture of Gaussian distribution which are obtained from a training set of fire pixels represented in the RGB color space.

Jivitesh Sharma [7] proposes the use of deeper Convolutional Neural Networks for fire detection in images, and enhancing these with fine tuning based on a fully connected layer. They uses two pre-trained state of the art Deep CNNs, VGG16 and Resnet50, to develop the fire detection system. The Deep CNNs are tested on our imbalanced dataset, which have assembled to replicate real world scenarios. Finally, it finds that deeper convolutional neural network shows best result on a more challenging dataset, with Resnet50 slightly outperforming VGG16.

Paper [8] proposes a novel method to detect fire and/or flames in real-time by processing the video data generated by an ordinary camera monitoring a scene. In addition to ordinary motion and color clues, flame and fire flicker is detected by analyzing the video in the wavelet domain. Quasi-periodic behavior in flame boundaries is detected by performing temporal wavelet transform. Color variations in flame regions are detected by computing the spatial wavelet transform of moving fire-colored regions. Another clue used in the fire detection algorithm is the irregularity of the boundary of the fire-colored region. All of the above clues are combined to reach a final decision. Experimental results show that the proposed method is very successful in detecting fire and/or flames. In addition, it drastically reduces the false alarms issued to ordinary fire-colored moving objects as compared to the methods using only motion and color clues.

To reduce loss of life and property from fire, an early warning is an imperative. A fire detection system based on light detection and analysis is proposed in the paper [9]. The system uses HSV and YCbCr color models with given conditions to separate orange, yellow, and high brightness light from background and ambient light. Fire growth is analyzed and calculated based on frame differences. The overall accuracy from the experiments has been greater than 90%.

Paper [10] presents an early fire-alarm raising method based on video processing. The basic idea of the proposed of fire-detection is to adopt a RGB (red, green, blue) model based chromatic and disorder measurement for extracting fire-pixels and smoke-pixels. The decision function of fire-pixels is mainly deduced by the intensity and saturation of R component. The extracted fire-pixels will be verified if it is a real fire by both dynamics of growth and disorder, and further smoke. Based on iterative checking on the growing ratio of flames, a fire-alarm is given when the alarm-raising condition is met.

### III. CONVOLUTIONAL NEURAL NETWORKS

A convolutional neural network is that class of artificial neural networks that has been used successfully to analyze visual images. CNNs are primarily used to solve difficult image-driven pattern recognition tasks. Convolutional Neural Networks (CNNs) are similar to traditional ANNs in that they are comprised of neurons that optimize themselves through learning. Each neuron will still receive an input and perform an operation. From the input image vectors to the final output that contains the class score, the whole of the network will still represent a single score function, which is the weight. The only notable difference between CNNs and traditional ANNs is that CNNs are primarily used in the field of pattern recognition within images. This permits us to encode image-specific features into the architecture, making the network more suited for image-specific tasks.

### IV. CNN ARCHITECTURE

The Convolutional Neural Network consists of three types of layers. These include the convolutional layers, the pooling layers and the fully-connected layers. CNN architecture is formed by stacking these 3 layers.

#### A. Convolution Layers

The convolutional layer is responsible for determining the output of the neurons. It performs by calculating the scalar product between their weights and the region connected to the input. The neurons are connected to local regions of the input. The rectified linear unit uses an 'element wise' activation function to the output produced from the previous layer.

#### B. Pooling Layers

The next layer in CNN is the pooling layer. This layer aims to gradually reduce and the computational complexity of the dimensionality of the representation, thereby reducing the number of parameters the model. The pooling layer operates on each activation map in the input, and scales its dimensionality using the "MAX" function.

#### C. Fully-Connected Layers

The final layer in CNN is the fully connected layer. The fully-connected layer consists of neurons that are connected directly to the neurons in the two adjacent layers, without being connected to any layers within them. This is analogous to the way how the neurons are arranged in traditional forms of ANN. The ReLU may be used between these layers, as to improve performance. The CNN converts the original input layer by layer using convolutional and down sampling techniques to obtain class scores for the purpose of classification.

## V. METHODOLOGY

The algorithm uses a convolutional neural network which takes successive frames of the video as input. The system is trained with a well formed dataset of labelled fire images.

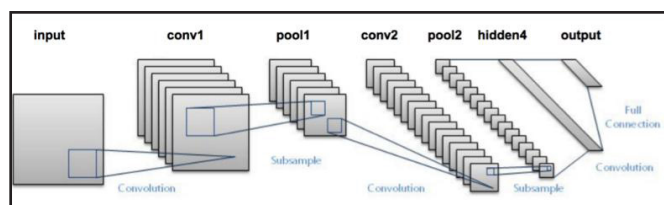


Fig. 1: CNN Architecture

The images was sourced from the internet due to lack of real images of fire. The system uses tensor-flow as machine learning framework and open-cv library is used for real-time computer vision. Then as a result of the system the video containing the fire images will be detected with its respective accuracy.

## VI. SYSTEM ARCHITECTURE

Fig. 2 shows the system architecture of the proposed system

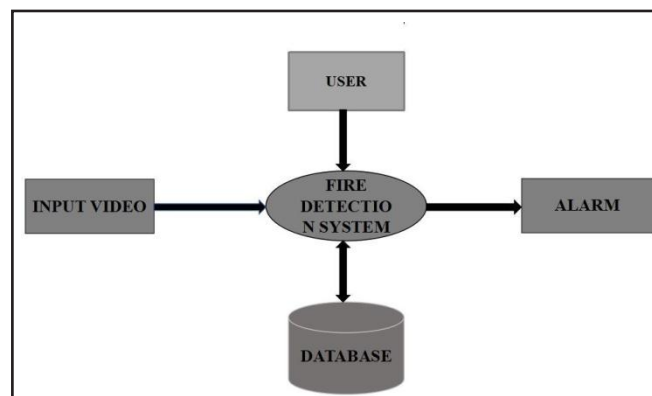


Fig. 2: System Architecture

The input to the system is given as video. The video is then processed inside the system, converting it into video frames. If fire is detected then the output is produced in the form of alarms. The database contains the details of users to which the alert messages are to be sent.

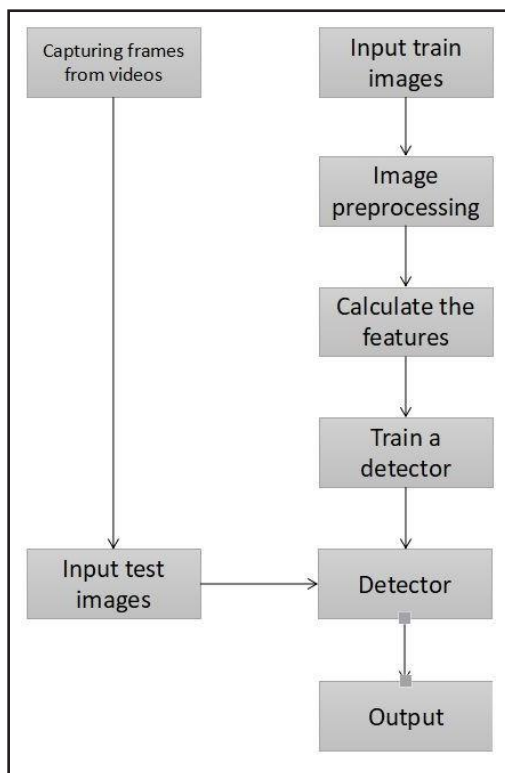
## B. Alarming System

After detecting the fire, it should be notified by rising an alarm. Therefore, an alarm system was designed and implemented. When a fire is detected from the input image frame, a program, write a signal to the serial port. Serial port sends this signal to the electronic device attached to the serial port and it issues an alarm.

## VII. DATA COLLECTION

Dataset used for training the system are set of images containing fire images which the fire part in the image is labelled for extracting the feature of fire and the labelled image is used for training. There are 3000 labelled fire images in RGB form with jpg format. The images are collected from various sources like internet, by capturing real time fire images etc.

## VIII. NETWORK ARCHITECTURE



The input video that is captured from the camera is first converted into video frames. These video frames, that acts as the input test images are then given as input to the detector. The detector is first trained with the help of a set of input train images from the collected dataset. This dataset consists of several images of fire. The detector is then trained by extracting the features from these train images so that it detects correctly. Based on the output from the detector, warning messages and alarms are produced.

## IX. NETWORK TRAINING

The initial training can be done using the entire dataset, where over 3000 images were processed over the course of ten hours. An increase in the accuracy of the model is given by an increase in the loss incurred during validation; hence the weights defining the network topology are only updated when such an increase in validation loss occurs.

The proposed CNN-based model is implemented based on the tensor-flow deep learning framework and executed on a NVIDIA GeForce GTX 1080ti GPU. We set the parameters of momentum to 0.9, and weight-decay to 0.0005. The initial learning rate is set to 0.001. The learning rate update policy is set to with the gamma value of 0.0001 and the power value of 0.75. We set the batch size for training to 64, namely 64 image patches (as positive and negative samples) are input for each iteration. After 200000 iterations, we obtained the trained CNN-based model with trained weights and parameters for testing

## X. EXPERIMENTAL RESULTS

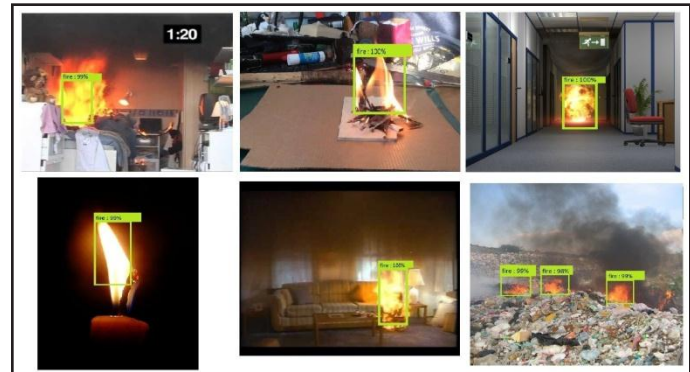


Fig. 3: Test Results

The results obtained show the detection of in the images. The area with fire is enclosed within a green box and it also gives the accuracy of fire as detected by the system.

## XI. CONCLUSION

Deep learning based detection systems have overcome the limitations of common smoke and heat detectors like since it detects the combustible instead of its by products such as smoke, heat etc. This paper proposed a video-based fire alarming system by analyzing the image sequences acquired from a video source. The performance of this system has been verified practically and following salient features were identified. The fire can be detected at its inception. The performance of the system was tested with a video sequence consist of a candle fire and it was detected. This gives a strong evidence for its ability to detect fire at its inception. This allows relevant authorities to combat fire immediately minimizing damages caused by fire.

The detection time is about 2 to 10 seconds at a range of about 3 meters. The detection time is comparatively lesser than other conventional fire detection system. By using deep learning technique, it is possible to get better results than conventional systems because images obtained from camera detect the fire itself. The range is increased by using high resolution cameras and the detection time is reduced by using high processing power CPU with real time image processing software like Open-CV. The reliability and efficiency of the conventional fire detection system can be increased by integrating proposed video-based system in parallel to the conventional system. The proposed algorithm can be easily integrated to existing security surveillance system by utilizing the existing CCTV cameras. Feature extraction of the image depends on the quality of the acquired images. Therefore, the accuracy can be enhanced by a proper selection of the imaging device. Due to all these drawbacks in the existing algorithms, we came to the conclusion that CNN's give more accurate results.

#### REFERENCES

1. S. Frizzi, R. Kaabi, M. Bouchouicha, J. M. Ginoux, E. Moreau, and F. Fnaiech, "Convolutional neural network for video fire and smoke detection," *42<sup>nd</sup> Annual Conference of the IEEE Industrial Electronics Society*, 2016.
2. C. Tao, J. Zhang, and P. Wang, "Smoke detection based on deep convolutional neural networks," *IEEE International Conference on Industrial Informatics*, 2016.
3. A. E. Gunawaardena, R. M. M. Ruwanthika, and A. G. B. P. Jayasekara, "Computer vision based fire alarming system," *IEEE* 2016.
4. P. Santana, P. Gomes, and J. Barata "A vision-based system for early fire detection," *2012 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 14-17, 2012 October.
5. T. H. Chan, K. Jia, S. Gao, J. Lu, Z. Zeng, Y. Ma, "PCA Net: A simple deep learning baseline for image classification," *IEEE Transactions on Image Processing*, vol. 24, no. 12, pp. 5017-5032, December 2015.
6. T. Celik, and K. K. Ma, "Computer vision based fire detection in color images," *IEEE Conference on Soft Computing in Industrial Applications (SMCia/08)*, June 2008.
7. J. Sharma, O. C. Granmo, M. Goodwin, and J. T. Fidge, "Deep convolutional neural networks for fire detection in images," *Springer International Publishing*, 2017.
8. B. U. Toreyin, Y. Dedeoglu, U. Gudukbay, and A. E. Cetin "Computer vision based method for real-time fire and flame detection," *Elsevier*, 2015.
9. J. Seebamrungsat, S. Praising, and P. Riyamongkol, "Fire detection in the buildings using image processing," *3<sup>rd</sup> ITC International IEEE Conference on Student Project*, 2014.
10. T. H. Chen, P. H. Wu, and Y. C. Chiou, "An early fire-detection method based on image processing," *IEEE International Conference on Image Processing*, 2004.