Fire Detection and Localization Using Surveillance Camera

Department of CSE (AIML)

Project report in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology In the Department of CSE (AIML)

Under the guidance of

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CERTIFICATE

This is to certify that the project titled **Fire Detection and Localization Using Surveillance Camera** submitted by Arindal Char **(University Roll No.**12021002028163), Subham Ghosh **(University Roll No.** 12021002028160), Trisha Roy Choudhury**(University Roll No.** 12021002028158), Subhayan Malick**(University Roll No.** 12021002028168) , Dipra Biswas**(University Roll No.** 12021002028008), Ankan Paul **(University Roll No.** 12021002028098), Ananya Roy **(University Roll No.** 12021002028115), Aindrila Mukherjee**(University Roll No.** 12021002028144), Rounak Chanda **(University Roll No.** 12021002028196), Abhijeet Chowdhury**(University Roll No.** 12021002028087) students of UNIVERSITY OF ENGINEERING & MANAGEMENT, KOLKATA, in partial fulfilment of requirement for the degree of Bachelor of Computer Science and Engineering, is a bonafede work carried out by them under the supervision and guidance of Prof. (Dr.) Rajendrani Mukherjee & Prof. Bijoya Mukherjee during 3rd Semester of academic session of 2021 - 2022. The content of this report has not been submitted to any other university or institute. I am glad to inform that the work is entirely original and its performance is found to be quite satisfactory.

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Abstract

Convolutional neural networks (CNNs) have yielded state-of-the-art performance in image classification and other computer vision tasks. Their application in fire detection systems will substantially improve detection accuracy, which will eventually minimize fire disasters and reduce the ecological and social ramifications. However, the major concern with CNN-based fire detection systems is their implementation in real-world surveillance networks, due to their high memory and computational requirements for inference. In this paper, we propose an original, energy-friendly, and computationally efficient CNN architecture, inspired by the SqueezeNet architecture for fire detection, localization, and semantic understanding of the scene of the fire. It uses smaller convolutional kernels and contains no dense, fully connected layers, which helps keep the computational requirements to a minimum. Despite its low computational needs, the experimental results demonstrate that our proposed solution achieves accuracies that are comparable to other, more complex models, mainly due to its increased depth. Moreover, this paper shows how a tradeoff can be reached between fire detection accuracy and efficiency, by considering the specific characteristics of the problem of interest and the variety of fire data. [1]

Keywords:

Convolutional neural networks, Colour Segmentation, K-Means Clustering,

Data Analysis, Image Processing, Fire Detection.

Introduction

Recently, a variety of sensors have been introduced for different applications such as setting off a fire alarm , vehicle obstacle detection, visualizing the interior of the human body for diagnosis , animal and ship monitoring, and surveillance . Of these applications, surveillance has primarily attracted the attention of researchers due to the enhanced embedded processing capabilities of cameras. Using smart surveillance systems, various abnormal events such as road accidents, fires, medical emergencies, etc., can be detected at early stages, and the appropriate authority can be autonomously informed . A fire is an abnormal event which can cause significant damage to lives and property within a very short time . The main causes of such disasters include human error or a system failure which results in severe loss of human life and other damage . In Europe, fire disasters affect 10000 km2 of vegetation zones each year; in North America and Russia, the damage is about 100000 km2. In June 2013, fire disasters killed 19 firefighters and ruined 100 houses in Arizona, USA. Similarly, another forest fire in August 2013 in California ruined an area of land the size of 1042 km2, causing a loss of 127.35million. According to an annual disaster report fire disasters alone affected494000people and resulted in a loss of 3.1 billion in 2015. In order to avoid such disasters, it is important to detect fires at early stages utilizing smart surveillance cameras.

A variety of sensors are used in different applications such as gas leakage, fire alarm, traffic monitoring. Using surveillance systems, various abnormal events are detected. A fire is also an abnormal event that causes damage to the property and human lives. This is caused due to system failure or human error. Traditional fire alarm system is used to detect fire. Fire alarm system based on sensors such as infrared and optical sensors. These sensors require human involvement to find the location of the fire and it does not provide the size and location of the fire. To detect the fire earlier without human involvement and to reduce false alarms and to improve the accuracy of the detection segmentation and classification based on CNN algorithm is used. The implementation is difficult as Alex net architecture requires 238MB which is large in size. To reduce the size Squeeze net architecture is used as it requires only 3MB and thus saving an extra space of 235MB. Thus the minimizing the cost and makes the implementation more feasible.

Literature Survey

1. **R. Gonzalez-Gonzalez et al.** put forward a method to identify fire by **smoke detection based on wavelet**. Within this method, video signals for image processing is implemented. The SWT (stationary wavelet transform) is implemented for the space or area identification of ROI's (region of interest). This method has three steps. The first step is preprocessing which is executed and then image resizing is done and then grayscale image transformation takes place. Finally indexation is used to index the image. Within second step high frequencies of image is removed implementing SWT (stationary wavelet transform) and then image is rebuild the by inverse SWT. The main purpose of image indexation is to group the intensity colors which are closed to each.

2. **T. Celik and Hasan Demirel et al.** proposed system that implements **statistical color model** for fire pixel classification with Fuzzy logic. Two models developed from the proposed system; luminance- on which the first model is based and chrominance-on which the second model is based on. For separating luminance from chrominance fuzzy logic implements the YCbCr color space (a family of color spaces used as a part of color image pipeline in video and digital platform) instead of color spaces such as RGB(red green blue). This model achieves up to 99.00% correct fire detection rate with a 9.50% false alarm rate.

3. **Hidenori Maruta et al.** put forward a method for detection of smoke which is based on **support vector machine**. In first step preprocessing is executed by identifying moving objects within the images. The preprocessing comprises of five steps: image subtraction and accumulation, image binarization, morphological operation, extraction of Feret's regions and creation of the image mask. Image subtraction is used to extract regions of moving object. In order to eliminate noise like regions binarization and morphological operations are used. The position and approximated shape of the object is obtained by identifying Feret's diameter is called feret's region. Preprocessing is followed by texture analysis and texture features extraction. The component of feature vector is these texture features.

4. **Mehdi Torabnezhad et al.** further enhanced another method that implements **image fusion technique** to detect smoke. Combination of visual and thermal information is used to upgrade the rate of fire detection, in this model. The smoke's invisibility in LWIR (long wave infrared) image can differentiate smoke from smoke alike objects.

[Infrared images can detect smoke like object but could not detect smoke in the images]. Smoke can be distinguished by fusing visible and IR images. In-order to reduce false alarms, PSM (fire detection system) is analyzed by energy calculations and disorder measurements. To detect short range smoke visible and IR image combination algorithm is implemented. This paper's scope is to detect smoke as fire's indicator.
Both smoke like objects and smoke are captured by visible images. Smoke could not be captured by infrared images. Combining these images provides accurate smoke information. Through this approach false alarm generation can be deduced to a great chance. The drawback of this method is Correct and punctual detection of fire is not possible and comparison is required to identify smoke.

This study investigated the performance of their fire detection model by examining a large database of various scene conditions. It shows that the delicacy of the model was 93.97 generation, while false alarms and misses were 7.08 generation and 6.86 generation, respectively. This study proposes a further stage of bank discovery as a strategy to enhance the performance of the fire detection model by removing the thick bank which covers nearly all of the fire. A bank discovery stage is established using both colour and stir characteristics of the bank pixels. It is demonstrated that this stage is effective in detecting the fire area since fire pixels are segmented using both colour and stir characteristics of the bank.
Originally, the areas analogous to fire were detected using the RGB-HIS model. The centroid movement of these areas was calculated using videotape shadows, and a new fire detection methodology was developed. Trial results indicate that this method is effective. The proposed system exhibits a certain practical significance for inner fire discovery as a series of trials demonstrate its capability of excluding the influence of common interferences and triggering fire advising in a timely manner.
Essentially, they trained and tested their system on our custom-built dataset, which consists of images taken from the internet and labelled manually to represent fire and banks. In comparison with the performance of styles based on state-of-the-art infrastructure, our systems performed better and were more complex. Experimental results based on real-world data indicate that our system's performance and complexity are superior.

Problem Statement

Accidents caused by undiscovered fires have cost the globe a lot of money. The demand for effective fire detection systems is on the rise. Because of the system's inefficiency, existing fire and smoke detectors are failing. Analysing live camera data allows for real-time fire detection. The fire flame features are investigated, and the fire is recognized using edge detection and thresholding methods, resulting in the creation of a fire detected model. It detects hazardous fires identified on the size, velocity, volume and the texture. In this paper we are proposing an emerging fire detection system based on Convolutional Neural Network. The model's experimental results on our dataset reveal that it has good fire detection capability and ability of detecting multi-scale fire in real-time.

The detection of objects visually and extensively utilized for alerting the necessary management into open environment as soon as possible. The various kinds of technologies related to detection of fire like the technology depending upon the vision are in demand in the view of researchers because of the constraints in the previously proposed systems of detection of fire as well as the progress in the technologies depending upon the visually processed objects. Detection of fire using vision technology provides three key advantages over traditional fire detection methods: available, controllable, and instant. The cameras ensures that areas in which we are monitoring will be accessing by a visual detection system, allowing preventing guards for controlling the condition in real time. Following that, an ability to control is evident in movements that were collected and accessed after the danger happened due to fire. Lastly, the instantaneity of fire is ensured by a low computing cost and an efficient method.

We avoid the time-consuming efforts of conventional hand-crafted features for fire detection, and explore deep learning architectures for early fire detection in closed- circuit television (CCTV) surveillance networks for both indoor and outdoor environments. Our proposed fire detection framework improves fire detection accuracy and reduces false alarms, compared to state-of-the-art methods. Thus, our algorithm can play a vital role in the early detection of fire to minimize damage.

Fire detection is one of the essential modules in an early warning system, which is used to identify abnormal events in a monitoring area. Fire detectors are used to provide the earliest possible warning of a fire. Conventional fire detectors currently use smoke and temperature sensors. If the sensor is placed in an open and wide area such as a forest, densely populated settlements, and roads, it will be less effective and cost a significant amount of money. In addition, conventional fire detectors have problems regarding delays and alarm sound errors. In other words, the utilization of camera monitoring is currently increasing to ensure citizens' safety. Therefore, it is possible for Closed Circuit Television (CCTV) cameras to detect fires using digital image processing and computer vision technology, referred to as image-based fire detection.

Proposed Solution

- Input Video: Use a Video Reader object to read files containing video data. The object contains information about the video file and enables you to read data from the video. You can create a Video Reader object using the Video Reader function, query information about the video using the object properties, and then read the video using object functions. Timestamp of the video frame to read, specified as a numeric scalar. The timestamp is specified in seconds from the start of the video file. The value of Current time can be between zero and the duration of the video. On some platforms, when you create a Video Reader object, the 'Current Time' property might contain a value close to, but not exactly, zero. This variation in the value of the 'Current Time' property is due to differences in how each platform processes and reads videos.

- Frame conversion: To select the path and file name to video given format upload the movie player. That file to be loaded after play the video it will be converter Frame row and column wise for the frames. At the same time for all frames will be converted and the number of panels. Then the frames all will be write on particular folder, we need to display our values for the frames.
- Preprocessing: In computer graphics and digital imaging, video scaling refers to the resizing of a digital Video. In video technology, the magnification of digital material is known as upscaling or resolution enhancement. When scaling a vector graphic Video, the graphic primitives that make up the Video can be scaled using geometric transformations, with no loss of Video quality. When scaling a raster graphics Video, a new Video with a higher or lower number of pixels must be generated. In the case of decreasing the pixel number (scaling down) this usually results in a visible quality loss. From the standpoint of digital signal processing, the scaling of raster graphics is a two-dimensional example of sample rate conversion, the conversion of a discrete signal from a sampling rate (in this case the local sampling rate) to another.

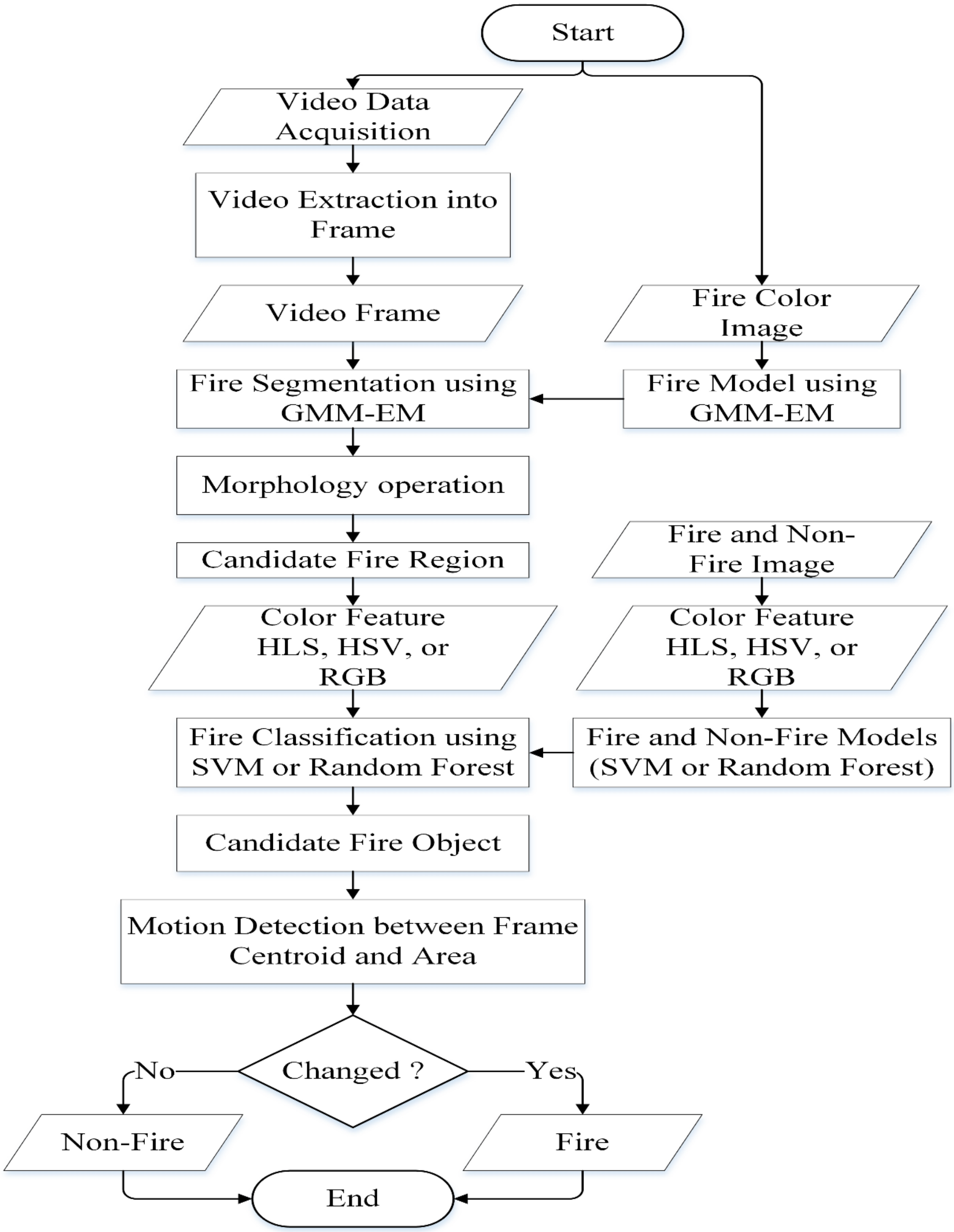
- Color Segmentation: Segment colors in an automated fashion using the L*a*b* color space and K-means clustering. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. You can measure the difference between two colors using the Euclidean distance metric. Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other.

- Segmentation: Video segmentation often requires that the scheme be time efficient to meet the requirement of real time and format compliance. It is not practical to encrypt the whole compressed video bit stream like what the traditional ciphers do because of the following two constraints, i.e., format compliance and computational cost. Alternatively, only a fraction of video data is encrypted to improve the efficiency while still achieving adequate security. The key issue is then how to select the sensitive data to tracks the objects. According to the analysis given, it is reasonable to encrypt both spatial information (IPM and residual data) and motion information (MVD) during encoding.

Training Data Acquisition

In this research, two training datasets were used: the dataset for fire segmentation and fire classification. The dataset for segmentation consisted of 30 images of fire regions in various conditions with the size of 100 × 100 pixels. The features were extracted on this dataset based on the RGB color model for representing the variation in fire colors in the color probability model. Figure 2 shows the selected samples of fire color images used for the segmentation stage. On the other hand, the fire classification stage utilized a dataset consisting of 1124 fire images and 1301 non-fire images created by Jadon et al. [20]. It was produced by capturing photographs of fire and non-fire objects in challenging situations, such as the fire image in the forest and non-fire images with fire-like objects in the background. The dataset was then divided into 80% and 20% for training and testing subsets. Figure 3 shows examples of fire and non-fire images in the forest environment.

(**a**) Fire image samples.



The fire detection system starts by forming a color probability model for the segmenting fire region using the Gaussian Mixture Model and Expectation Maximization (GMM-EM) methods. Then, the model is trained based on a dataset containing varying fire colors. This model would find the fire region candidates in the video frames extracted from the video input. After obtaining the candidates, the machine learning strategies were performed for verifying them based on the color histogram (e.g., HSV, YCbCr, or RGB). This research utilized two machine learning methods: support vector machine (SVM) and random forest (RF). SVM is used because of its ability to classify an object into two classes linearly. On the other hand, RF was chosen because of its ability to combine color and motion features in object classification.

Experimental Setup and Result Analysis

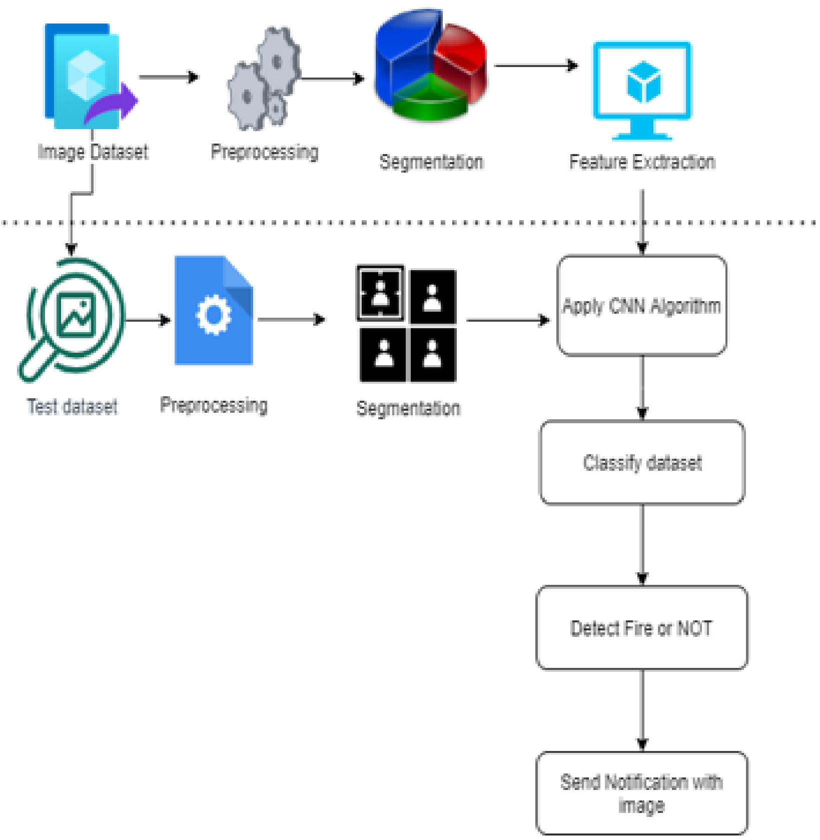
A. Outline

The steps listed below comprise the working model of our system are:

- Collecting footage and converting it into useful information/data
- Data acquisition and analysis
    - Decision making to check fire activity
    - Trigger the alert system via registered mail

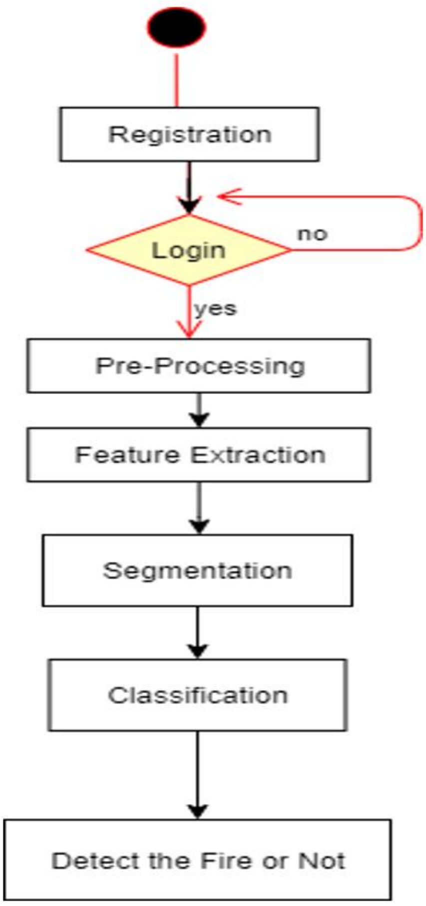
B. Capturing Video And Turning It Into Usable Information

The video is captured using an IP camera that is connected to the remote organiser. The video is processed and broken down into visual outlines once it has been shot. Machine learning models are fed these image outlines. A lexicon of one-of-a-kind terms that appear in all of the dataset photo captions is produced and saved on disc during data cleaning. Informing. The corresponding data is subsequently passed into the following phase.



In the above figure, we get complete information of how image capture to the how image detected and how we get alert message

1. ***Pre-processing****:* In this method we collect all raw data from capturing image frame and perform operation on it is called pre-processing. For example: Training algorithm i.e. CNN on photo which capture by it is result in not good classification results.
2. ***Feature Extraction****:* A CNN is a neural network that extracts image attributes from an input image and classifies them using another neural network. The feature extraction network works with the input image. The neural network makes use of the feature signals extracted.
3. ***Segmentation****:* R-CNN (Regions with CNN feature) is an application of region-based approaches in the real world. On the basis of the object detection results, it does semantic segmentation. R-CNN employs selective search to extract a large number of object ideas before computing CNN characteristics for each one.



Data Flow Diagram

In this diagram we can see how data is used in each step first it take as input then some pre-processing activity is done on it then after we apply CNN algorithm on that data. after that we can detect fire using this data in this process data can be converted into different format like video to frame.

Algorithm

- Create a function to play an alarm sound
- Create a function to send an alert email to the user regarding the fire
- Set Alarm status as false
- Take the video or camera live recording
- Start an infinite loop
- Grab a frame from the video or live recording and store it
- Break out from the loop when there are no more frames to grab
- Blur the image to cancel out some of the noise
- Convert the frame to HSV(hue, saturation ,value) mode
- Set Lower limit [18,50,50] and upper limit [35,255,255]
- If the HSV value is in between upper and lower value then a counter is incremented by one
- If the counter is greater than 1 then
- Check if alarm status is false then
- Switch on the alarm and set alarm status as true
- Send an alert message to the user

Conclusion

The embedded processing capabilities of smart cameras have given rise to intelligent CCTV surveillance systems. Various abnormal events such as accidents, medical emergencies, and fires can be detected using these smart cameras. Of these, fire is the most dangerous abnormal event, as failing to control it at an early stage can result in huge disasters, leading to human, ecological and economic losses. Inspired by the great potential of CNNs, we propose a lightweight CNN based on the Squeeze Net architecture for fire detection in CCTV surveillance networks. Our approach can both localize fire and identify the object under surveillance. Furthermore, our proposed system balances the accuracy of fire detection and the size of the model using fine-tuning and the Squeeze Net architecture, respectively. We conduct experiments using two benchmark datasets and verify the feasibility of the proposed system for deployment in real CCTV networks. In view of the CNN model's reasonable accuracy for fire detection and localization, its size, and the rate of false alarms, the system can be helpful to disaster management teams in controlling fire disasters in a timely manner, thus avoiding huge losses. This paper mainly focuses on the detection of fire and its localization, with comparatively little emphasis on understanding the objects and scenes under observation. Future studies may focus on making challenging and specific scene understanding datasets for fire detection methods and detailed experiments. Furthermore, reasoning theories and information hiding algorithms can be combined with fire detection systems to intelligently observe and authenticate the video stream and initiate appropriate action, in an autonomous way.