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# Adaptive Approach based on CNN-Deep Learning for Fire Detection and Localization in Video Surveillance Applications

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**ABSTRACT:** 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 this research. This paper presents an adaptive approach for fire detection and localization in video surveillance applications. Convolutional neural networks (CNNs) have yielded state-of-the-art performance in image classification and other computer vision tasks. The simulation is performed in the MATLAB software. The simulation results shows that the accuracy is achieved 98.2% while in previous it is 94.5%.

**KEYWORDS:** Fire, Detection, MATLAB, Accuracy, CNN, Colour, Network, Machine Learning.

## I. INTRODUCTION

A digital Video from a photo in that the values are all discrete. Usually they take on only integer values. The brightness values also ranging from 0 (black) to 255 (white). A digital Video can be considered as a large array of discrete dots, each of which has a brightness associated with it. These dots are called picture elements, or more simply pixels. The pixels surrounding a given pixel constitute its neighborhood. A neighborhood can be characterized by its shape in the same way as a matrix: we can speak of a neighborhood, except in very special circumstances, neighborhoods have odd numbers of rows and columns; this ensures that the current pixel is in the center of the neighborhood.



Figure 1: Fire Detection

However, the world is in constant motion: stare at something for long enough and it will change in some way. Even a large solid structure, like a building or a mountain, will change its appearance depending on the time of day (day or night); amount of sunlight (clear or cloudy), or various shadows falling upon it. We are concerned with single Videos: snapshots, if you like, of a visual scene. Although video processing can deal with changing scenes, we shall not discuss it in any detail in this text. For our purposes, video is a single picture which represents something. It may be a picture of a person, of people or animals, or of an outdoor scene, or a microphotograph of an electronic component, or the result of medical imaging. Even if the picture is not immediately recognizable, it will not be just a random blur.

## II. METHODOLOGY

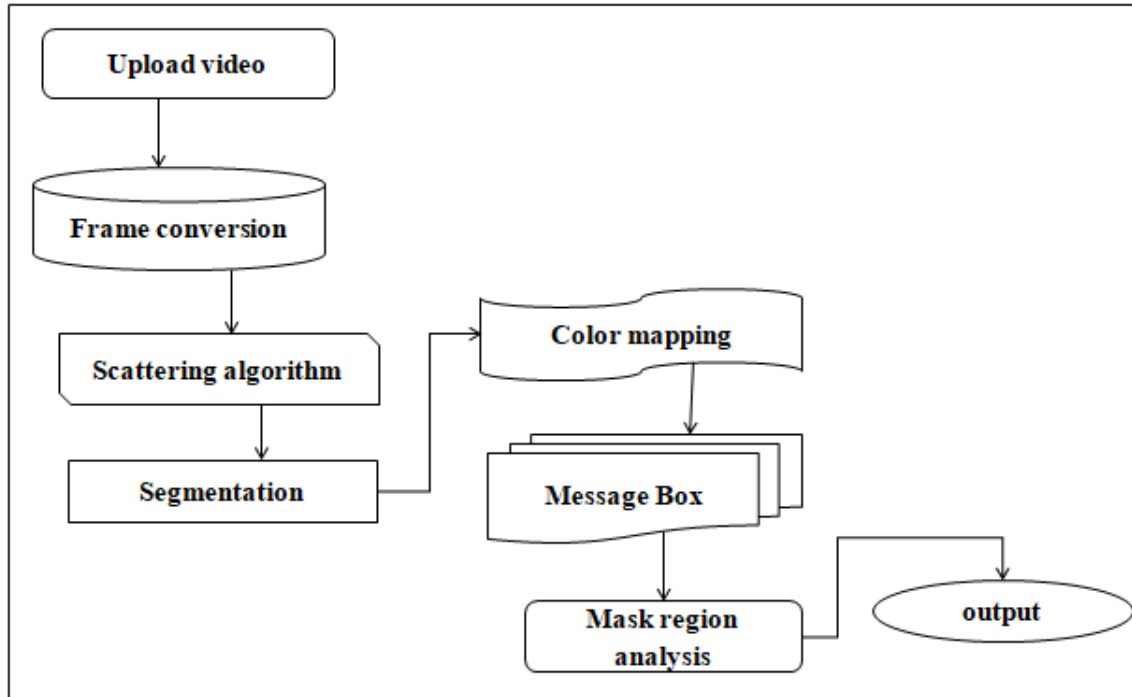


Figure 2: Flow Chart

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.

### K-Means Clustering

- The most common algorithm uses an iterative refinement technique. Due to its ubiquity it is often called the *k*-means algorithm; it is also referred to as Lloyd's algorithm, particularly in the computer science community.
- Given an initial set of *k* means  $m_1^{(1)}, \dots, m_k^{(1)}$  (see below), the algorithm proceeds by alternating between two steps
- K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining.
- K-means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest *m* there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms.
- Additionally, they both use cluster centers to model the data; however, *k*-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.
- The algorithm has a loose relationship to the *k*-nearest neighbor classifier, a popular machine learning technique for classification that is often confused with *k*-means because of the *k* in the name.
- One can apply the 1-nearest neighbor classifier on the cluster centers obtained by k-means to classify new data into the existing clusters an, serving as a prototype of the cluster.

### III. SIMULATION RESULTS

The implementation of the proposed algorithm is done over MATLAB 9.4.0.813654 (R2018a). The image processing toolbox helps us to use the functions available in MATLAB Library for various functions and commands.

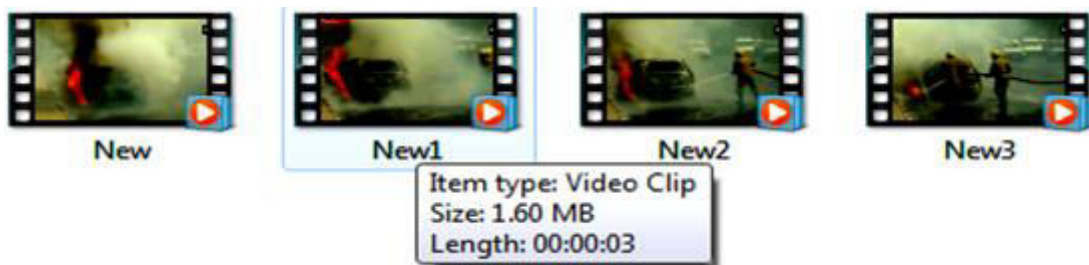


Figure 3: Dataset

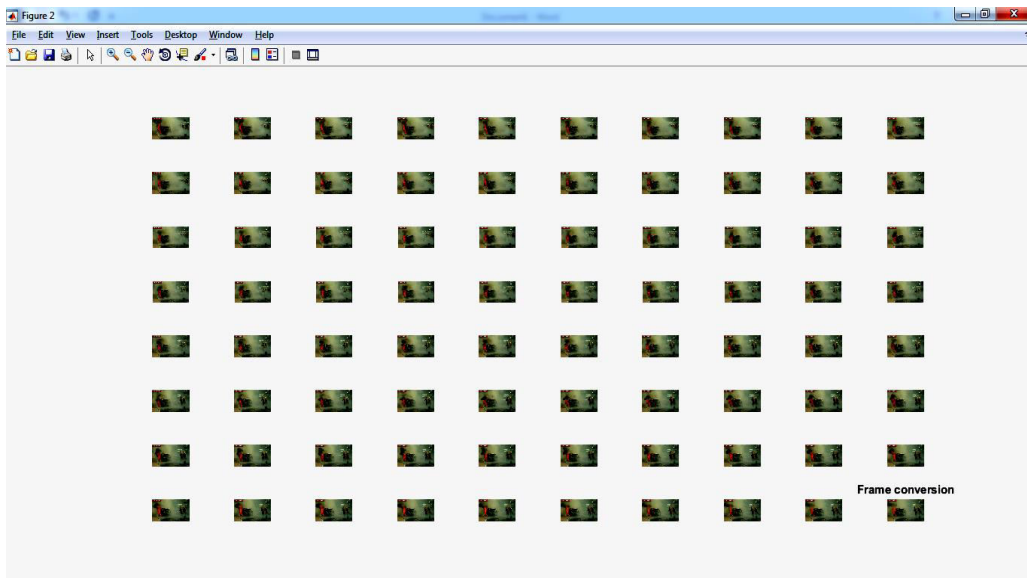


Figure 4: Video conversion in Frames

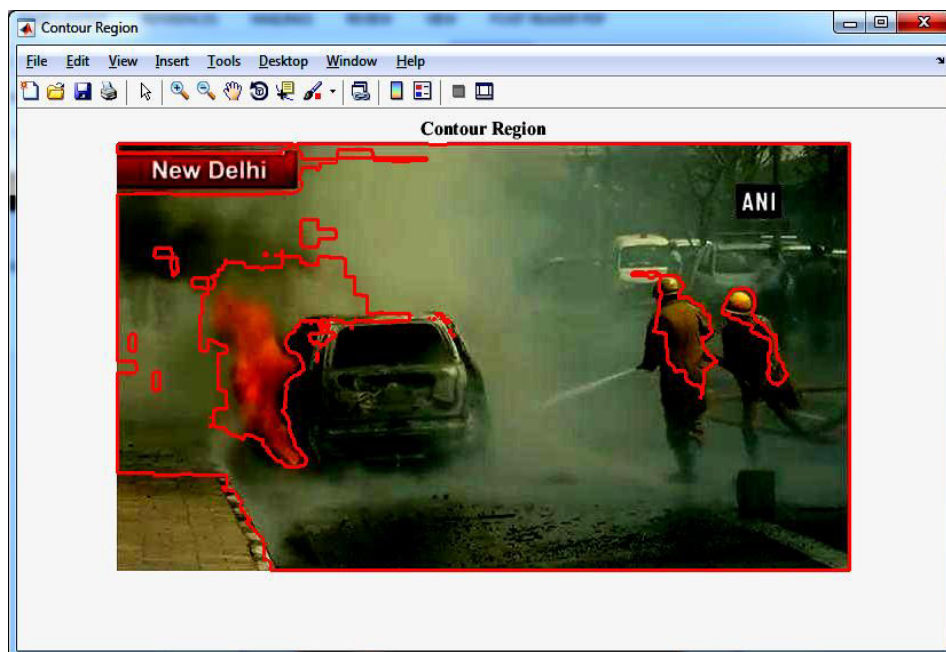


Figure 5: Contour region

Table 1: Result comparison

Sr No.	Parameters	Existing work result	Proposed Work result
5	Accuracy	94.5 %	98.28 %
6	Precision	86 %	93 %
7	Recall	97 %	98 %
8	F_Measure	97 %	98 %



Table 1 is showing the simulation results parameters calculation. The accuracy is achieved 98.2% while in previous it is 94.5%. The other parameters are also improved. Therefore proposed research work provides significant better simulation result than previous simulation results.

#### IV. CONCLUSION

The performance of the proposed process is performed using MATLAB software and results shows that the improvement in the performance parameters with the comparison of the existing methods for fire detection in videos. The problems like segmentation of the similar objects with same color as the fire were handled. The unnecessary moving portions in the videos were effectively eliminated.

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