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Enriching Indoor and outdoor Fire Detection through CNN

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***Abstract*— Fire is a highly useful as well as a dangerous resource that has been utilized by humans since centuries. The only type of fire that is highly useful is the type of fire that is controlled and the energy generated can be used for different purposes. But not all fires are like that and some fires can be extremely devastating. These fires can become large and take down acres and acres of forests leading to extreme death and destruction. There have been recent and highly devastating fires that have rocked major rainforests and decimated a lot of wildlife close to extinction and endangerment. These fires can be stopped if detected when they are in their starting stages and lead to effective reduction in the destruction. There are several techniques such as sensors and other equipment that have been useful in the detection of the fire, but they have not been highly effective and efficient in the deployment. Therefore, an image processing based approach is defined in this research article to achieve effective realization of the fire detection. The proposed approach utilizes Convolutional Neural Networks along with Decision Tree to achieve the effective Fire detection. The experimental results confirm the accurate deployment of the fire detection mechanism.**

Keywords*—Video surveillance, fire detection, Convolutional Neural Networks, Decision Tree.*

1. INTRODUCTION

In our modern life, fire protection has become a top concern, since there are still fire threats surrounding us that can cause a great loss of property and human life. As a result, using a fire alarm system was critical in preventing and responding to the fire when it happened. Both fire detection and alarm systems (FDAS) are designed and implemented with the same basic goal in mind: to detect a fire, to effectively alarm and provide information to residents, and to advise and provide information to first responders. The manner in which these goals are met is determined by the specific circumstances – as well as the norm of the world region in question.

Fire warning systems, on the other hand, are not new; they have been around for a long time. According to the website of Life Safety Consultants, Dr. William F. Channing and Moses Farmer designed the first fire alarm device in 1852. The machine consisted of two fire alarm sets, one with a telegraphic key and the other with a handle. Someone would need to reach into one of the boxes and wrench the handle to transmit a warning to a nearby alarm station if a fire was discovered in a home or company.

When smoke, fire, or other threats arise, a fire alarm system contains modules that work together to identify and warn users using visual and audio methods. It can also call the fire department to monitor all of the area's fire alarm systems. That is as we currently see it.

In several nations, a fire alarm system is one of the most common systems that must be mounted in every home and building. Installing the technology assists in notifying residents of a potential fire and providing early warnings; immediately calling emergency departments and contacts, reducing the time it takes for the fire department to arrive; reducing the possibility of false fire alarms; identifying the exact issue in the case of a fault; and reducing fire damage to buildings.

The message would be relayed to a station dispatcher, who would then contact the fire department, who would dispatch assistance. It was a lengthy process that included multiple phases. Since then, as technology advances, the fire alarm system has evolved as well. The world of fire alarm systems has always been evolving as one of the most prime systems in real life. It will become one of the key focuses of smart house technologies in the future.

Fire, unlike typical substances, has a vigorous texture and it is a dynamic but rare optical spectacle. Computational vision-based fire detection algorithms rely on multi-feature-based approaches due to repeated form and size variations. The aim of such algorithms is to find a set of characteristics whose common occurrence eliminates fire as a possible source. Color, motion, form, development, flickering, and smoke patterns, to name a few low-level characteristics of fire areas. In addition to these defining characteristics, spectral, spatial, and chronological characteristics are often used to differentiate fire zones.

This research article dedicates the section 2 for the related works on fire detection approaches, whereas the section 3 details our solution for the implementation. The section 4 describes the experimental evaluations and the final section concludes the article and provides future directions for the research.

2. RELATED WORK

Ali Rafiee, et al. [1] have described the technique for utilizing image processing to determine fire and distorted smoke caught in an image. They've also created an algorithm for the same reason, in which they tested all of the compounds before checking for the portion of the entity that determines whether or not there's smoke or flames. They used wavelet analysis in addition to motion and colour, which helped to enahnce the system's accuracy and reduce the number of false alarms.

With the specification of Fuzzy Finite Automata, Byoung ChulKo, et al. [2] suggested a system for flame and fire detection (FFA). This approach is extremely effective at identifying unusual fire forms and ambiguous color patterns. The ability to detect asymmetry in fire patterns is improved by combining fuzzy logic with finite automata. Moving objects can be quickly detected using the frame subtraction process, and the fire area can then be identified using the classic color model. This technology has been reviewed on different types of fire videos and has outperformed the competition.

Xiaojun Qi, et al. [3] suggested a system that can detect the existence of fire in a video by itself. They used the temporal difference method to do different studies on fire frames. These tests indicate that the proposed device can recognize fire in a variety of contexts and environments. This scheme takes into account the spatial variety in fire frames, as well as the proneness of fire to congregate near the middle.

Thou-Ho Chen, et.al [4] suggested a method that uses a simple color model to find chrominance, luminance, and a continuously evolving calculation to distinguish fire and smoke pixels. The existence of fire is verified using the RGB color model, which is then double-checked using the growth in motion of fire and the presence of smoke. To set the fire alarm, the machine looks for an improvement in flame ratio. As a result, the device has a lower overall cost as well as a lower false alarm rate.

A range of motion features based on motion estimators has been proposed by Martin Mueller et al. [5]. They used the turbulence effect, as well as the non-smoothness and varying strength of fire, to detect the fire. A characteristic attribute is used to differentiate between the presence of a fire object and the presence of a non-fire object. This technology has been put to the test on a large archive of video to ensure that it works in the real world.
Che-Bin Liu, et al. [6] developed an algorithm that uses geometrical, spatial, and time-related properties to detect the form and presence of fire accurately. After that, the seed region is clipped, which is a promising field of burning. The Fourier transform is used to collect information about the position of pixels that define the shape of fire. The form of fire will never be the same and will evolve over time. As a result, the temporal disparity, together with the AR model, confirms the existence of fire earlier in the process.

S. E. Memane et al. [7] have presented a framework that provides a unified result where both smoke and fire are present. The video analysis provides additional detail about smoke and flames, such as the degree and direction of the fire. The neural network algorithm is used to enhance the method, and optical flow is utilize to track motion. The machine first measures the likelihood of fire and smoke, then applies the feature extraction procedure, and eventually eliminates the unnecessary pixels. For both smoke and heat, the combined production is determined.

Supriya Bhargava, et al. [8] suggested a technique that uses a combination of various category of fire detection mechanisms. In the previous step, they used the gray cycle technique to detect smoke. It immediately confirms the existence of flames. The RGB and YCbCr color models have been utilized to detect the appropriate pixels of fire, and the Area Spread technique has been utilized to define the increasing or declining area of fire. The system's ability to track fire has vastly improved thanks to this mix of techniques.

Turgay Celik and colleagues [9] suggested a fire detection method that uses the YCbCr color model and fuzzy logic to discover the fire area and recognize fire flicker. The YCbCr model is utilized to differentiate between the chrominance and luminance parts of an image. Fuzzy logic is mostly used to differentiate between real fire images and non-fire objects in an image that appears to be a fire image. Through checking the device on two separate databases of images including both fire and non-fire images, the system achieves a very high accuracy rate and a very low false alarm rate.

Chunyu Yu, et al. [10] have proposed a methodology for identifying smoke and fire flames based on front picture aggregation and the optical flow technique. To define the flame field, a mathematical model is utilized. The foreground picture is utilized to build this mathematical model. Optical flow is used to distinguish the areas of smoke. The technique is used to describe the fire zone in three different situations: areas of fire, flame, and smoke, areas of fire but no flame or smoke, and areas of fire and flame but no smoke.

3. PROPOSED SYSTEM

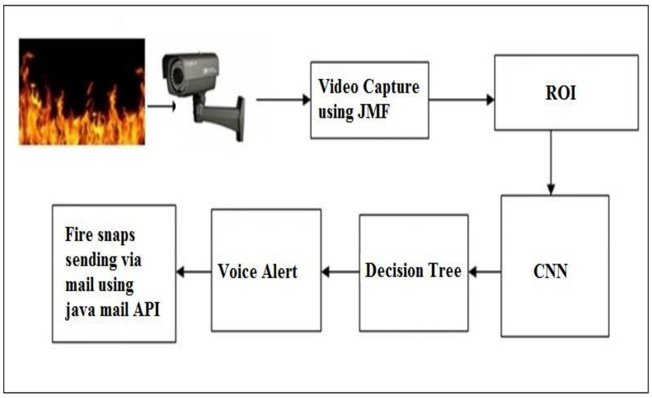

Figure 1: System Overview for fire Detection model

The presented approach for effective and accurate fire detection approach has been elaborated in this research article. The approach specified in this research article has been achieved through the use of Convolutional Neural Networks and Decision Tree, which has been depicted in the figure 1 above, with the steps for the same detailed above.

Step 1: Video Capturing using Open CV – The initial step of this methodology deals with the capturing of the video frames throguh the use of an integrated or a dedicated webcamera. The process of extraction of the video frames from the input stream utilizes the Open CV library.

The frames are extracted from the live stream on a predetermined interval such as 1 or 2 or 3 seconds. The relative frames are grabbed based on the interval and stored in the form of a JPEG file. The obtained frames are then subjected to effective processing in the subsequent steps of the procedure.

Step 2: Region of Interest & CNN (First Layer) – The frames captured in the previous step are utilized as an input in this step of the approach. The captured frames are subjected to color identification of the fire. The color is detected through the effective conversion of the image into a gray-scale image. This is achieved through the extraction of the color components in the image consisting of the Red, Green, and blue components heuristically. Through this process the mean value of the color components is achieved for each of the pixel and the brightness is verified for the threshold for the detection of the color of the fire. The threshold value is usually set as 180.

The pixels that have been identified as the ones containing the fire are effectively tagged as the fire pixels in white color value of 255, otherwise black color value of 0. This procedure is described in the algorithm given below.

ALGORITHM 1: ROI Estimation

```
// Input: Frame image F_IMG ,T_H ( Threshold Value)
//Output: Region of Interest  R_IMG
// function: roiEstimation (F_IMG)
Start
R_IMG = Ø
avg[766]
    for i = 0 to size of avg
        avg[i] = ( (i / 3)
    end if
        for i = 0 to size of Width of F_IMG
        for j=0 to size of Height of F_IMG
            P_SIGN = F_IMG (ij) RGB
            R= ( P_SIGN >> 16 & H_D)
            G= (P_SIGN >> 8 & H_D)
            B= (P_SIGN >> 0 & H_D)
                newpixel=R+G+B
                newpixel= avg[newpixel]

if (newpixel < T_H )
    R_IMG (ij) RGB =(0,0,0)
    else
    R_IMG (ij) RGB =(255,255,255)
    end for
    end for
return R_IMG
Stop
```

Step 3: Network Layer – This is the second layer of the CNN architecture that is being deployed in our fire detection system. This step is performed to achieve the identification of the fire shape in the fire detected frames obtained from the previous layer. The pixel values of the pixels containing the fire are subjected to the calculation of the coaxial ratio, which is the ratio of the current pixel location vs. the height/width of the frame. This ratio, termed as the coaxial ratio is measured through the use of the equations 1 and 2 given below. This is performed for all the fire pixels and the resultant ratio stream can effectively indicates the shape of the fire.

$$M(x) = \sum_{i=1}^{N} P(i,j)/WIDTH \quad \_\_\_\_\_\_\_\_\_\_\_\_\_\_(1)$$

$$M(y) = \sum_{i=1}^{N} P(i,j)/HEIGHT \quad \_\_\_\_\_\_\_\_\_\_\_\_\_\_(2)$$

Where M(x) – Morphology vector related to X axis.
M(y) – Morphology vector related to Y axis.
P(i,j) – Pixel at position i and j
N – Number of pixels in the image

Step 4: Deep Layer – This step of the procedure is the deep layer of the CNN module which is tasked with the identification of the motion of the fire. The fire frames are provided as an input to this layer of the procedure which performs the various processes to achieve the recognition of the motion of the fire. The frames are being grabbed at a set interval of time, T, therefore, at a certain moment there are two frames, the current frame and the previous frame. These two frames are used to identify any differences in the color and shape of the fire which is subjected to a classification through a threshold value. Once the threshold value has been breached, a motion of the fire is recognized. The process is illustrated in the figure 2 given below.

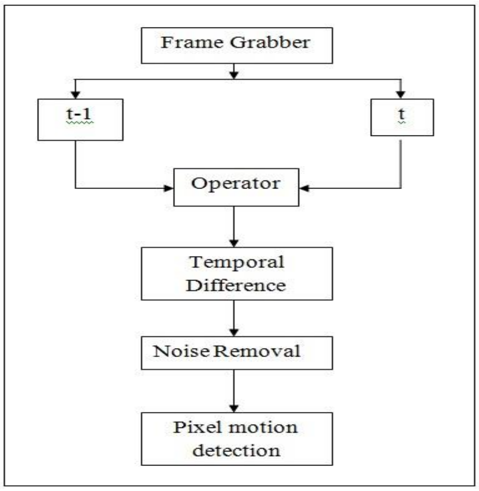

Figure 2: Overview of Fire detection by motion

Step 5: Decision Tree – This is the final step of the approach where the actual detection of the fire is achieved through the use of the parameters achieved previously. The color, shape and the motion of the fire detected in the frames need to be consolidated to identify if there is really a fire. This step of the procedure also eliminates any false positives that are noticed in a large number of implementations that use image processing to achieve the fire detection methodology.

The parameters received in the previous steps are subjected to classification for the detection of real fire. The values achieved are evaluated using if-then rules of the Decision tree that are used for the classification based on threshold values that need to be fulfilled for the fire detection. The threshold values when satisfied through the classification approach, the requisite alarm for the fire is triggered to warn the users of the proposed fire recognition approach.

4. RESULTS AND DISCUSSIONS

The presented technique for the fire detection through the use of Convolutional Neural Networks and Decision tree has been achieved through the use of Java programming language. The NetBeans IDE has been utilized to achieve the coding of the approach on a development machine consisting of 500GB of storage and 4GB of RAM.

The evaluation of the performance metrics of the prescribed approach has been achieved through the use of extensive experimentation using the dataset obtained from this URL - *http://mivia.unisa.it/datasets/video-analysis-datasets/fire-detection-dataset/* .

This dataset consists of a large number of images containing fire which are provided for evaluation by our system as depicted below.

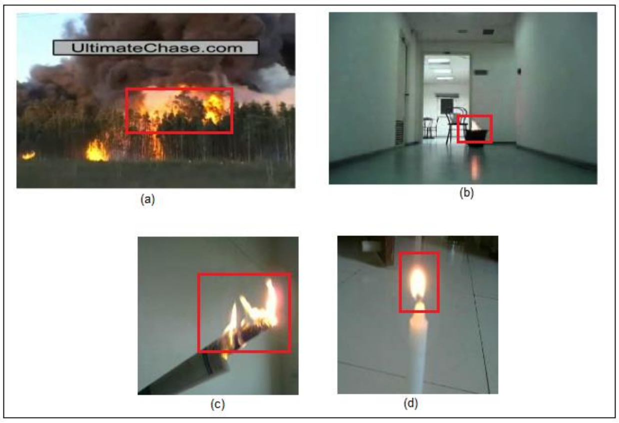

Figure 3: (a) and (b) images shown detection of fire and they are taken from the datasets. (c) and (d) images showing the detection of fire which are collected form the live streaming the videos from our camera.

The realization of the accuracy of the fire detection approach has been evaluated by providing these dataset images to the system and assessing the output received. The use of the MRR or Mean Reciprocal Ratio has been used for the purpose of enabling an evaluation of the fire detection accuracy through the use of human verification. Humans can accurately identify the presence of the fire which can be a great tool in realization of the accuracy of the fire detection system.

Through the use of MRR a rank is designated to the output image between 1 to 6 has been given to the detection performed by the system. The rank of 1 is given to the accurate fire detection whereas the rank of 6 is given to the most inaccurate detection of fire. These ranks are then converted to the respective reciprocal, which transforms the rank of 1 into 1, rank of 2 into ½ so on and so forth with the rank 6 being considered as 0.

The equation 3 and 4 are used for the mean rank identification for the given set of images.

$$S = \sum_{i=1}^{n} 1/(Ranki) \text{ \_\_\_\_\_\_\_ } (3)$$

$$MRR = S/N \text{ \_\_\_\_\_\_\_ } (4)$$

Where n – Number of sample images

MRR is measured for a collection of 25 images that are used for the purpose of evaluation. The outcomes of the evaluation are displayed in the table 1 below.

Table 1: Recorded MRR

Sr. No	Fire Image Types	MRR
1	Office	0.76
2	Forest	0.88
3	Building	0.78
4	Corridor	0.86
	Mean	0.82

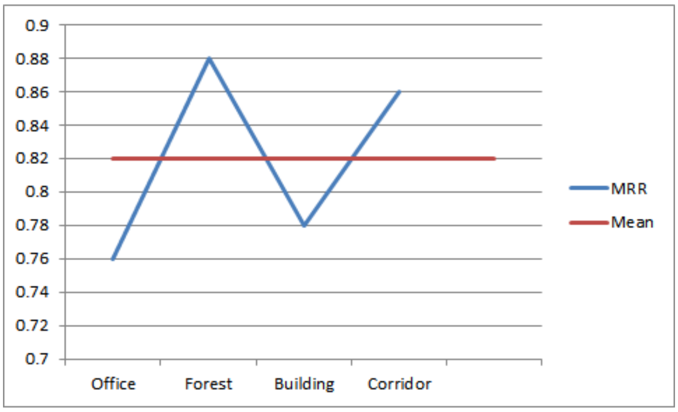

Figure 4: MRR Comparison for Different Types of Images

The figure 4 given above displays the tabulated values in a graphical format for easier reading and understanding. The presented approach for the purpose of achieving fire detection through the use of CNN and Decision tree achieves the MRR of 0.82, which is a respectable outcome for a first-time implementation of such a system for fire recognition.

5. CONCLUSION AND FUTURESCOPE

The presented approach for the purpose of achieving a mechanism for the detection of fire through the use of CNN and Decision tree has been elaborated in this research article. The approach utilizes the Open CV library for grabbing frames from the live video stream from the webcam. These frames are then utilized for resizing and subjected to Region of interest evaluation and color identification through the first layer of the CNN module. The fire pixels according to color is counted and then provided to the next layer for the shape identification. The shape is identified using the second layer called the Network Layer which utilizes the coaxial ratio. The identified fire pixels are useful in this approach which enhances the shape detection of the fire. Once the shape of the fire is identified, it is subjected to the next layer of the CNN. The final layer of the CNN approach is called the deep layer which is tasked with the realization of the motion of the fire. The motion of the fire is achieved through the use of the temporal difference between two consecutive frames. The parameters achieved through the use of CNN module, namely, the color, shape and motion of the fire are provided to the Decision Tree approach for classification. The Decision tree approach utilizes these parameters to classify the actual fire; this implementation also significantly reduces the false positives. The experimental evaluations achieve a MRR of 0.82 which is satisfactory.

The future research directions for such a system would be explored by the realization of such a system in the form of an API for ease in integration.

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