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Onspot Fire Detection and Recovery using Dark Neural Network in IoT

M.Shanmuganathan¹, Jawahar P², Jerry Johnson³, Praveen H⁴

Assistant Professor, Dept. of CSE, Panimalar Engineering College, Chennai, India¹

UG Student, Dept. of CSE, Panimalar Engineering College, Chennai, India^{2,3,4}

ABSTRACT: Convolutional neural networks (CNN Network Dark) have yielded state-of-the-art performance in image classification and other computer vision tasks. Application in fire detection systems will substantially improve detection accuracy, will eventually minimize fire disasters and reduce the ecological and social ramifications. The major concern with CNN Networks-based fire detection systems is the implementation in real-world surveillance networks, due to the high memory and computational requirements for inference. We propose an original, energy-friendly, and computationally efficient CNN Networks architecture, fire detection, localization, and semantic understanding of the scene of the fire. 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. 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

I.INTRODUCTION

With the rapid spread of urbanization in the world, both the number of permanent residents in cities and the population density are increasing. When a fire occurs, it seriously threatens people's lives and causes major economic losses. According to incomplete statistics, there were 312,000 fires in the country in 2019, with 1,572 people killed and 1,065 injured, and a direct property loss of 3.72 billion dollars. Fire detection is vitally important to protecting people's lives and property. The current detection methods in cities rely on various sensors for detection including smoke alarms, temperature alarms, and infrared ray alarms. Although these alarms can play a role, they have major flaws. First, a certain concentration of particles in the air must be reached to trigger an alarm. When an alarm is triggered, a fire may already be too strong to control, defeating the purpose of early warning. Second, most of the alarms can only be functional in a closed environment, which is ineffective for a wide space, such as outdoors or public spaces. Third, there may be false alarms. When the non-fire particle concentration reaches the alarm concentration, it will automatically sound the alarm. Human beings cannot intervene and get the latest information in time. To prevent fires and hinder their rapid growth, it is necessary to establish a monitoring system that can detect early fires. Establishing a camera-based automatic fire monitoring algorithm and FaceNet model. Greatly reducing the cost increases the economic feasibility of such systems. In the preprocessing module, the frame difference detection operates quickly and does not include complex calculations, has low environmental requirements, and does not need to consider the time of day, weather, and other factors. The camera-based fire monitoring system can monitor the specified area in real time through video processing. When a fire is detected based on the video, it will send a captured alarm image to the administrator. The administrator makes a final confirmation based on the submitted alarm image. For example, when an accident occurs on a highway and causes a fire, based on the image transmitted by the detection algorithm, one can immediately rescue the victims, saving precious time and minimizing damage. We combine motion detection based on frame difference with color detection based on the RGB/HSI model. Color detection is only for regions of motion that the motion detection phase is completed. Our method has improved the precision and reduced redundant calculation. In addition, we have improved the frame difference method. According to the spatial correlation between consecutive image frames, we have improved the traditional methods of detecting fire from one single image frame. Temporal information is combined with the flame features through a space-time flame centroid stability-based detection method. At the same time, we combine the data obtained during the fire preprocessing phase to reduce computational redundancy and computational complexity. We extracted various flame features, spatial variability, shape variability, and area variability.

II. LITERATURE SURVEY

Real-time Fire Detection for Video Surveillance Applications using a Combination of Experts based on Color, Shape and Motion Pasquale Foggia, Alessia Saggese and Mario Vento

Propose a method able to detect fires by analyzing the videos acquired by surveillance cameras. Two main novelties have been introduced: first, complementary information, respectively based on colour, shape variation and motion analysis, are combined by a multi expert system. The main advantage deriving from this approach lies in the fact that the overall performance of the system significantly increases with a relatively small effort made by designer. Second, a novel descriptor based on a bag-of-words approach has been proposed for representing motion. The proposed method has been tested on a very large dataset of fire videos acquired both in real environments and from the web. The obtained results confirm a consistent reduction in the number of false positives, without paying in terms of accuracy or renouncing the possibility to run the system on embedded platforms.

An Autoadaptive Edge-Detection Algorithm for Flame and Fire Image Processing, Tian Qiu, Yong Yan and Gang Lu

Proposed that the determination of flame or fire edges is the process of identifying a boundary between the area where there is thermochemical reaction and those without. It is a precursor to image-based flame monitoring, early fire detection, fire evaluation, and the determination of flame and fire parameters. Several traditional edge-detection methods have been tested to identify flame edges, but the results achieved have been disappointing. Some research works related to flame and fire edge detection were reported for different applications; however, the methods do not emphasize the continuity and clarity of the flame and fire edges. A computing algorithm is thus proposed to define flame and fire edges clearly and continuously. The algorithm detects the coarse and superfluous edges in a flame/fire image first and then identifies the edges of the flame/fire and removes the irrelevant artifacts. The autoadaptive feature of the algorithm ensures that the primary symbolic flame/fire edges are identified for different scenarios. Experimental results for different flame images and video frames proved the effectiveness and robustness of the algorithm.

Non-Temporal Lightweight Fire Detection Network for Intelligent Surveillance Systems Hunjun Yang 1, Hyeok Jang 2, Taeyong Kim³ And Bowon Lee¹

Proposed a Convolutional neural networks (CNNs) have been recently applied to tackle a variety of computer vision problems. However, because of its high computational cost, careful considerations are required to design cost-effective CNNs. In this paper, we propose a CNN inspired by MobileNet for fire detection in surveillance systems. In the proposed network, color features emphasized by the channel multiplier are extracted through depthwise separable convolution, and squeeze and excitation modules further increase the representation of the channel-wise convolution. Custom Swish is used as an activation function to limit exceedingly high weights from the effects of the channel multiplier. Our proposed network achieves 95.44% accuracy for fire detection, which is higher than those achieved other existing networks. Furthermore, the number of parameters used is 37.50% fewer than that of MobileNetV2, the smallest among other networks. We believe that using the proposed CNN, CNN-based surveillance systems could be implemented in lightweight devices without using expensive dedicated processors.

III. EXISTING SYSTEM

Convolutional neural networks (CNN) have yielded state-of-the-art performance in image classification and other computer vision tasks. Application in fire detection systems will substantially improve detection accuracy, will eventually minimize fire disasters and reduce the ecological and social ramifications. The major concern with CNN based fire detection systems is the implementation in real-world surveillance networks, due to the high memory and computational requirements for inference. We propose an original, energy-friendly, and computationally efficient CNNs architecture, fire detection, localization, and semantic understanding of the scene of the fire. Uses smaller convolutional kernels and contains no dense, fully connected layers, which helps keep the computational requirements to a minimum.

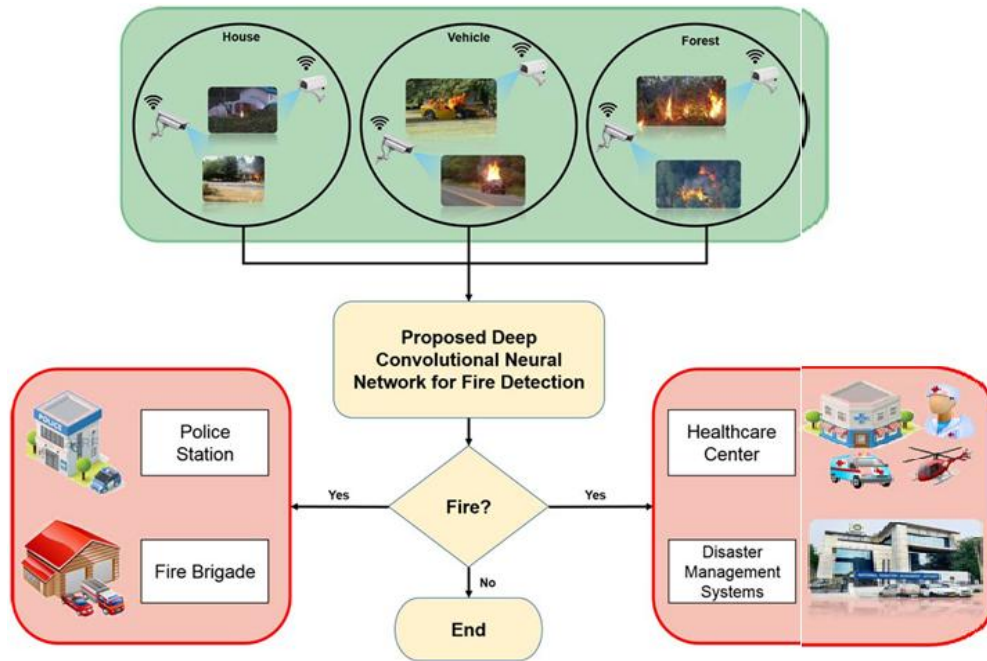


FIG1: Proposed Deep Convolution Neural Network For Fire detection

Algorithm 1 Feature Map Selection Algorithm for Localization

Input: Training samples (TS), ground truth (GT), and the proposed deep CNN model (CNN-M)

1. Forward propagate TS through CNN-M
2. Select the feature maps F_N from layer L of CNN-M
3. Resize GT and F_N to 256×256 pixels
4. Compute mean activations map F_{MAi} for F_N
5. Binarize each feature map F_i as follows:

$$F_{(x,y)bin(i)} = \begin{cases} 1, & F_{(x,y)i} > F_{MA(i)} \\ 0, & \text{Otherwise} \end{cases}$$

6 Calculate the hamming distance H_{Di} between GT and each feature map $F_{bin(i)}$ as follows: $H_{Di} =$

$$\frac{F_{bin(i)} \oplus GT}{\max(F_{bin(i)}, GT)}$$

This results in $TS \times FN$ hamming distances

7. Calculate the sum of all resultant hamming distances, and shortlist the minimum hamming distances using threshold T
8. Select appropriate feature maps according to the shortlisted hamming distances

Output: Feature maps sensitive to fire

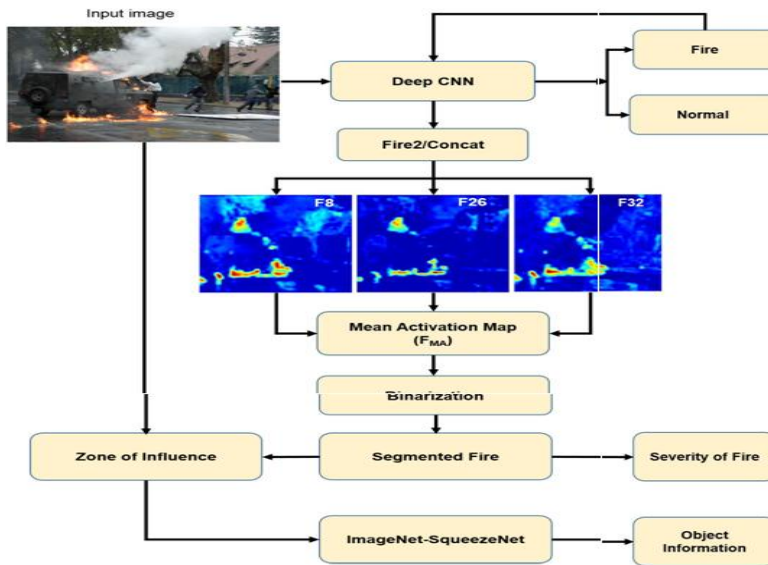


FIG 2: Onspot Fire Detection

IV. PROPOSED SYSTEM

The major concern with CNN Network s-based fire detection systems is the implementation in real-world surveillance networks, due to the high memory and computational requirements for inference. We propose an original, energy-friendly, and computationally efficient CNN Network s architecture, fire detection, localization, and semantic understanding of the scene of the fire. Using Customized dark net CNN Network model Efficiency and Accuracy is improved than the existing model.

Algorithm 2 Fire Localization Algorithm

Input: Image I of the video sequence and the proposed deep CNN model (CNN-M)

1. Select a frame from the video sequence and forward propagate it through CNN-M
2. **IF** predicted label = non-fire **THEN** No action **ELSE**
 - a) Extract feature maps 8, 26, and 32 (F_8, F_{26}, F_{32}) from the “Fire2/Concat” layer of CNN-M
 - b) Calculate mean activations map (F_{MA}) for $F_8, F_{26},$ and F_{32}
 - c) Apply binarization on FMA through threshold T as follows:

$$F_{\text{Localize}} = 1, F_{MA} > T$$

0, Otherwise

- d) Segment fire regions from F_{MA} END

Output: Binary image with segmented fire Ilocalize

V. SYSTEM MODULES

MODULE DESCRIPTION

Data Collection

The anomaly detection system applies Convolutional Neural Network (CNN) to classify 5000 data sets and provides major developments in the experimental result. The CNN Model gives the detection result based on features

established by training dataset. A Deep Learning is established on event classifier trained through 4000 frames of videos. First, randomly selected 1000 images per event category are a training set and 1000 images are a validation set for 4 categories. The CNN model accomplished 100% anomaly detection accuracy on the validation data set after training.

Feature Extractor

In the proposed system, the convolutional network model is constructed with some crucial parameters. The three convolution layers are implemented by the activation function of layers namely, Relu and max pooling layer. In this layer, it has filters. The kernel size is 2×2 . The model is trained for four classes. Since there are four neurons in the output layer. The special activation function of this network for classifying the dataset is categorical-cross entropy.

Training

The training phase of this work has 6 epochs and 4000 training samples to implement the model for extracting crucial features and good training. The needed dataset of video frames are stored in a stack array and modified size as 150×150 . The stacked array of the dataset is changed into a batch file and provides data to the CNN model for the training process. The model extracts the features through epochs to detect the anomaly using separate labels (0,1,2,3) for anomalies namely.

Testing

The final phase of testing in the CNN model detecting the anomaly is in different video events is taken and converted these into frames. 100 datasets of video events are stored in a stack array of a batch file and modified size as 150×150 . The event video frames are collected from different events namely Sports, Protest, Temple, etc. From each video, 30 frames are collected and stored for a test container. In that, 10 false datasets are collected from other videos and stored in the test container. From the batch file, the testing data is sent to the trained model. The CNN model finds four categories of the anomaly and shows anomaly name for each category correctly

VI. CONCLUSION

This project show that reduced complexity CNN, experimentally defined from leading architectures in the field, can achieve 0.93 accuracy for the binary classification task of fire detection. This significantly outperforms prior work in the field on non-temporal fire detection at lower complexity than prior CNN based fire detection. Furthermore, reduced complexity FireNet and InceptionV1-OnFire architectures offer classification accuracy within less than 1% of their more complex parent architectures at 3-4_ of the speed (FireNet offering 17 fps).

To these ends, project illustrate more generally a architectural reduction strategy for the experimentally driven complexity reduction of leading multi-class CNN architectures towards efficient, yet robust performance on simpler binary classification problems.

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