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EFFICIENT FIRE DETECTION FOR UNCERTAIN SURVEILLANCE ENVIRONMENT

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ABSTRACT

Tactile Internet can combine multiple technologies by enabling intelligence via mobile edge computing and data transmission over a 5G network. Recently, several convolutional neural networks (CNN) based methods via edge intelligence are utilized for fire detection in certain environment with reasonable accuracy and running time. However, these methods fail to detect fire in uncertain Internet of Things (IoT) environment having smoke, fog, and snow. Furthermore, achieving good accuracy with reduced running time and model size is challenging for resource constrained devices.

Therefore, in this paper, we propose an efficient CNN based system for fire detection in videos captured in uncertain surveillance scenarios. Our approach uses light-weight deep neural networks with no dense fully connected layers, making it computationally inexpensive. Experiments are conducted on benchmark fire datasets and the results reveal the better performance of our approach compared to state-of-the-art. Considering the accuracy, false alarms, size, and running time of our system, we believe that it is a suitable candidate for fire detection in uncertain IoT environment for mobile and embedded vision applications during surveillance.

Keywords – 5G, Convolutional Neural Networks (CNNs), disaster management, embedded vision, fire detection, image classification, MobileNet, surveillance, Tactile Internet (TI), uncertain Internet of Things (IoT) environment.

1. INTRODUCTION

The connectivity of billions of smart devices have resulted in Internet of Things (IoT) and the maturity of installed sensors is ready for the emergence of tactile Internet (TI), which have several useful applications for E-health, smarter surveillance, law enforcement, and disaster management [1]–[7]. In smart surveillance, edge intelligence plays an important role in security and disaster management. The instant reporting of unusual situations such as disaster in surveillance is very necessary for quick actions. The recent employed approach for instant transmission of such alarming information is 5G TI networks. Disaster management is mainly based on smoke/fire detection, which can be performed using mobile edge computing. The main causes of fire are human mistakes or systems failure, which endangers human lives and properties. The statistics presented in [8] shows that wildfire disaster alone made an overall damage of 3.1 billion USD in 2015 .

For instance, color features for fire detection by exploring different color models including HSI [12], YUV [13], YCbCr [14], RGB [15], and YUC [9] are used in [9]–[16]. The major issue with these methods is their high rate of false alarms. Several attempts have been made to solve this issue by combing the color information with motion and analyses of fire's shape and other characteristics [17]–[20]. However, maintaining a well-agreed tradeoff between the accuracy, false alarms, and computational efficiency still remained a challenge. In addition, several methods from this domain fail to detect fire at a larger distance or small amount of fire

2. MODULE DESCRIPTION

The time-consuming efforts of features engineering makes fire detection a tedious job especially when the surveillance environment is uncertain with snow, fog, smoke etc., or the fire is very small in size or at a long distance. In such situations, generally, the traditional fire detection systems produce a significant number of false alarms with limited fire detection accuracy. Recently, CNN-based approaches are also explored for fire detection but their running time, size, and limited performance in several challenging situations (shadows, fire-like objects, uncertain scenes with smoke, snow, and fog etc.) make them infeasible for resource-constrained surveillance networks. Considering these challenges, we propose an efficient CNN-based method for fire detection in videos captured in uncertain environment. To keep our method computationally inexpensive and effective for small-sized fire at a larger distance, we use light- weight deep neural networks with no dense fully connected layers.

A. CNN-BASED FIRE DETECTION

The literature shows that CNNs have achieved state-of-theart performance for many real- world and challenging problems such as image classification, object detection and recognition [26], action and activity recognition [27], [28], segmentation, localization, image reconstruction, authentication [29], prioritization, indexing [30], and retrieval [31], [32]. The underlying factor behind this success is their hierarchical architecture consisting of convolution, pooling, and fully connected layers via which they automatically learn rich features from raw data.

A convolution layer results in large

number of feature maps from which high activations are selected by a pooling layer for dimensionality reduction and translation invariance. A fully connected layer learns high-level information needed for the target classification problem. In case of fire detection, a CNN architecture is usually changed such that the final fully connected layer has two classes, i.e., fire and nonfire. The input fire data is provided to the intended CNN for training during which the weights of a large number of neurons are adjusted and learnt for classification.

B. DETAILS OF THE PROPOSED ARCHITECTURE FOR FIRE DETECTION

The research community agrees that CNNs can automatically learn rich and discriminative features from raw data. However, much effort is needed to obtain the optimal setting, considering results through evaluation metrics, the amount of available data and its quality, and the problem under consideration.

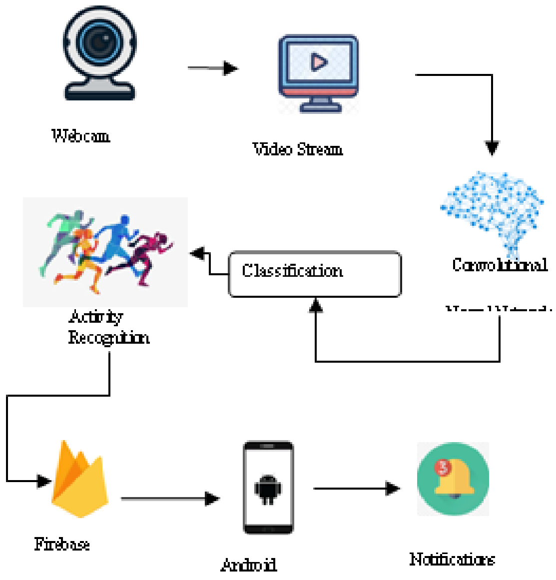
We explored different CNNs with different parameter settings for fire detection considering both certain and uncertain scenarios. After extensive experimentations, we found MobileNet version (V2) better than other models such as AlexNet [33], GoogleNet [34], and SqueezeNet [35]. Thus, we use a model with similar architecture to MobileNet [36] and modify it according to fire detection problem in uncertain surveillance environment. Similar to AlexNet, SqueezeNet, and GoogleNet, the baseline MobileNet is trained on an ImageNet dataset for classification of objects into 1000 classes. Since MobileNet learns much rich features than other CNN models, thus we focused on reusing its learned features for accurate fire detection.

To this end, we kept the number of neurons to two instead of 1000 in the final layer of our architecture, enabling classification into fire and non fire.

C. MOTIVATIONS OF USING MOBILENET (V2) FOR FIRE DETEECTION

Model selection is a critical step especially in resource constrained environment and for applications of critical nature such as disaster management where minor delay can result in a huge loss in terms of humanity and economy. Compared to other CNN models, we use MobileNet due to its higher feasibility for memory and bandwidth-restricted hardware architectures such as field- programmable gate arrays (FPGAs), smart sensors, and raspberry Pi and its suitability to 5G TI- enabled surveillance. The motivation of using MobileNet (V2) [36] compared to MobileNet version 1 (V1) [37] is its reduced size both in terms of number of computations and learned parameters with comparable accuracy.

3. ARCHITECTURE DIAGRAM



4. EXPERIMENTAL RESULTS AND DISCUSSIONS

Comparison of our method with CNN and hand-engineered features based fire detection methods. Next, the robustness of our system is evaluated compared to existing methods with discussion on system parameters and its feasibility to uncertain surveillance environment. Finally, the discussion is concluded by highlighting the importance of the proposed framework for 5G TI- enabled fire detection system for surveillance in uncertain industrial environments. Similar to CNNFire [25], we call our method "EMN_Fire," [23] "ANetFire," and [24] "GNetFire" in the remaining of this paper for ease of interpretation.

A. DETAILS OF THE DATASET

We have created a new dataset from two benchmark datasets: dataset1 (DS1) [9] and dataset2 (DS2) [38] with two classes "fire" and "nonfire." . Smoke and snow images from Internet are included to the newly created dataset to cover the uncertain environment. The integrated dataset comprises of a total of 30 776 images. To train and test the system, we used our recent strategy [25] by using 20% data of the dataset for training and rest of 80% for testing. With this approach, our model is trained with 1844 fire images and 6188 nonfire images. The statistics of training and testing data is given in Table II. A few representative images from DS1 and DS2 with their remarks.

B. COMPARISON WITH THE CNN-BASED FIRE DETECTION

In this section, the performance of our system is compared with the CNN-based fire detection methods using the results, collected on both datasets of DS1 and DS2. Two different sets of evaluation metrics are employed to evaluate the performance of each method from all perspectives. The first set of metrics contain accuracy, false negatives, and false positives (also referred as false alarm rate) [25]. Using this setup, the proposed system is compared with the most recent work [25] and the two other CNN-based fire detection systems [23], [24].

It can be seen that ANetFire achieved the best false negatives (0.08); however, its false positives rate is high as well as its accuracy is

94.27%. GNetFire achieved similar false alarm rate to our proposed method; however, its accuracy is the worst using DS1. Our proposed system achieved the best combination of accuracy, false alarm rate, and false negatives using DS1, thus dominating other CNN models. Overall, the performance of ANetFire is worst on DS1, considering the precision and F-measure score. The performance of GNetFire and CNN Fire [25] is almost same. The proposed system dominated other competing methods in terms of precision, recall, and Fmeasure score, showing its strength on DS1. Referring to DS2, GNetFire performed worst both in terms of precision and Fmeasure. ANetFire is better than GNetFire; however, it failed to beat CNN Fire [25]. As shown, the proposed system successfully outperformed the competing fire detection systems, both in terms of precision and F-measure. The improvement is due to the deep but light-weighted neural networks used in the employed architecture for effectively learning discriminative features for fire detection.

C. ROBUSTNESS ANALYSIS

For uncertain environment, it is important that the fire detection system is robust against well-known attacks. In this section, we have evaluated the robustness of our system against noise and fire blockage attack and have compared its results with state-of-the-art. It can be noted that the proposed method provides best result in majority of the cases while second best result in some cases, reflecting its superiority for fire detection in uncertain environments with different weather conditions.

D. SYSTEM FEASIBILITY ANALYSIS FOR UNCERTAIN ENVIRONMENT

Besides simulation, it is important to investigate the feasibility of a system for deployment in real world. This section is aimed at providing similar details about our system for deployment in uncertain 5G TI-enabled IoT surveillance environment. To this end, we tested our system on two settings with: first, NVidia TITAN X (Pascal) having 12 GB onboard memory with a deep learning framework [42] running with Intel Core i5 CPU with Ubuntu OS and 64 GB RAM, and second, a Raspberry Pi 3 having** 1024 MiB SDRAM and 1.2 GHz 64-bit ARMv8 Cortex- A53. Based on these two settings, our proposed system can process 34 fps and 5 fps, respectively. Since processing few frames in real time are enough for detection of fire and the conventional cameras can capture 25~30 fps, thus our system is significant enough for real-time fire detection. The comparison of our system in terms of fps, accuracy, and false alarm rate with state-of-the-art using DS1.

Besides the better performance, our employed architecture is light weighted with fewer mega floating-point operations per second (MFLOPS) and reasonable size, as given in Table VIII. It can be seen that our method needs fewer MFLOPS/image compared to other models, enabling it to execute several surveillance streams. Similarly, the size of our model (13.23 MB) is also reasonable and easily deployable on resource constrained devices. Another motivational point of our system is that it can be easily run on a raspberry Pi device (such as raspberry Pi 3), whose price is much affordable ($35). Considering the overall performance evaluation metrics, model size, and MFLOPS/image, we can claim that our system is the best candidate for early fire detection in certain surveillance, in general, and uncertain surveillance environment, in particular, compared to existing fire detection systems.

E. 5G-TI ENABLED FIRE DETECTION STSTEM FOR SURVEILLANCE IN UNCERTAIN INDUSTRIAL ENVIRONMENTS

According to the International Telecommunication Union, the TI is an Internet network that combines ultralow latency with extremely high availability, reliability, and security. Unlike IoT that interconnects smart devices, the TI is going to control the IoT in real time, needing ultra reliable infrastructure [1]. The reason is that several tasks of critical nature (e.g., early fire detection in uncertain scenes during industrial surveillance) need to be executed remotely and instantly, requiring cheap edge infrastructure for ease of scalability. Considering these constraints, 5G can be a suitable underlying network infrastructure for such environment. The TI can intelligently combine multiple technologies at network and application level, enabling intelligence via mobile edge computing and data transmission over a 5G network. As described in previous sections, recently, several CNN-based fire detection approaches using edge intelligence are presented. These methods achieved reasonable accuracy for surveillance in certain IoT environment. However, their performance is limited in terms of fire detection in uncertain environment such as smoke, fog, and snow that can happen frequently in surveillance. Furthermore, the fire detection alert and representative video frames need reliable and instant reporting, considering the critical nature of disaster management. This goal can be achieved using a 5G TI-enabled fire detection system for which our proposed framework fits well, considering its promising accuracy, minimum false alarm rate, and response time. Furthermore, the size of the proposed model is reasonable due to usage of light-weight deep neural networks that favours its running time, making it suitable for fire detection during surveillance in uncertain industrial environments for mobile and embedded vision applications.

5. CONCLUSION

With the recent achievements of CNNs for solving numerous problems, researchers have applied them for abnormal event detection such as fire. Early detection of fire is very important for disaster management systems for which several CNN-based fire detection methods using edge intelligence are presented to date. These methods have reasonable accuracy and execution time and are applicable to only certain environment. In case of uncertain environment having fog, smoke, and snow, their performance is limited. In addition, it is difficult to deploy computationally expensive fire detection models on resource constrained devices. Considering these motivations, an efficient CNN-based method is proposed in this paper for fire detection in videos of uncertain environment. Our method provides several advantages compared to recent fire detection approaches of complex and huge-sized CNN models such as AlexNet, SqueezeNet, and GoogleNet. First, our method is based on light-weight deep neural networks with no dense fully connected layers, making it computationally inexpensive. Second, the size of the resultant model is approximately 13 MB, which is easily deployable on mobile devices with embedded vision. Lastly, our method dominates state-of-the-art in terms of fire detection accuracy and number of false alarms as verified from experimental results.

6. REFERENCES

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