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Fire SM: new dataset for anomaly detection of fire in video surveillance

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ABSTRACT
Tiny datasets of restricted range operations, as well as flawed assessment criteria, are currently stifling progress in video anomaly detection science. This paper aims at assisting the progress of this research topic, incorporating a wide and diverse new dataset known as Fire SM. Further, additional information can be derived by a precise estimation in early fire detection using an indicator, Average Precision. In addition to the proposed dataset, the investigations under anomaly situations have been supported by results. In this paper different anomaly detection methods that offer efficient way to detect Fire incidences have been compared with two existing popular techniques. The findings were analysed using Average Precision (AP) as a performance measure. It indicates about 78 % accuracy on the proposed dataset, compared to 71 % and 61 % on Foggia dataset, for InceptionNet and FireNet algorithm, respectively. The proposed dataset can be useful in a variety of cases. Findings show that the crucial advantage is its diversity.

Section: RESEARCH PAPER

Keywords: Anomalous; convolutional neural network; dataset; fire; smoke

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1. INTRODUCTION

Surveillance cameras are widespread, and it is not feasible to have people actively tracking them. In most instances, nearly all footage of surveillance camera is unimportant. Only rare pieces of video are of the main concern. Thus, the key inspiration for creating video anomaly detection along with image-based is, to automatically locate areas of video/image which are irregular. This would mark those for human inspection.

Recently, the research study of the identification of video/image anomaly has been characterised by two parameters. The training videos are made using a secure event. The anomalous event identification would be task followed after examining the video. In order to define what is usual for a specific scene, it is important to have training footage of normal behaviour. By an anomalous case that implies the localized video section, which is substantially dissimilar, happen inside a training video. More difficult is to choose very different attributes, that have been handled in point of interest application. Such disparity would be due to many causes, the majority usually remarkable presence of the things inside video.

Interestingly note, most researchers conferred on anomaly detection after experimentation [1], [2], [3], [4] and some have published their findings with different techniques [5], [6], [7]. Few studies have discussed about the usual anomaly video which either coming from one or two same scene. The attribute that may attach in identification purpose, the unique index of geographical space in an instance of video. For certain instances, the detection algorithm one can identify the anomalous scene that for other instance may not be a case of anomalous. The problem in little moment was needed to take care under such research study.

The quality-wise distinct issue in one scene may create a difficulty in superimposed multiple-scenes. The identification and analysis of single instance indicates to very uniquely handle feature in surveillance system, this study focused on such aspect. So, measurement technology plays a vital role in anomaly detection and surveillance applications. The formulation explains about the differences which lastly act spatially. The detection of anomalous activity in video/image directly related to performance and accuracy of detection algorithm. There would always be a scope of improvement in anomalous detection algorithm.

Table 1. Fire Instances in Fire SM Dataset.

Anomaly Class	Instances
1. Outside Offices	78
2. Outside Apartment	88
3. In Bushes	26
4. Outside Light	15
5. Street Light	13
6. Decorative Lighting	11
7. Bon-fire	9
8. Cooking Gas	25

The number of challenges would come to place while dealing with anomalous detection in fire related datasets. The shortcoming involves the unique kind dataset solely based on fire anomalous instances, low resolution of existing datasets, variations in anomalous. Few more cases, in which uncertainty, inconsistencies, and loss in quality have been identified.

The main focus of the paper has been on the detection of anomaly, analysis of obtained result after application on experimental dataset with the help of few assessment indices. The induction of new dataset of early fire and smoke (refer to Table 1) would be helpful in many applications. Maintaining diversities in dataset would be a key point, which checks anomalous things in different direction and more complex way.

2. EXISTING DATASET

Fires are man-made hazards that inflict human. It causes social, and economic damage. Early fire alarm and an automatic approach are important and useful to emergency recovery services to minimize these losses. Existing fire alarm devices have been shown to be unreliable in terms of numerous real-world situations. The vital disadvantage of the sensor-based framework is that it should be situated close to a fire or warmth source. However, this makes them impractical to use in a variety of frequently occurring scenarios such as long-distance fire occurrences as seen in Figure 1. Due to this, the traditional approach has failed to avoid a number of fire deaths. Solutions to this usually involve a reasonable amount of fire or heat sensation to stimulate the alarm. In addition, the fire or smoke regions are not precisely located.

Due to shortcomings of fire detection, researchers have been researching computer vision related approaches that have become alternatives for improving the fire and smoke detection system. Existing vision-based approaches focusing solely on the transformation of colour space for fire area detection [1], [2]. Rule-based methodology, along with colour space, has a promising future in delivering improved results. However, such devices are also vulnerable to other lit items such as streetlights.

Figure 1. Test Images of Training Data.

Figure 2. Sample confusing images which look like fire or smoke.

Additional methods applied to the decision-making algorithm additional features to colour-based methods such as location, boundary and motion cues [3], [4]. Classifiers such as Bayes Classifier, Dual Optical Flow and Multi-Expert Scheme have been used to minimize false detection or misclassification. However, these strategies are vulnerable to error and fail in many complex real-world scenarios as seen in Figure 2. However, due to the complexities of the condition, fire detection is a challenging task. As it does not have a definite form, area of incidence, complex temporal behaviour so as to extract the function. The hand-crafted collection of features involves a considerable amount of domain information. Table 2 listed details of existing dataset.

The Foggia video dataset [8] and the Chino dataset [9] were the two basic datasets. The first dataset includes of 31 enclosed environment and open-air videos. In that, seventeen are with not fire related while fourteen categorized of fire. As a result, colour-based methods are incapable for recognizing genuine fire and

Table 2. Existing Datasets.

Type	Size	Per Image Rate	No. of Frames	Related Fire	Remark or Observations
Fire1	320x240	15	705	yes	See [10]
Fire2	320x240	29	116	yes	Refer [10] and [11]
Fire3	400x256	15	255	yes	
Fire4	400x256	15	240	yes	
Fire5	400x256	15	195	yes	
Fire6	320x240	10	1200	yes	
Fire7	400x256	15	195	yes	
Fire8	400x256	15	240	yes	
Fire9	400x256	15	240	yes	
Fire10	400x256	15	210	yes	
Fire11	400x256	15	210	yes	
Fire12	400x256	15	210	yes	
Fire13	320x240	25	1650	yes	
Fire14	320x240	15	5535	yes	Foggia et al. [8]
Fire15	320x240	15	240	no	Refer [11] and [10]
Fire16	320x240	10	900	no	
Fire17	320x240	25	1725	no	
Fire18	352x288	10	600	no	
Fire19	320x240	10	630	no	
Fire20	320x240	9	5958	no	
Fire21	720x480	10	80	no	
Fire22	480x272	25	22500	no	Foggia et al. [8]
Fire23	720x576	7	6097	no	Refer [11] and [10]
Fire24	320x240	10	342	no	
Fire25	352x288	10	140	no	
Fire26	720x576	7	847	no	
Fire27	320x240	10	1400	no	
Fire28	352x288	25	6025	no	
Fire29	720x576	10	600	no	
Fire30	800x600	15	1920	no	Foggia et al. [8]
Fire31	800x600	15	1485	no	

scenes with red shading parts. Additionally, movement-based strategies may mistakenly portray a mountain scene of smoke, fog, or haze. These pieces have made the informational collection more troublesome, empowering us to push our engineering and assess its exhibition in different genuine settings. Another issue that arises during data processing is the difference between the fire and the non-fire. At a greater distance, for example, Fire2 [10] video contains so little fire. In the other hand, the Fire13 [10] video shows no fire, but only within a very small range. Thus, red designs and grounds like billboard (Fire14) and radish grass (Fire6) are available in numerous photos, making the dataset hard to decipher. The second dataset is relatively limited but very difficult. This dataset contains a total of 226 images, 119 of which contain fire while the other 107 are fire-like pictures including night falls, fire-like stars, and daylight coming through windows and so on.

An enormous amount of data is required in training for Convolutional Neural Networks (CNNs). Conversely, the current image/video fire collections are insufficient to meet the demands. Table 3 displays some limited scale fire picture/video information repositories. The data collection includes 13,400 fire images in all. These photographs were taken both outside and inside. There are 9695 "fire" and 7442 "smoke" facets in the data collection. In addition, the dataset includes 15,780 images that do not have flames. These data were acquired from 16 separate user environments and involve 49,614 distorted images. Each picture usually involves distortion such as due to surrounding noise or climatic condition. For this investigation, half of the pictures in the information assortment are utilized as the preparation/approval set. The remaining half is utilized as the test set.

3. EXPERIMENTAL DETAILS

Experiments were carried out using a deep neural network technique has been applied on proposed dataset. For which the system was used, the NVidia RTX 2080 processor with 10 GB on-board ram, as well as Ubuntu OS16.04 based on system. The CPU would be of Intel Core i5. This system was having RAM of 64GB. The analyses utilized 68,457 pictures acquired from notable fire datasets. This includes Foggia et al. [8] of 62,690 pictures. The planning and testing periods of the tests followed the trial system, where 20 % and 80 % of the information were utilized for preparing and testing, separately. The technique was applied with a qualified proposed updated EfficientDet [13]. The modified EfficientDet algorithm incorporated with Leaky Relu as activation function has been replaced Hardswish.

A training data of 2717 pictures was generated by using a model of 2529 fire pictures and 190 non-fire pictures. The planned network, however, with only 2-classes, i.e. fire and not fire class. Data sets are one of the essential components for evaluating the output of any given device. Evaluating the algorithm against a regular data set is one of the most difficult activities. In the suggested datasets, all photographs are original and taken by real people. This dataset is therefore the most demanding and diversified dataset ever produced. This hand-crafted research dataset was designed to explain the generalization of a qualified model. This involves an average of 2 boxes per picture of varying size and aspect ratio. Activation mapping has been exploited. This was required to get the approximate bounding box.

The loss function was used as a binary cross-entropy during the study of this dataset. In addition, the optimizer is found to be RMSProp with an early learning score of 0.001s. The number of 300 epochs was taken into account. The accompanying segments present subtleties of results got utilizing different fire datasets and their correlation with cutting edge fire information base methodologies.

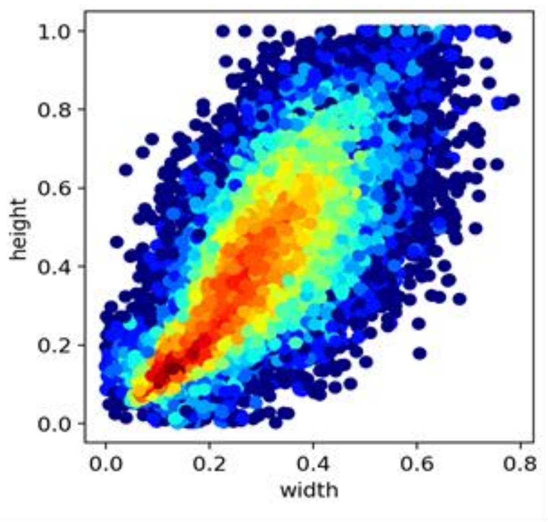


Figure 3. Fire location in images with distribution in relative coordinate in Fire SM dataset (Red-at middle, Orange, Yellow- at corner, Sky Blue, Dark Blue- not at middle and corner).

4. FIRE SM DATASET DESCRIPTION AND RESULTS

This proposed Fire SM dataset was verified for density of occurrences of actual fire location in an image. The dataset contains images of the fire which was located not only at centre of image but also at corner, top, bottom side as well included. The density of fire location in an image was shown in Figure 3. This figure shows the fire location in relative coordinate plane. In this, red colour signifies fire at middle, orange, yellow colour

Table 3. Number of fire image/video datasets present [12].

Institution	Format	Object	Website
Bilkent University	Video	Fire, smoke, disturbance	http://signal.ee.bilkent.edu.tr/visitfire/index.html
CVPR Lab, at Keimyung University	Video	Fire, smoke, disturbance	https://cvpr.kmu.ac.kr
UMRCNRS 6134 SPE, Corsica University	Dataset	Fire	http://cfdb.univ-crse.fr/index.php?menu=1
Faculty of Electrical Engineering, split university	Image, video	Smoke	http://wildfire.fesb.hr/
Institute of microelectronics, Seville, Spain	Image, video	Smoke	https://www2.imse-cnm.csic.es/vmote/english_version/
National fire Research Laboratory, NIST	Video	Fire	https://www.nist.gov/topics/fire
State Key Laboratory of Fire Science, University of Science and Technology of China	Image, Video	Smoke	http://smoke.ustc.edu.en/datasets.htm

	1	1	1		
	1	1	1		
	1	1	1		

Figure 4. Representation of framework of areas petitioning frame. '1' defines depicted as true region. Gives an idea of detection method.

signifies fire at corner, while sky blue, dark blue colour signifies fire not at middle and corner position. This figure supported to the diversified distribution dataset of fire was proposed for anomaly fire detection technique.

In reality, with a phenomenon that appears over several frames, it is necessary to discover an irregularity in probably a portion of the images. However, confirming the area in every frame of the track is typically needless. This is especially true where there is uncertainty regarding when to start and finish the previously described phenomenon, as well as when anomalous activity is heavily occluded for a few frames. Below mentioned feature are nothing but a measure of classification quality.

4.1. Feature Indices

4.1.1. Localized Detection Index/Rate

The Localized Detection Rate LDR is defined as
LDR = (Number of true regions detected)/(total number of regions).

True region in an image detected if intersection of true area and recognized local portion is more or equivalent to σ as shown in Figure 4.

4.1.2. Region based Detection Rate

The Region based Detection Rate RBDR is defined as RBDR= (Number of positive image detected)/(total number of regions).

σ ranges between 0 to 1. Default, σ=0.1.

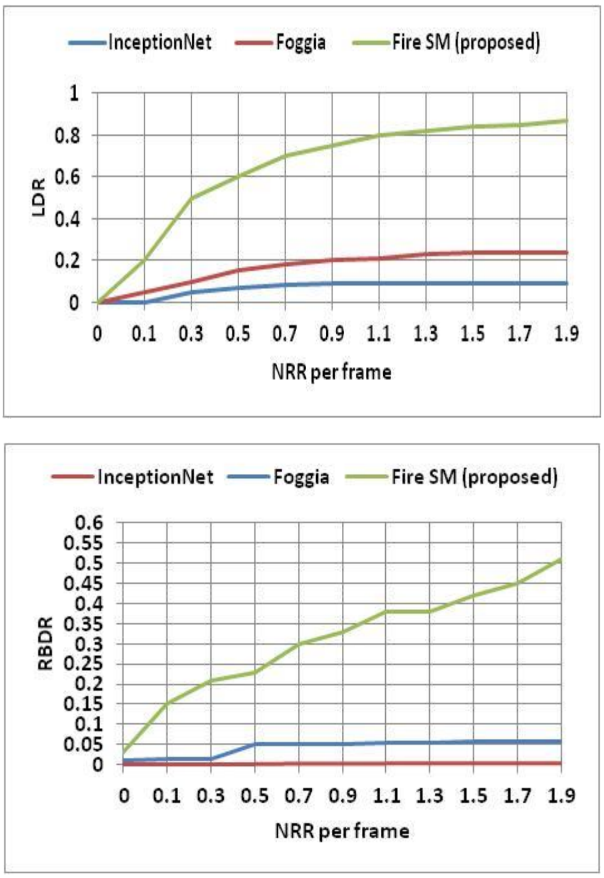
The Negative Region Rate NRR is defined as
NRR= (total non-positive regions) / (total frames or images)

The average detection rate for negative region rate, NRR, will ranging from 0 to 1.

There is a compromise between the discovery rate (genuine positive rate) and the bogus positive rate, likewise with any location rule. This can be caught in the ROC bend determined by changing the inconsistency score edge that characterises what locales are seen as abnormality.

Figure 5 and Figure 6, show characteristic curves for InceptionNet method, Foggia and Fire SM datasets. The nature of the curve signifies those values favorable to proposed dataset i.e., Fire SM compared to Foggia. Khan et al. [14] described InceptionNet method on fire instance dataset. The dataset mentioned was less diversified as compared to proposed Fire SM dataset.

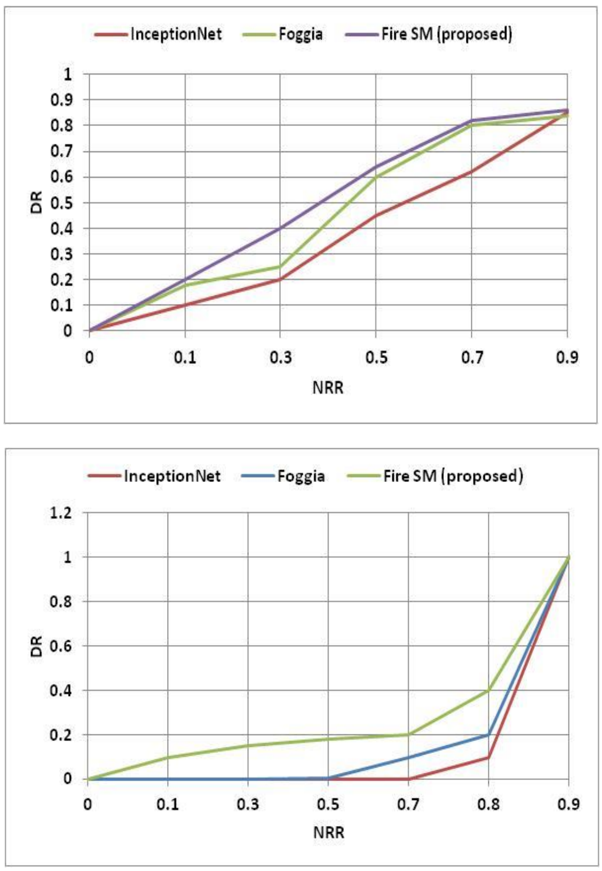
Khan et al. [14] and FireNet [15] proposed approaches focused on the classification of the leave-one-out strategy to be used for each level. In comparison to these algorithms, the updated EfficientDet [16]-[19] based more on the degree of detection. This paper considered the Average Precision (AP) indicator for quantitative analysis. Results were collected and



a)

b)

Figure 5. a, b NRR Per Frame characteristic curves for different dataset.



a)

b)

Figure 6. a, b NRR frame level characteristic curves for different dataset.

Table 4. Comparison of Updated Efficientdet to Inceptionnet and Firenet (*AP@50: 50 % above overlap, AP@75: 75 % above overlap).

Method	Early Fire and Smoke (proposed)		Foggia dataset	
	AP@50	AP@75	AP@50	AP@75
Khan et. al [14] InceptionNet	53.41	50.63	65.23	61.28
FireNet [15]	68.46	57.94	73.23	70.65
modified EfficientDet D0	**73.35**	**70.78**	**81.92**	**78.23**

seen in Table 4 for the proposed dataset relative to the Foggia dataset. Activation mapping has been used to get an estimated bounding box.

Table 4 shows the updated EfficientDet performance better relative to other algorithms. At present, both Average Precision (AP) at 50 and AP at 75 were compared. The EfficientDet result obtained given the proposed Early Fire dataset was approximately 73 per cent and 71 per cent compared to approximately 53 per cent, 51 per cent and approximately 68 per cent respectively, and 58 per cent for InceptionNet and FireNet. On the other hand, when taking into account the Foggia dataset, the findings obtained were approximately 82 per cent, 78 per cent. These have been compared to about 65 %, 61 % and around 73 %, and 71 % for InceptionNet and FireNet respectively, for AP@50 and AP@75 both. Figure 7 shows the detection of fire and smoke.

Figure 7. Detection of Fire and Smoke in Proposed Dataset.

5. CONCLUSIONS

This paper introduces a new Fire SM database of fire anomaly scenarios. The database has been therefore the most demanding and diversified dataset ever produced. This hand-crafted research dataset was designed to explain the generalization of a qualified model. This research study proposes novel lightweight and real-time for detecting smoke and fire in videos or photographs. Exiting datasets are either restricted or produced synthetically for testing purposes. In this study, validation was carried out on a real-world challenging proposed dataset that includes the majority of fire and smoke event scenarios.

Further, the weighted bi-directional Feature Pyramid Network (BiFPN) as well as compound scaling, consistently achieve better efficiency in EfficientDet. Experiment findings show that Google's newest model, EfficientDet, outperforms Foggia on the proposed dataset. These results were obtained using Average Precision (AP) as an indicator; on the proposed dataset, it shows around 78 %, compared to 71 % and 61 % for InceptionNet and FireNet, respectively, on the Foggia dataset. The new assessment criteria address the shortcomings of the traditional criteria in this field. It provides a more accurate picture of how well an algorithm performs in real environment. Furthermore, in this study, two variants of a latest fire anomaly detection algorithm used as a benchmark to which future work was measured. The new database would be helpful to encourage new novel techniques under this research field.

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