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Deep Convolutional Network for Detecting Probable Emergency Situations

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***Abstract*—Paper describes the developed approaches to detecting emergency situations that primed based on color segmentation, frame difference and deep convolutional networks. The main objective was to test the interaction of computer vision traditional methods, combined with modern methods of machine learning. Experimentally proved that detection quality for the combination of such methods is 96.7%. In this work, in particular, was developed own images dataset with emergencies and conducted comparison of neural networks AlexNet and GoogLeNet.**

Keywords— detection; convolutional neural network; machine learning; emergency situations

I. Introduction

Rapid technological development of information technology has led to a significant reduction in price various means of obtaining information. One of such means became video cameras, which are currently used in almost every organization, institution, crowded places. In many cases it allows operatively make decisions about related action concerning hazards. However, it should be noted that for the round the clock qualitative and reliable monitor video streaming should minimize interference of human factor and maximize the automation of identifying hazards.

One such hazards, which requires the rapid response implementation in case of occurrence is the process of fire. For example, in Ukraine only in 2014 registered 68,879 fires and a ten-year dynamics characterized by the total number of fires trend growth [1]. Implicitly, modern thermal, smoke and fire sensors allows quickly react to fire. However, the camera is more versatile means of obtaining data which, in terms of developing appropriate algorithms, on the one hand will rather receive information (even compared to modern sensors) on the other, due to the large array of received information, will handle such data as the number of people in the premises, the threat of terrorist activity, unconsciousness people etc.

As shown an analysis of research papers, the main methods for detecting such object like a flame in images considered the use of various color models and motion history images. However, taking into account heterogeneity of burning colors, these detectors are characterized by a significant level of error (the color of flame or smoke depends on temperature and substance that burns). Motion although it can significantly improve detection, however, can work only with static cameras. Despite the existing problems, in most cases accompanied by irregular wear of objects to which the grounds are like flames or smoke, these methods show quite good results. To solve these problems, we offer a combination of computer vision (CV) traditional methods (color segmentation and motion detection) and deep convolutional neural network (CNN), the results of which allowed to get a quality detection to 96.7%.

The structure of the paper is organized as follows: in Sec. 2 we review the current vision-based fire detection methods, in Sec. 3 we introduce our dataset for neural network. training. Sec. 4 is devoted to approaches used during training the classifier in Sec. 5 shows the experimental results. Conclusions of the work presented in Sec. 6.

II. Related work

The problem of flames and smoke detection in images devoted a lot of scientific paper. Most of them involve the use of various color models such as RGB [2], YCbCr [3], CIE L*a*b [4], HSV [5] etc. For this, interactive segmentation performed in the image area surveillance and, according to the statistical distribution of pixels forming the boundary conditions within which is determined pixel belongs to the desired area.

According to color segmentation efficiency values listed in [6], we can state that the use of color models is not sufficient for an effective detection system. Largely improves classification using various methods that can determine movement in the video stream (difference frames, forming the background, etc.) [2].

In contrast, traditional methods for detecting emergency, we offer the use of CNN. The use of deep convolutional neural networks devoted a number of works [7, 8, 9]. In comparison with the data practices, our approach is not limited to detection of only one manifestation of ES (flame or smoke). Additional HSV color model used and the method of frames difference, allowing classifier speed up and reduce the number of false positives, and the use of modern neural models Inspection-v.3, which showed the quality grading 96.7%.

III. DATASET

Dataset was filled with an online resource Imagenet [10]. Currently the image base is divided into 2 categories - flame and smoke, and the 4 categories that include objects which by their appearance resemble the previous categories, which in turn can reduce the percentage of improper classifier operation (cloud, light, light source, fairy light).

Numbers of used copies for each category listed in the table. 1. All images have been reduced to the size of 256x256.

TABLE I. NUMBERS OF IMAGES USED IN DATASET

№	Category	# images
1.	Flame	1876
2.	Smoke	595
3.	Cloud	1399
4.	Light	147
5.	Light source	1683
6.	Fairy light	810

Unlike commonly used approaches to the division dataset on the one train and one test sample, we decided also use the method of cross-validation, which will more accurately assess the classifier results, especially in case of retraining.

IV. PROPOSED METHOD

Fires are one of the most dangerous types of emergency, reacting on which should be done as quickly, because dissemination not only complicate the localization and elimination, but also can lead to loss of life and considerable material damage. Therefore, the classifier should work carried out quickly and efficiently. Taking into account, that only 1 second of video can be 24 frames, their ongoing analysis by the neural network causes considerable resources calculated that poses some obstacles to the development of universal classifier. To solve this problem, we offer traditional methods combination of detection ES that require a small amount of computer resources, and on the basis of already received data analysis by CNN. To implement the method of color segmentation and motion detection was chosen programming language Python with using CV library OpenCV.

A. *Color segmentation*

Conduct own experimental research, the most successful choice flame and smoke segmentation is using a HSV color model. It is clear that the color settings for smoke and flame is completely different, which makes the parallel performance analysis model values given for every different types of emergency. Example color segmentation in video stream shown in Fig. 1.

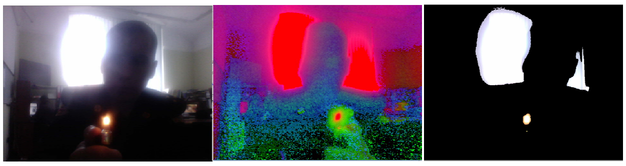


Figure 1. Real-time color segmentation based on HSV color model. From left to right: original RGB frame, RGB to HSV convert, used thresholds.

B. *Motion detect*

Taking into account the significant level of errors when using only one color segmentation method, it is considered appropriate reduction options for classification based on the moving objects selection. For this we used the method of subtracting frame, which described in detail in [11]. Results of the used method encircled by using Bounding Rectangle, then this area served to analyze by neural network.

When we implementing the method of frame difference it encountered considerable noise, which could cause incorrect classification. To solve this problem, the morphological operations dilation and erosion was used.

Example of detecting moving objects in conjunction with morphological operations shown in Fig.2.

Figure 2. Real-time frame difference. From left to right: without any morphological operations, with morphological operations, example of motion.

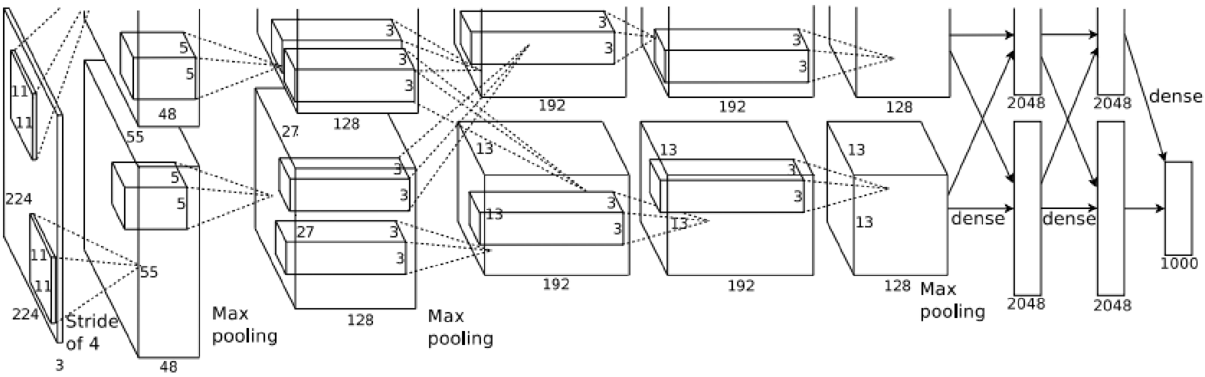


Figure 3. The architecture of AlexNet for model training

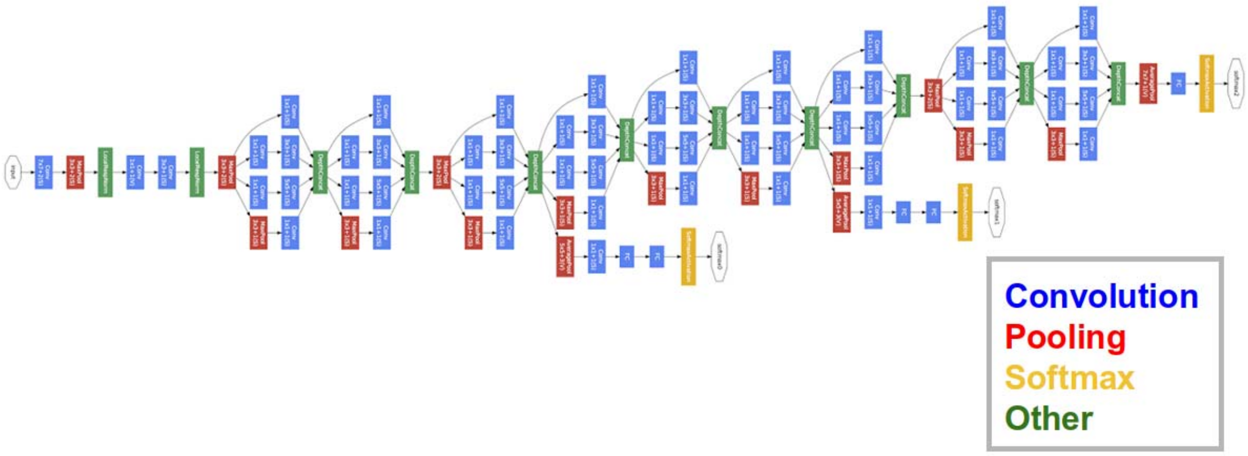


Figure 4. The architecture of GoogLeNet for model training

C. *CNN*

There are various frameworks, which allow you to work with CNN. The most common are Theano, Torch7, Caffe and becomes widespread announced by Google in November 2015 library TensorFlow. To solve this problem we have used Caffe. The choice was due to simple configuration of existing neural patterns and the ability to accelerate graphics learning models by using NVIDIA CUDA.

To train the neural network was chosen 2 models - AlexNet [12] (fig. 3), which proposed by Krizhevsky et al . and GoogLeNet [13] (fig. 4) with inception modules and deeper layer- by-layer convolutions structure. These models are flexible and allows to easily make changes in their structure, which led to their selection. Model is based on used stochastic gradient descent with 0.9 momentum, numbers of training epochs - 30, base learning rate - 0.01.

Results of models training are shown in Fig.5

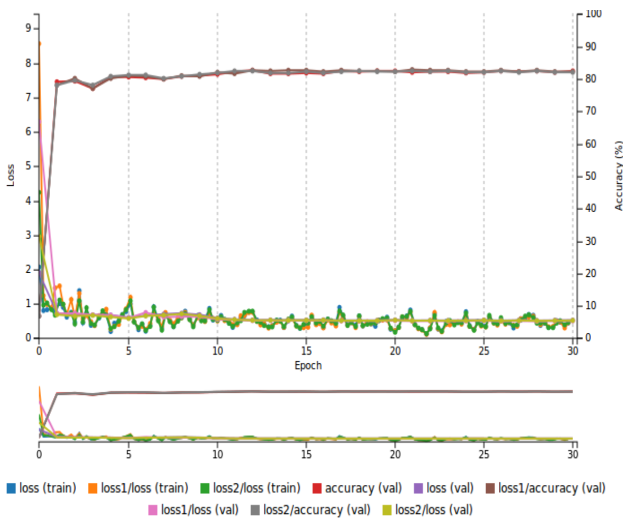


Figure 5. Training neural network for emergency situations detection based by Alexnet model

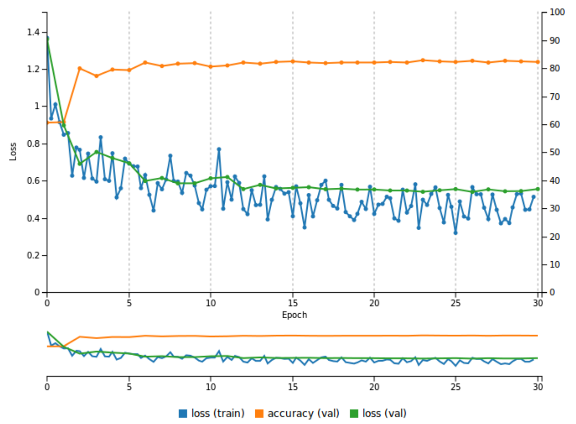


Figure 6. Training neural network for emergency situations detection based by Alexnet model

V. EXPERIMENTS AND ANALYSIS

Alexnet the first successful CNN model, which won first place in the competition ImageNet Large Scale Visual Recognition Competition in 2012 and 2014. However, implementing to training dataset (185 images of flames, smoke and 224 images on which they are not), it received relatively low result - 95.4%. GoogLeNet showed significant improved efficiency grading 96.7%. For each separate category quality of classification is given. An example of a classification is shown in Fig.7.The worst percent of efficiency is shown in category "smoke" and "clouds". The overall quality of flame detection, and objects which according to external signs remind it's have quite high rates.

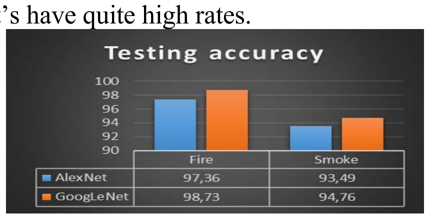
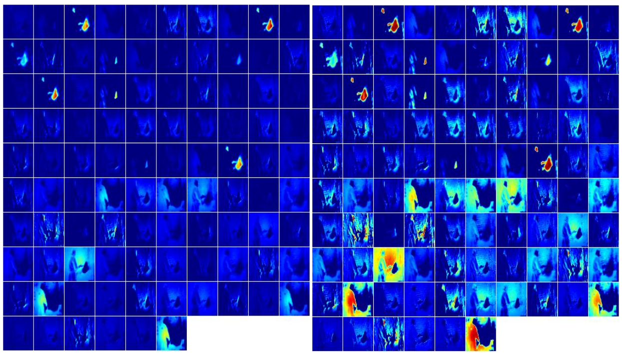


Figure 7. Comparison between AlexNet and GoogLeNet on testing accuracy

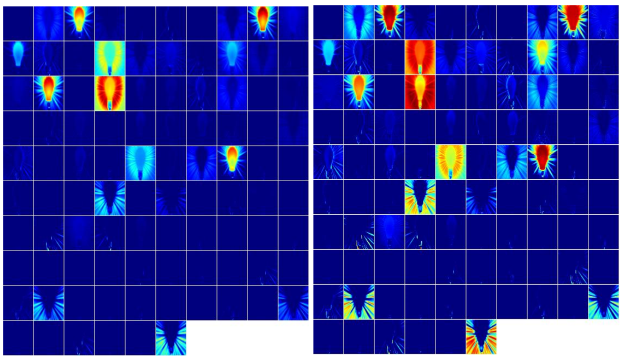
Figure 8. Fire classification example.



a) b)

Figure 9. Conv1 (a) and norm1 (b) layers example for image above.

Figure 10. Light source classification example.



a) b)

Figure 11. Conv1 (a) and norm1 (b) layers example for image above.

VI. Conclusion

In this paper we offered use traditional methods for detecting objects in video stream (color segmentation and motion information) combined with deep convolutional networks. Despite the small number of training set, we managed to achieve high performance of neural networks that are supported by the experimental results of the detector.

Further work to improve ES detection system is expected in the following areas:

- use of deep learning modern methods;
- extending dataset, especially in the categories of "smoke" and "clouds";
- improving the method of moving objects selection during smoke detection, which based on its movement

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