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The effectiveness of fire detection with convolutional neural networks

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Abstract

The article presents problems related to the detection of fire phenomena using convolutional neural network techniques. The main issue described in the article focuses on determining the precision of flame detection depending on lighting conditions and the selection of CNN architecture. The types of neural networks tested are primarily SSD architectures, which, with their speed of operation and energy consumption, are the most common in mobile applications. The study shows which of the neural network architectures used have the highest average precision in detecting the fire phenomenon. The selection of networks under testing was analyzed in terms of the speed of the algorithm and its precision. Four pre-trained neural network models were used during the testing of two training bases. The complexity of each model directly affected the training time of the model, which oscillated between 2-8 [h], and the precision achieved.

Keywords: fire detection, convolutional neural networks, CNN, effectiveness of CNN, monitoring of vast areas

1 INTRODUCTION

Rapid economic development, the increasing complexity of architectural structures pose major challenges for fire control. Early detection of fires and alerting of the incident are essential activities to reduce the negative effects of the element. Traditional fire detection technologies such as smoke and heat detectors are not an effective solution for the surveillance of large spaces.

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A topic that has become popular in fire applications in recent years is image-based detection. This technique has many advantages, such as early detection, high accuracy, flexibility of the installed system, and the ability to effectively detect fires over wide areas. This paper focuses on analysing the ability to detect fire under different lighting conditions using convolutional neural networks (CNN).

2 Preparation of fire training bases

A focus with a flame between 0.1 - 1.8 [m] in height was taken as the object of observation. The tests were carried out under different lighting conditions, i.e. full sunlight and medium darkness. The images used to create the training base were taken at the four directions of the flame source (evenly every 90°) at the following distances of 2; 4.7; 7.5; 10.7 [m], and with an adjustable tripod height between 0.8 and 1.5 [m]. Two training bases containing 834 images each of the test fire were created. The first base was composed of images taken at full exposure (images taken at midday, cloudless sky). The fire was recorded using a camera with a resolution of 1920 x 1080p and a 12 Mpix sensor with an f1/6 aperture and optical image stabilization. Base 2 was created using the same distances and camera. The difference was the use of worse lighting conditions, i.e. 8 pm (partial darkness). The complete image databases were then used to conduct the learning process and test the neural networks.

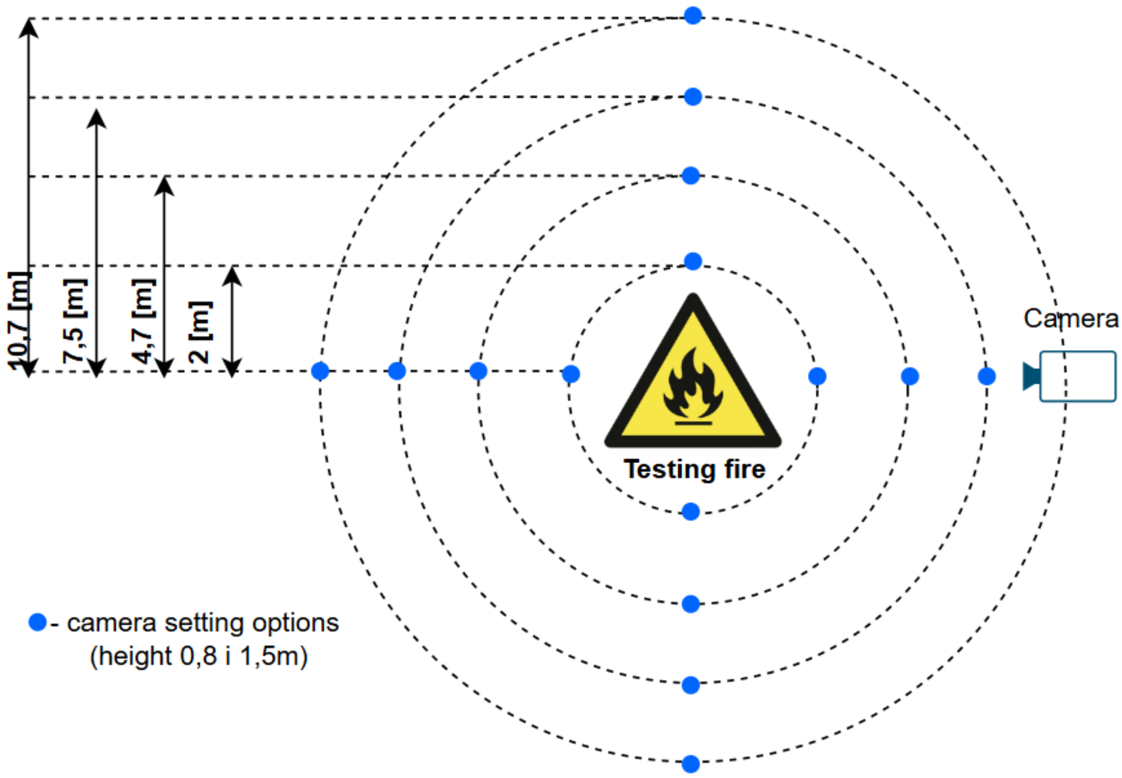

Figure 1. *Method of recording the flame (measuring station)*

Appropriately selected images were subjected to labeling, i.e. flame framing. Framing is a technique used in machine learning, slowing down the transformation of the graphical indication of the detected object into coordinates, written in the appropriate programming language. There are many guidelines for correct object framing. Nevertheless, the vast majority apply to static objects whose shape is fixed. In the case of a fire phenomenon, flames form irregular shapes, the framing of which can be questionable. This means that the procedure of indicating a fire in a photo can be done with a single frame or many of them. However, in the conducted research it was decided that a single frame would be highlighted in each photo regardless of the shape of the flames. The above assumptions of the uniformity of the training bases, the placement of the camera and the way in which the photos are framed are intended to allow conclusions to be drawn only as to the effect of CNN architecture and lighting conditions on the accuracy of flame detection.

Figure 2. *Framing of images, use of labelingimg application*

3 What algorithm for fire detection?

Object detection is a key area of computer vision and artificial intelligence. The current state of the art presents us with many types of algorithms. Among the most popular of these are YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector) and Faster R-CNN. These models are nowadays an indispensable component in the software of autonomous cars, medical imaging, etc. Each is characterized by different parameters, so which one is best to use to detect fire phenomena?

In the research presented here, three different CNN architectures were used for testing. The first, and the most important, is SSD, which is a single-stage object detection model that discretizes the output space of bounding boxes into a set of default boxes with different proportions and scales for each location in the object map. The main advantage of the above architecture is the high efficiency of real-time object detection. Two of the networks classified as SSD types, namely SSD *mobilenet-v2-fpnlite-320* and *mobilenet-v2-fpnlite-640x640,* were used for the conducted tests. Due to the fact that the conducted research is an integral part of the mobile fire detection algorithm, the results of the flame detection accuracy of SSD networks, is the key issue of this work. In addition, the *EfficientDetD0* network was used for testing, which, according to engineers, is characterized by high object detection accuracy with limited computational resources. The fourth architecture tested was the Faster R-CNN *ResNet101 V1 640x640* network, whose big advantage is primarily high accuracy.

4 Evaluation of the effectiveness of fire phenomena detection

Learning a neural network is a complex and time-consuming process. The purpose of evaluating the correctness of learning the model are the loss functions and the learning rate. Loss functions are used to measure the error between the result of a forecast and the given target value. A smaller loss means that the model performs better with forecasts closer to the target values. Figure 3 shows graphs of loss function parameters. Classification loss is a measure of the correctness of the assignment of an object to a given detected class. Another error is the localization error, which by its measure represents the difference in the location and size of a frame relative to its reference location (marked in the framing process). In the case of ongoing research, the most relevant indicator is the total loss. The closer its value is to zero, the more accurate the matching of the network to the training base.

training base.

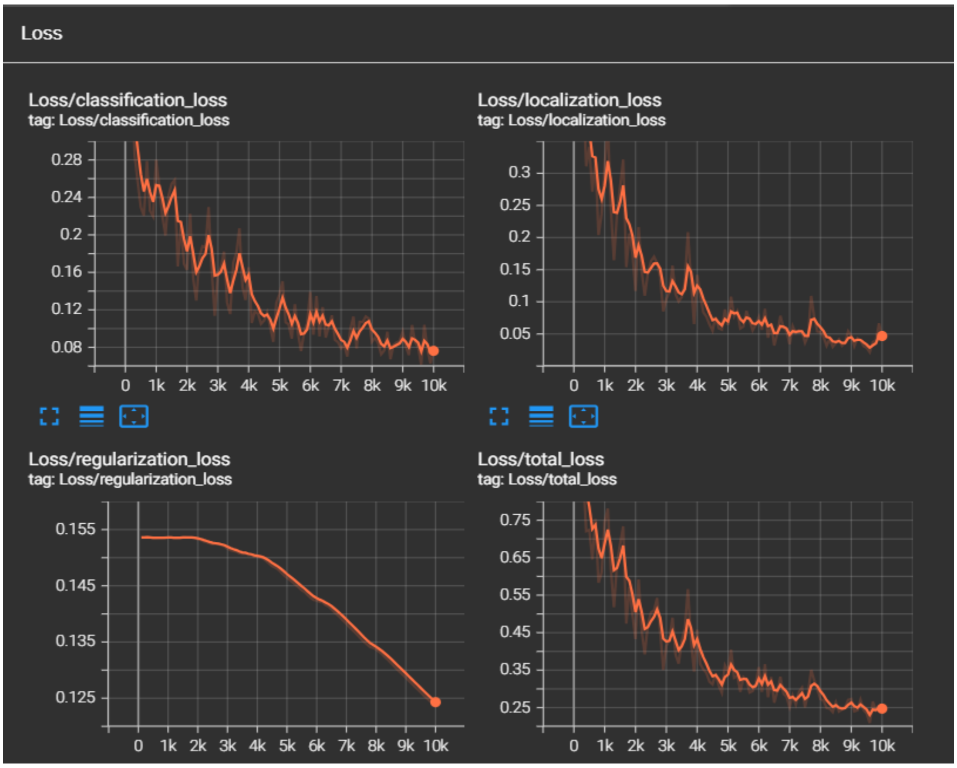

Figure 3. *Loss functions, SSD network training mobilenet-v2-fpnlite-320*

The metrics discussed above are used to monitor and assess the correctness of model training. To assess the accuracy and correctness of detection, engineers use the measure of average precision. The mean precision value (*mAP*) is calculated based on the call value from 0 to 1. To determine the *mAP*, the confidence threshold of the *IoU* model is determined. Then, based on it, the detection should be classified into one of the different classes TP, TN, FP, FN. TP means that the model predicted the label and matched it correctly according to the truth. In Table 1, showing the results of the tests carried out, the third column contains information about the benchmark *mAP* value of a given neural network architecture. Benchmark values are the average precision of a given network obtained on the *COCO* dataset. The *COCO* dataset contains more than 330,000 images each with annotations, containing 80 object categories, for the study is the benchmark value. The relationships of the mean precision (*mAP*) and confidence threshold (*IoU*) are shown below.

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i$$

The results of the tests are shown in the table below. Both the level of exposure and the type of architecture used, have a significant impact on the value of flame detection accuracy. For both image bases, the Faster R-CNN network showed the highest accuracy. However, it should be noted that networks of this type are characterized by high accuracy. Nevertheless, the process of training and inferring them is very complex and energy intensive. In the case of the *EfficientDetD0* network, the lowest accuracy and insufficient detection characteristics were obtained. The low *mAP* value for this network is partly due to the insufficient number of steps, which is 10,000 for each architecture. The value of fire detection precision is significantly affected by illumination. Note that higher ambient contrast contributed to more effective flame detection. The difference due to illumination oscillates between

24-28% *mAP*. Figure 4 and Figure 5 show the differences in the exposure conditions of the image bases and how the algorithm detects fire.

Architecture of CNN	Speed of detection [ms]	COCO [mAP]	Base 1 [mAP] Full sunlight	Base 2 [mAP] Partial blackout
SSD Mobilenet-v2-fpnlite-320	22	22,2	30,72	58,22
SSD Mobilenet-v2-fpnlite 640x640	39	28,2	34,21	58,38
EfficientDet D0	39	33,6	11,61	37,56
Faster R-CNN ResNet101 V1 640x640	55	31,8	36,78	62,34

Table 1. *Fire phenomenon detection precision results depending on the neural network architecture used and the selected image base.*

Figure 4. *Fire phenomenon detection using SSD network Mobilenet-v2-fpnlite 640x640 (partial blackout)*

Figure 5. *Fire phenomenon detection using SSD network Mobilenet-v2-fpnlite 640x640 (full sun)*

5 Summary

Selection of the right architecture and consideration of lighting conditions are both key issues at the stage of developing a fire detection algorithm. The highest detection precision was achieved by the Faster R-CNN *ResNet101 V1 640x640*. Nevertheless conclusion should be drawn from the study that the SSD *Mobilenet-v2-fpnlite 640x640* model is the most effective architecture to implement a real fire detection algorithm. Despite not the highest accuracy, it is a model that is compatible with Edge TPU functions and an energy-efficient structure. It should be noted that there are models whose claimed precision is higher, but their hardware requirements, and the training process is much more difficult compared to the with the presented structures.

Bibliography

1. Ahmed, A., (2020). *A Fire Detection Algorithm Using Convolutional Neural Network.* Place: Jeddah Saudi Arabia. Publisher: journal of King Abdulaziz University Engineering Science.
2. Gauer, A., (2020). *Fire Sensing Technologies.* Place: U.S. Publisher: A Review, in *IEEE Sensors Journal*, vol. 19, no. 9, pp. 3191-3202.
3. Klimczak, T., Paś, J., Deuer, S., Rośiński, A., Wetoszka P., Białek, K., (2023). *Selected Issues Associated with the Operational and Power Supply Reliability of Fire Alarm Systems.* Place: Warsaw Publisher: Energies 15(22), 8409.
4. Nagababu, P., Dhakshitha, K., Chandrika, G., (2023). *Automated Fire Detection System Using Image Surveillance System (ISS) and Convolutional Neural Networks (CNN)*. Place: India Publisher: 9th International Conference on Advanced Computing and Communication Systems (ICACCS).
5. Priya, R., Vani, K., (2019). *Deep Learning Based Forest Fire Classification and Detection in Satellite Images.* Place: Australia. Publisher: 11th International Conference on Advanced Computing.
6. Wangda, Z., (2020). *Image fire detection algorithms based on convolutional neural networks.* Place: Holland. Publisher: Case Studies in Thermal Engineering 19, 2020, 00625, ISSN 2214-157X.

7. Yuan, C., Zhang, M., (2015). *A survey on technologies for automatic forestfire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques.* Place: Canada. Publisher: Canadian Journal of Forest Research, vol. 45, no. 7, 2015, pp. 783–792.