ADVANCES IN FOREST FIRE RESEARCH

2022

Edited by

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Crowdsourcing Holistic Deep Approach for Fire Identification

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Keywords:

Deep Learning, Fire Identification, Crowdsourcing

Abstract

Forest fires have become a global problem that affects large areas of the globe, and has received contributions from citizen science, namely the reporting of fire sighting by citizens with location and images, often using smartphones, which is becoming a frequent source of information to firefighting teams.

Nevertheless, such contributions need validation before resources are deployed and that is the focus of this work. This paper describes a novel approach to identify forest fires in real crowdsourced images using a deep learning (DL) approach.

The approach is based on YOLO networks to train optimized models that identify the real cases that need to be addressed, using a holistic methodology that considers all objects detected in each image before producing a decision. For our experiments, we used benchmark and real datasets of fire and smoke. In the experiments, the performance is compared under different experimental setups. Our approach results show that the proposed crowdsourcing holistic deep approach for fire identification can be successfully used in real scenarios.

1. Introduction

Fire is one of the leading hazards endangering human life, the economy, and the environment (Hall 2014), (Saponara et al. 2020). Identifying a forest fire in its early stages is essential for a faster and more effective response from fire and civil protection authorities. An effective initial response can decrease fire damage and, in certain cases, can prevent the loss of lives and property, e.g., houses and other belongings.

Crowdsourcing approaches (Zanca et al. 2020) involve the use of people to aid in solving problems that technology still struggles. For firefighting, crowdsourcing, or citizen science, can be extremely important in early detection, when communication systems are in place for such reporting. However, such contributions are sometimes malicious with the goal of diverting resources from real fires, often provoked by arsonists, and require validation before resources are deployed.

In this work, citizens are able to report ongoing fires through an app developed in the scope of the Fireloc project (https://fireloc.org), a system that enables the report of forest fires by identifying, locating, and reporting them, using crowdsourced data, i.e. geolocated images with a potential fire. The development of a contribution validation mechanism becomes imperative, allowing for faster and more accurate communication of the occurrence. With the increase of the volume of information received, processing by human visual analysis of each reported situation, even if done by an expert, becomes too time-consuming, and therefore not useful for a rapid response. Therefore, the development of an intelligent system that can automatically identify fire in the submitted images is proposed. This system can then be applied to each report made using the Fireloc application, assessing if there is a current fire or not and discarding false reports, which aims to improve firefighters' intervention. This system can enhance the process of analyzing crowdsourced data, ultimately enhancing firefighters' response.

We explore how the optimization of parameters in YOLO networks (Redmon and Farhadi 2018), (Redmon and Farhadi 2017), (Zhang et al. 2018), (Redmon et al. 2016), a deep architecture for object detection, can be used to allow a better performance in Fireloc project, i.e., to support the determination of validity of an image obtained through crowdsourcing, a.k.a. citizen science. For this purpose, we construct a dataset with real images obtained in a simulacrum that result in a set of parameters to apply to real situations. We introduce a new concept in post-processing, proposing a holistic approach generalizing the YOLO object detection to an image classification system that fully supports the necessary validation before resources are deployed for firefighting.

In the following, Section 2 describes the related work in deep learning for fire identification. Section 3 describes the proposed holistic deep approach for fire identification, presents and analyses the experimental results. Finally, Section 4 shows the conclusions and future lines of research.

2. Fire Identification with Deep Learning

Fire identification and detection in images using deep learning (DL) (Lecun et al. 2015) have been source of much interest in the research community (Mao et al. 2018), (Qiang et al. 2014), (Lee et al. 2017), (Zhang et al. 2018), (Ayala et al, 2020). In (Mao et al. 2018), a novel fire recognition method based on multi-channel convolutional neural network is proposed, constructing 3 channel color images and using a CNN. The CNN can take as input videos or images and gives as output the probabilities of it belonging to each class considered. All videos are first converted to images frames and all images are then resized to fit the input size of the model. Each image is given to the model as a matrix with each RGB channel, and discriminating features are extracted. Parameter adjustment was achieved using backpropagation. The resulting model could be applied to both video and image inputs, classifying them as belonging the class fire or not.

In (Lee et al. 2017), the images are obtained using an Unmanned Aerial Vehicle (UAV) as a cost-effective means to provide high resolution images for wildfire detection. Results show that such images result in wide range of aerial photographs that can be used for object detection.

In (Zhang et al. 2018), given the difficulty of obtaining real images, a synthetic smoke dataset was constructed by inserting real smoke or simulated smoke into forest background to solve the lack of training data. The published results show that simulated smoke is the better choice, and the model is insensitive to thin smoke.

3. Holistic Deep Approach for Fire Identification

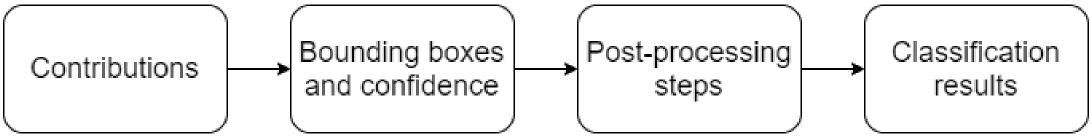

Figure 1- Holistic deep approach for fire identification system

In this work we propose a holistic deep approach for fire identification. Figure 1 shows the operating steps for smoke and fire detection in static images, integrated into the Fireloc project's system. Initially, using the mobile application and the camera of their smartphone or tablet, users can send photos of the forest fire or smoke they observe (contributions).

Then, for each contribution presented to the system, parameter tuning is performed, and the model identifies the parts of the image that contain smoke or fire with bounding boxes and an associated confidence score for each object detected.

Finally, given the specificity of the Fireloc project, a holistic post-processing mechanism is performed before the final classification results are presented to the firefighting team for decision making.

There are several challenges that must be tackled, namely the accurate predictions that avoid misuse of resources and the heterogeneity of submitted contributions in terms of different images formats, sizes, and quality.

The development of the object detection module focuses on the optimization of the parameters: the size of the initial anchors and confidence threshold. The main goal is hence to provide accurate prediction on crowdsourced images on the presence of fire (or smoke) in the given images.

3.1. Datasets

For the fire and smoke detection system implementation, custom datasets were used, manually annotated according to the YOLO format. Two independent sets of images were used to train and test the models, chosen according to the module real conditions of use.

The dataset chosen for the training step was an open source set of images. This dataset is publicly available at https://github.com/DeepQuestAI/Fire-Smoke-Dataset/releases/download and contains an equal number of images with fire and smoke, presenting fires in urban contexts with other objects present in the background and some overlapping objects to be detected (smoke and fire). Although the size of the images is smaller than the typical resolution of photos taken by smartphones and don't contain a high number of images, the variety of examples with smoke and fire makes it use feasible for training YOLO models.

To complement this set of training images, images of smoke and fire were collected in a forest fire context, with characteristics more similar to the actual use of the Fireloc system. These images are, therefore, more suitable for testing the performance of models and were collected in a simulacrum performed by firefighters on May 15, 2019, in tests carried out in Serra da Lousã by Association for Development and Industrial Aerodynamics (ADAI). The manual annotation of the proposed datasets for training and testing the models was carried and the distribution of examples of each class for training and testing datasets is presented in Table I.

Table I- Number of examples present in each dataset

	Total Fire examples	Total Smoke examples
Train dataset	2598	2348
Test dataset	460	421

3.2 Model evaluation

The approach followed to develop the object detection module went through an iterative process, optimizing selected parameters to improve the objects' detection results in the images. The mean Average Precision (mAP) and Average Precision (AP) values per class were analyzed for the evaluation of results. These can be considered standard metrics of YOLO models' performance since they allow an assessment of the relationship between false positives and detected false negatives (Everingham et al. 2010). An adaptation of (Everingham et al. 2010), from the (Cartucho et al. 2018) project, was used.

With the different parameters optimized, the process focused on analyzing the classification results of the images, using the confusion matrices obtained for the classification of the test images to evaluate the models after the application of the post-processing.

3.2. Experiments and results

In the experiments, the trained models were pre-trained with *Imagenet* and the following parameters were considered, defined in the configuration file of each model: (i) Number of classes = 2 (since the classes of objects considered for detection in the images are Smoke and Fire); (ii) Channels = 3 (RGB); (iii) Number of iterations = 6000 (number of iterations recommended by the author of YOLOv4 (Bochkovskiy et al. 2004) for training models with custom datasets).

3.2.1.Experiments and results for anchor adjustment

The definition of the initial anchors of the models can directly influence the detection results obtained. When adjusting the anchors initial size to approximate the bounding boxes sizes in the training dataset, it is possible to suit the boxes size that signals the detected fire and smoke objects in the images. It is to be expected that this approach, by improving the location of objects in the test images, will result in an improvement in the obtained mAP results. In the following experiments, the anchors are adjusted to the bounding boxes marked in the training dataset using the k-means algorithm and aim to improve object detection results.

Table II - Anchor Adjustment Performance Results – Average Precision (AP)

		EPOCHS					
		1000	2000	3000	4000	5000	6000
Fire Smoke	v4	23.08%	41.14%	40.69%	36.20%	46.00%	43.90%
	v4-anch	17.58%	32.53%	37.69%	**40.11%**	38.49%	38.65%
Fire	v4	4.83%	22.30%	15.52%	20.08%	**24.96%**	23.06%
	v4-anch	1.55%	5.92%	7.50%	11.74%	14.56%	13.28%
Smoke	v4	41.34%	59.98%	65.86%	52.32%	67.05%	64.74%
	v4-anch	33.61%	59.13%	67.89%	**68.67%**	64.42%	64.02%

Results show that the YOLOv4 model trained with the default values of anchor size presents better performance in detecting objects of the considered classes. The best result obtained with the model after performing the anchor adjustment is only 40.11% mAP, after 3000 training epochs, inferior to the best result achieved using the original anchors, 46% mAP obtained after 5000 training epochs.

When analyzing the AP results for each class of objects considered, the models present a significant difference in the fire detection performance, reaching a maximum of 24.96% AP/Fire with the model trained with default anchors. In the detection of objects of the Smoke class, both models present good results, reaching 68.47% of AP/Smoke.

3.2.2.Experiments and results for confidence threshold adjustment

This experiment aims to evaluate the effects of the variation of the confidence threshold defined not only on the results of object detection but also on the classification results of the images in the test dataset. In all previous experiments, the specified limit used for this confidence was the default value, used in the studies YOLOv3 (Redmon and Farhadi 2018) and YOLOv4 (Bochkovskiy et al. 2004).

To assess the effects of changing the confidence threshold on the object detections performed, the mAP results obtained after every 1000 iterations of training of the model were evaluated. Values 5%, 10%, 15%, 20%, and 25% were considered for changes in the confidence threshold. The experiment results can be seen in Figure 2, showing the increase of the defined confidence threshold, regardless of the number of training iterations of the model, results in a decrease of mAP results. These results indicate that the higher the defined confidence threshold, the lower the number of correct detections. When considering the results obtained, the confidence thresholds of 5% and 15% stand out positively.

4. Conclusions and future work

We have studied the problem of identifying fire and smoke in crowdsourced images that citizens submit to the Fireloc system to ultimately alert firefighters of ongoing fires. We have explored how the optimization of parameters in YOLO networks can be used to allow a better performance in fire identification. For this purpose, we have constructed a dataset with real images obtained in a simulacrum that result in a set of parameters to apply to real situations. We have additionally introduced a new concept in post-processing, proposing a holistic approach generalizing the YOLO object detection to an image classification system that fully supports the necessary validation before resources are deployed for firefighting.

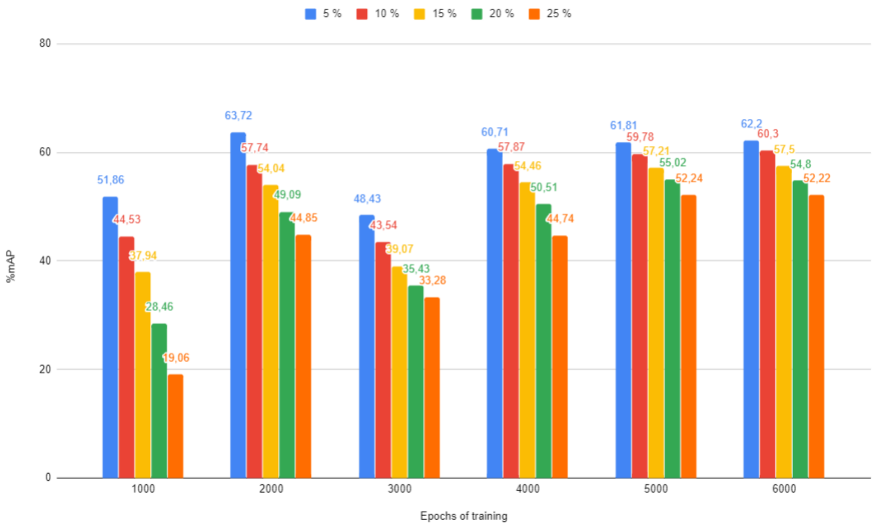

Figure 2 - Results obtained considering varying confidence threshold (5% to 25%)

Figure 3 shows the detection results for comparison of the two operating points. The results obtained with both thresholds are similar, although the image resulting from the detections carried out with 5% threshold shows a more significant number of repeated fire detection. The video is available at https://www.dropbox.com/s/fwtls664s5uukcy/fire_video demo.mp4?dl=0.

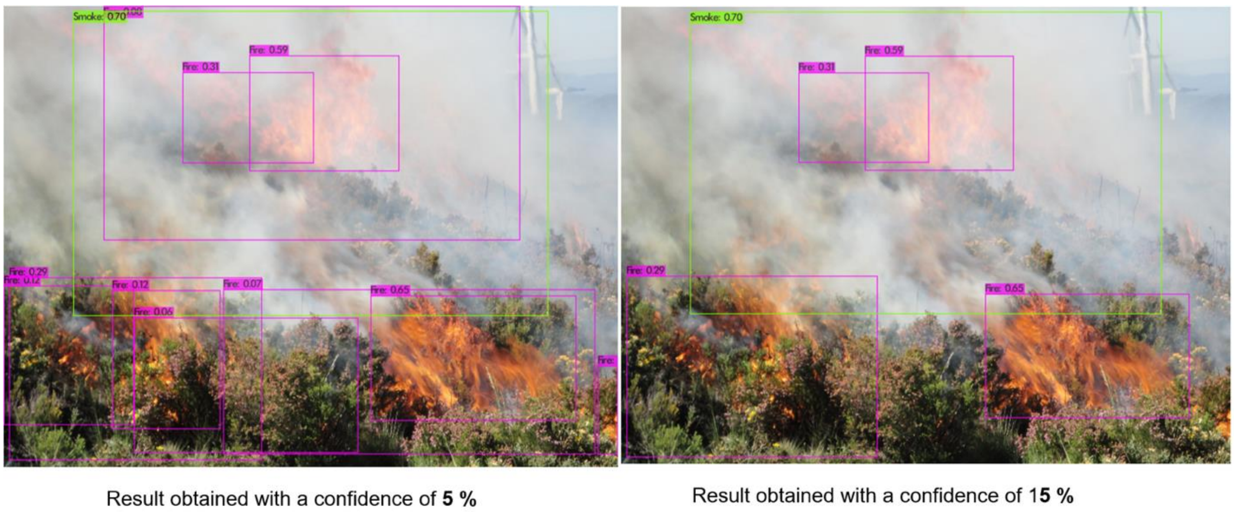

Figure 3 - Test results image detection comparison, example 2

Future work is foreseen in two paths. First, the augmentation of the dataset, as it has become clear that it is a potential source of improvement, e.g., through the use of Generative Adversarial Networks (GAN). Second, due to the recent interest in the image and video object recognition the generalization of the post-processing holistic approach to video sequences is also anticipated given that initial tests with video images suggest the viability of the proposed approach.

5. Acknowledgments

This work is funded by the FCT - Foundation for Science and Technology, I.P./MCTES through national funds (PIDDAC), within the scope of CISUC R&D Unit - UIDB/00326/2020 or project code UIDP/00326/2020. This work is also funded by project FireLoc, supported by the Portuguese Foundation for Science andTechnology (Fundação para a Ciência e a Tecnologia - FCT) under project grants PCIF/MPG/0128/2017.

6. References

(Ayala et al, 2020) A. Ayala, B. Fernandes, F. Cruz, D. Macedo, A. L. I. Oliveira and C. Zanchettin, ”KutralNet: A Portable Deep Learning Model for Fire Recognition,” 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, United Kingdom, 2020, pp. 1-8.

(Bochkovskiy et al. 2004) A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of Object Detection,” https://arxiv.org/abs/2004.10934

(Cartucho et al. 2018) J. Cartucho, R. Ventura, and M. Veloso. Robust object recognition through symbiotic deep learning in mobile robots. In 2018 IEEE/RSJ Int Conf Intelligent Robots and Systems, pages 2336–2341, 2018.

(Everingham et al. 2010) M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (VOC) challenge,” International Journal of

(Hall 2014) Hall, J.R.: The total cost of fire in the United States. National Fire Protection Association, Quincy (2014)

(Lecun et al. 2015) Yann Lecun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553):436–444, 2015.

(Lee et al. 2017) Wonjae Lee, Seonghyun Kim, Yong-Tae Lee, Hyun-Woo Lee, and Min Choi. Deep neural networks for wild fire detection with unmanned aerial vehicle. pages 252–253, Jan 2017.

(Mao et al. 2018) Wentao Mao, Wenpeng Wang, Zhi Dou, and Yuan Li. Fire Recognition Based On Multi-Channel Convolutional Neural Network. Fire Technology, 54(2):531–554, mar 2018.

(Qiang et al. 2014) Y. Qiang, B. Pei, and J. Zhao. Forest Fire Image Intelligent Recognition based on the Neural Network. Journal of Multimedia, 9(3), 2014.

(Redmon et al. 2016) Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi, You Only Look Once: Unified, Real-Time Object Detection, CVPR 2016.

(Redmon and Farhadi 2017) J. Redmon and A. Farhadi,” YOLO9000: Better, Faster, Stronger,” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 6517-6525.

(Redmon and Farhadi 2018) Joseph Redmon and Ali Farhadi. YOLOv3: An Incremental Improvement. 2018.

(Saponara et al. 2020) Saponara, S., Elhanashi, A. & Gagliardi, A. Real-time video fire/smoke detection based on CNN in antifire surveillance systems. J Real-Time Image Proc (2020).

(Zanca et al. 2020) D. Zanca, S. Melacci and M. Gori,” Toward Improving the Evaluation of Visual Attention Models: a Crowdsourcing Approach,” 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, United Kingdom, 2020, pp. 1-8.

(Zhang et al. 2018) Qi Xing Zhang, Gao Hua Lin, Yong Ming Zhang, Gao Xu, and Jin Jun Wang. Wildland Forest Fire Smoke Detection Based on Faster R-CNN using Synthetic Smoke Images. In Procedia Engineering, v.211, 2018.