Classification, Localization and Captioning of Dangerous Situations using Inception-v3 Network and CAM

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Abstract: An early situation assessment is an important aspect during emergency missions and provides useful information for fast decision making. However, many situations can be dangerous and visually hard to analyze due to the complexity. With the recent development in the field of artificial intelligence and computer vision there exists a wide range of application possibilities including automatic situation detection. However, many related works focused either on event captioning or on dangerous object detection. Therefore in this paper, a novel approach for simultaneous recognition and localization of dangerous situation is proposed: Two different CNN architectures are used, whereas one of the CNN, the Inception-v3, is modified to generate Class Activation Map (CAM). With CAM it is possible to generate bounding boxes for recognized objects without being explicitly trained for it. This eliminates the need for large image dataset with manually annotated boxes. The information about the detected objects from both networks, their spatial-relationships and the severity of the situation are then analyzed in the situation detection module. The detected situation is finally summarized in a short description and made available for the emergency managers to support them in fast decision makings.

1 INTRODUCTION

Hazardous situations happen everywhere and everytime, which may cause damages to its surroundings. For such situations UAVs like drones equipped with cameras are increasingly used in the past few years. They have the advantage to capture the dangers from a safe distance without humans being exposed to the hazards. Recorded real-time images are processed on cloud server and the analyzed information is given back to the ground operators to support them in situation assessment and monitoring (Figure 1).

However, the biggest challenge of the situation assessment is analyzing and extracting important information, especially in emergency cases and dangerous situations. Detecting objects captured by cameras can be difficult with traditional computer vision methods due to the many image features to be known beforehand. Therefore, solving this problem with AI-based methods brings more advantages, because image features are learned on its own during the training phase.

In this paper an AI-based model is presented for detecting and captioning dangerous situations.

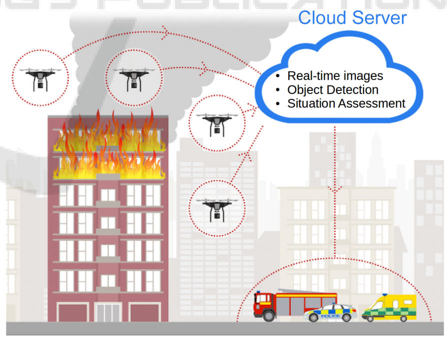

Figure 1: Example use of drones in emergency operations (Russon, 2019).

In detail, the proposed model consists of two parts: object detection and situation detection. In object detection part, two different Convolutional Neural Networks (CNN) for recognizing different object classes are implemented. While the pretrained SSD MobileNet V2 (Liu et al., 2015) is responsible for detecting normal neutral objects, the Inception-v3 network is retrained for identifying dangerous objects. In addition, the Inception-v3 is modified to generate

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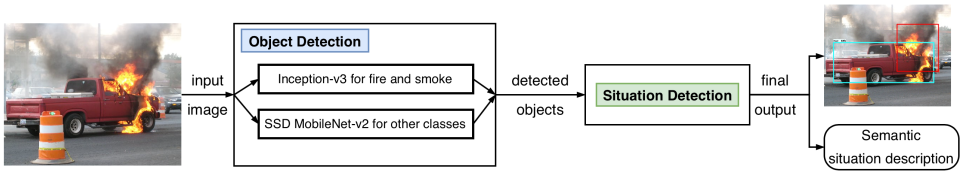


Figure 2: Proposed model architecture for detecting and describing dangerous situation.

Class Activation Map (CAM) based on the work of Zhou et al. (2015). It gives the network the ability to locate objects by drawing a bounding box around the predicted object without being explicitly trained with annotated ground truth boxes. This significantly reduces the time and effort in creating an annotated image dataset. Afterwards, the outputs from both networks are joined and passed forward to the situation detection part, where the correlation between the location of the detected objects is analyzed and their size roughly estimated. Finally, the model outputs a semantic description about the detected situation. The developed model is evaluated with test dataset on their effectiveness and detection performance.

The main contribution of this paper is the development of a model, which is able to detect, locate and describe dangerous situation simultaneously only with image-level annotations in the training dataset. Also, the results shows, that the performance achieved similar results to related works, which are trained explicitly with large annotated dataset containing bounding boxes.

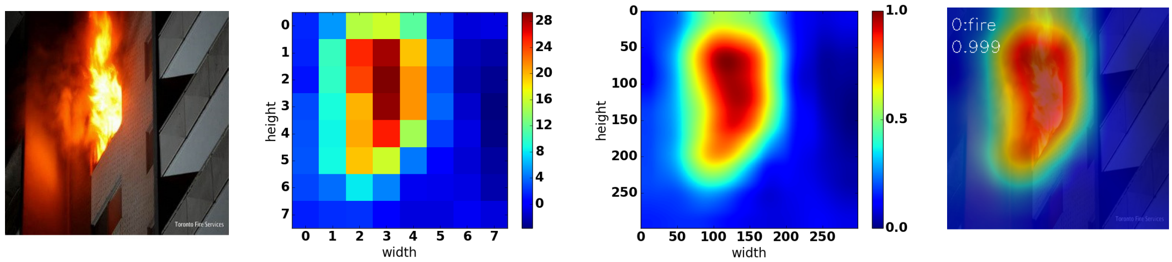
2 RELATED WORK

Fundamental image captioning and object detection with CNN is well researched and applied successfully on different fields. Most of the related work focused either on image event captioning or locating dangerous objects with CNN, but not simultaneously. For example in Muhammad et al. (2018), Wang et al. (2015), Ahsan et al. (2017), Arriaga et al. (2017), they are able to recognize situations and events captured in the images, but they lack the information about the location of the dangerous objects. In order to achieve that, the network needs to be trained with large annotated datasets like ImageNet (Russakovsky et al., 2014), Places Dataset (Zhou et al., 2016) and OpenImages (Kuznetsova et al., 2018). Existing well-known object detection networks are SSD (Liu et al., 2015), Faster R-CNN (Ren et al., 2015) and YOLO (Redmon and Farhadi, 2016), which are trainined with those large datasets. Furthermore, many papers have shown, that the feature maps in deep CNNs are actually highlighting the parts in the images, which are responsible for the high classification score (Zeiler and Fergus, 2013), (Yosinski et al., 2015), (Zhou et al., 2014). Some works, like Muhammad et al. (2018) and Zhou et al. (2015) use the feature maps to locate the detected objects, although both used methods are different. In Muhammad et al. (2018) they produced a binary image highlighting the location by averaging different feature maps from the SqueezeNet CNN (Iandola et al., 2016). They achieved a F1-score of 91%. Zhou et al. (2015) instead used global average pooling to calculate weighted feature maps for generating Class Activation Maps (CAM). They achieved 42.9% top-5 error for object localization without explicitly trained on any annotated bounding boxes and thus, saving timing and efforts.

3 METHODOLOGY

3.1 Proposed Model

The proposed model consists of two parts as depicted in Figure 2: object detection and situation detection. In object detection part, two different CNN are used. Fire and smoke objects are detected with Inception-v3 network (Szegedy et al., 2015) and other neutral objects with SSD MobileNetV2 (Sandler et al., 2018). SSD MobileNetV2 comes as pretrained model and detects normal images containing people, car and house objects. Inception-v3 is retrained on self-made image dataset containing fire and smoke classes. At the same time, the Inception-v3 is modified based on the work of Zhou et al. (2015) by generating CAM. By combining the advantages of CAM and the high accuracy classification performance of Inception-v3 network, it is possible to locate class-specific image regions in a single forward-pass without providing annotated bounding box in the training dataset. A bounding box is then drawn directly from CAM around the segmented area with predefined threshold value.



(a) Input image 299×299 pixel (b) CAM 8×8 pixel (c) CAM 299×299 pixel (d) CAM overlay

Figure 3: The initial CAM is calculated from the feature maps in the last convolutional layer and has the dimension 8×8 pixel (b), which is then upscaled with bicubic interpolation to 299×299 pixels (c). The final CAM is overlaid on the input image along with the predicted class and probability (d).

3.2 Modifying Inception-v3 with CAM

The last prediction layer of Inception-v3 is modified for classifying three classes: fire, smoke and non-fire-smoke. The pretrained weight parameters before the last layer are maintained. In order to generate CAM based on Zhou et al. (2015) the original average pooling layer in Inception-v3 network is changed to global average pooling layer. In mathematical form, the CAM is then calculated as follows:

$$CAM_c(x,y) = \sum_{n=0}^{N} w_n^c f_n(x,y) \qquad (1)$$

where w_n^c is the weight corresponding to one class c and n for the number of feature maps computed in the previous convolution layer. $f_n(x,y)$ denotes the activation values of the n-th feature map stored in spatial form (x,y). The sum of weights and the activation values over all feature maps yields in the CAM. In the last prediction layer, the probability for a given class is calculated with sigmoid function instead with softmax, because the probability of each class needs to be predicted independently with its own score. In this way multiple objects in the image can be detected at the same time.

3.3 Localization with modified Inception-v3

The resolution of the initial CAM with 8×8 pixels created from Inception-v3 is very low and inaccurate for localization tasks. Thus, it is upscaled to 299×299 pixels using bicubic interpolation to match the input image size of Inception-v3 network. At last, the normalized CAM is overlaid on the input image together with the predicted class and probability. The image processing steps are pictured in Figure 3. In order to locate objects from CAM, the regions associated with predicted class are segmented, where the activation value is above a predefined threshold value. For example a threshold value of 0.5 means, that CAM activation values, which are above 0.5, are extracted. A straight bounding box is then drawn around the borderline of the smallest possible area enclosing the segmented contour. By varying the threshold value, the size of the bounding box also changes, which would directly affect the localization performance. In Figure 4, the different size of segmented area and the corresponding bounding box is shown with example threshold value 0.5 and 0.8.

(a) Threshold value: 0.5

(b) Threshold value: 0.8

Figure 4: Creating different bounding box sizes with segment threshold value 0.5 (a) and 0.8 (b) from the CAM.

3.4 Situation Description

After the fire and smoke objects have been classified and located through Inception-v3 and CAM, the detection of other non-hazardous objects like houses, cars and people is done with pretrained SSD MobileNetV2 model, which also outputs object bounding box coordinates. The given information of both networks are then processed in the situation detection

Table 1: Categorization of severity based on reference objects and their size percentage differences.

	(-100%, -50%)	(-50%,-10%)	(-10%,10%)	(10%,100%)	(100%,∞)
person	small a	small a	small b	small b	medium
car	small a	small b	smallb	medium	large
house	small b	medium	medium	large	large

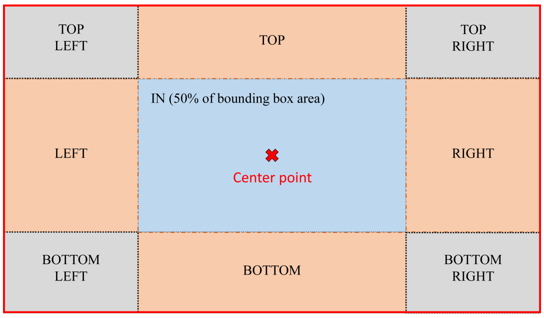


Figure 5: Comparing the center point of the object bounding box to determine their spatial relationship.

part, where the composition of dangerous and normal objects are estimated and analyzed as well as the severity of the detected situation. The size of fire and smoke is measured firstly by taking a non-hazardous objects as a reference object. For instance, the bounding box of a car can be specified as a reference box and the size of other dangerous objects like fire are then compared to it. The percentage size difference of a dangerous object to the reference object defines the size difference description. The assignment is listed in Table 2.

Table 2: Description of object size according to the percentage size difference to the reference object.

Percentage size difference to reference object	Description
below -50%	half as small than
-50% to -10%	smaller than
-10% to 10%	about the same size
+10% to +100%	bigger than
above +100%	twice as big than

Next, the situation description can be extended with defining the severity of fire or smoke based on the standard DIN 14010. In DIN 14010 the severity of fire are categorized by the number of water hoses used for extinguishing the fire. The categorization of smoke severity is assumed to be identical as fire. The severity categorization is shown in the Table 1. For simplicity, only three major objects are considered as reference objects: person, car and house. They also represent three major average size magnitudes.

With the size and severity described, the spatial relationship between dangerous and normal objects in the image are then measured by analyzing their bounding box positions. There exists five elementary composition cases in the image plane, which can be combined together: left, right, top, bottom and inside. In detail, the center points of all detected object bounding boxes in the image are obtained beforehand and the position relative to each other are then compared. Boxes, which center points lies outside the inner box, are then assigned to the preposition description according to their occupied areas shown in Figure 5. Furthermore, objects of the same class closely to each other are grouped together.

Table 3: Statistics of used dataset.

Dataset	fire	smoke	other	**Total**
Train / validation	200	100	500	**800**
Test	60	60	80	**200**

4 EXPERIMENTS

4.1 Dataset Overview

The dataset for training and evaluating the model contains a total of 1000 images, which is divided into 80% training/validation and 20% test dataset. The images are mainly collected from Sharma et al. (2017), but extra images with different resolutions were added from the internet. Table 3 gives an overview about the number of used image data and its distribution over the two datasets. The image classes are imbalanced in order to reproduce real world occurrences, i.e. fire and smoke occur much less frequently than normal objects. Figure 6 shows some sample images from the training/validation dataset for each class. Various fire and smoke shapes, sizes, colors under different light conditions like daytime and nighttime are included in the dataset in order to increase diversity. Also, some images contain different view angles like aerial views, which were captured from drones or helicopters during emergency operations. The negative image subset contains humans, pets, cars and other ordinary non-hazardous items.

Also images, which resemble fire and smoke in shape and color, such as sunsets, orange light bulbs and autumn leaves, were added to the negative image dataset. At last, the model is evaluated with the test

(a) fire (b) smoke (c) negative (no fire and smoke)

Figure 6: Sample images from the training dataset containing fire, smoke and other objects.

dataset, which contains 60 images each for fire and smoke and 80 images for negative objects, totaling 200 images. For evaluating the localization performance, each positive image from the test dataset was manually labeled with bounding boxes whereas negative images do not contain any boxes. The labeling tool used for this work is LabelImg (Lin, 2015).

4.2 Training

The final layers of the modified Inception-v3 network are retrained with RMSprop optimizer and a batch size of 8 using cross-validation. The pretrained weights were loaded from the Tensorflow Model Zoo (Silberman and Guadarrama, 2016). The learning rate is initially set to 0.001, but decreases exponentially with decay factor of 0.94. The loss in the prediction layer is computed with the sigmoid cross entropy function. During the cross-validation training, the model achieved the highest accuracy, lowest training loss and lowest evaluation loss at around 3300 global training steps, where the final model is also selected and evaluated.

5 RESULTS

5.1 Results of Image Classification

In Figure 7 the image classification precision-recall curve is shown for fire and smoke objects respectively. The model achieved in image classification an AP of 0.938 for fire and 0.907 for smoke class respectively. The overall mAP score is 0.923, which is calculated by averaging both AP values of both classes. The Table 4 lists both AP and mAP scores along with the corresponding F1-score.

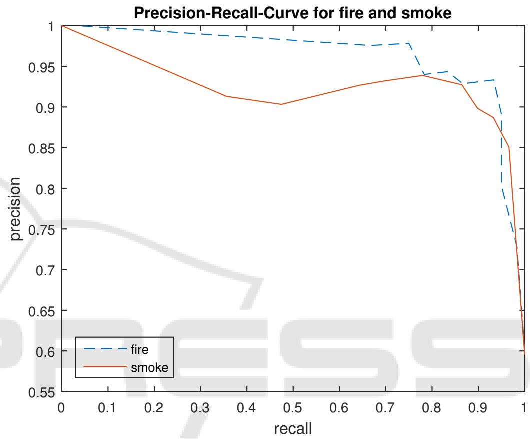


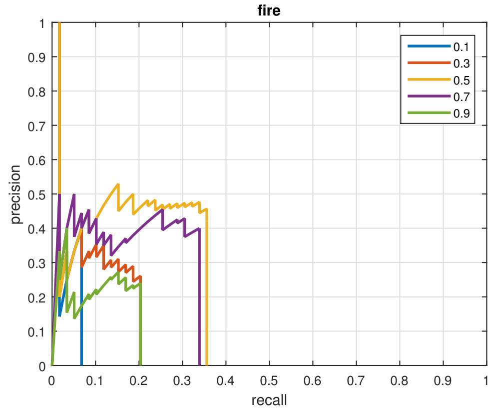
Figure 7: Classification precision-recall curve for fire (blue) and smoke (orange).

Table 4: AP of image classification for each class and the mAP.

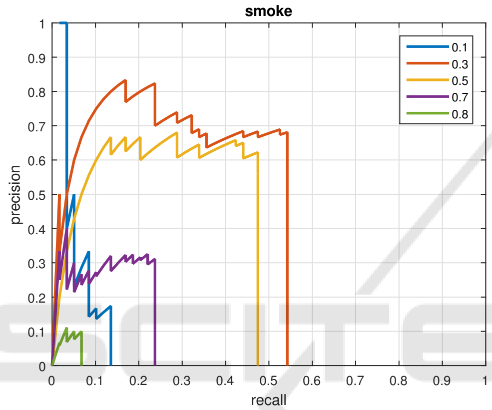
	fire	smoke	**mean value**
AP	0.94	0.91	**0.925 (mAP)**
F1-score	0.90	0.85	**0.875**

5.2 Results of Object Detection

As prerequisite, images with a confidence score over 0.5 in classification task are considered for generating bounding boxes from the resulting CAM. The Intersection-over-Union (IoU) scores of the predicted bounding boxes are determined against the ground truth. The localization results from the CAM is measured by adjusting the threshold value for segmenting the regions (Section 3.3). The segmentation threshold moves between 0.1 to 0.9 in 0.2 steps. Figure 8 shows the precision-recall curve for fire and smoke class respectively. It can be seen from the figures, that the threshold value affects the localization performance in general. The best performance can be



(a) fire



(b) smoke

Figure 8: Precision-recall curve at different segmentation thresholds for fire (a) and smoke (b).

found at threshold of 0.5 for fire and 0.3 for smoke. Further increase of the threshold value cause the performance to drop significantly. The AP scores for the localization task are listed in the Table 5 along with the corresponding mAP scores. For smoke objects the model achieved the best AP score of 0.42 at the threshold 0.3. On the contrary, the best AP score for fire object is 0.23 at the threshold 0.5, which is nearly 55% less than the AP score for smoke. By considering both classes, the model performed the best at the threshold 0.3 with an overall score of 0.285.

Table 5: AP and mAP for fire and smoke at different segmentation threshold value.

threshold	0.1	0.3	0.5	0.7	0.8	0.9
fire	0.10	0.15	**0.23**	0.17	0.17	0.08
smoke	0.11	**0.42**	0.31	0.10	0.01	0.00
mAP	0.105	**0.285**	0.270	0.135	0.090	0.040

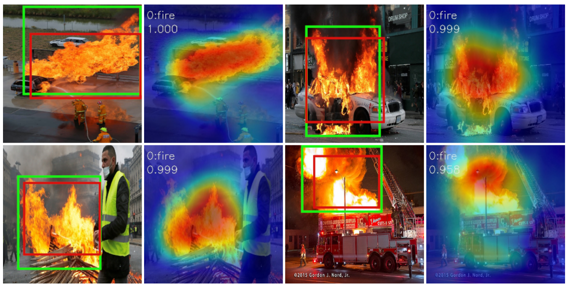
In Figure 9 and Figure 10 the generated bounding boxes are shown for fire and smoke respectively. The red rectangle represents the predicted bounding box and the green one is the ground truth which is annotated manually. The CAM along with the classification score is illustrated at the right side, visualizing the segmented region. In Figure 9b and Figure 10b the segmented regions from the CAM is inaccurate, resulting in an IoU score lower than 0.5. But on closer inspection, the center of the ROI actually shows accurately the location of fire and smoke, even though the size of the predicted bounding box does not match the ground truth. For false positive images, the CAM highlights locations, where it thinks the predicted object should be. For example the pizza salami as fire in Figure 9c and clouds as smoke in Figure 10c.

5.3 Results of Situation Detection

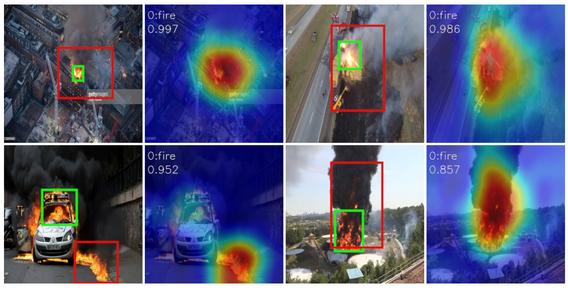
The output results from object detection part are passed forward to the situation detection part, where these information are analyzed for object size, their spatial relationship and the severity of the situation. The accuracy and logical plausibility of the situation description output therefore depends on the outputs in the previous part and are evaluated manually. Some of the best outputs from the model are given for fire in Figure 11 and smoke in Figure 12. The predicted bounding boxes from fire and smoke are marked as red, whereas the blue boxes locate non-hazardous object. The dark blue box represents the detected object group of the same class and the number of these objects is given in the description. It can be seen from the figures, that based on the correct object detection, the given situation is described accurately. Also, the severity is assigned properly according to the definition in DIN 14010. When the detection is inaccurate, the model then gives a wrong description, which can be seen in the first image of Figure 13a.

6 DISCUSSION

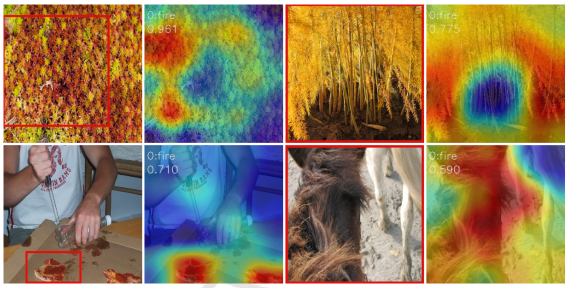
The classification of dangerous objects achieved high accuracy, even after the pretrained Inception-v3 network is modified with CAM and sigmoid prediction layer. Furthermore, it can be observed in Figure 9b and Figure 10b, that the model has problems in detecting small or distorted objects, like instead segmenting the smoke in vertical way, the CAM shows a round area, which is not accurate. However, the main location of smoke in the image is identified correctly, when the center points of the boxes are considered. The network also has difficulties in distinguishing fire and smoke from other neutral objects, which have a high resemblance in shape and color



(a) Bounding boxes with IoU scores over 0.5

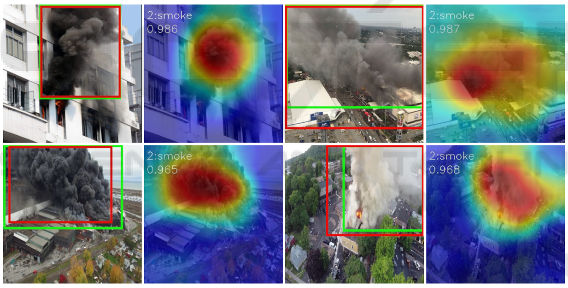


(b) Bounding boxes with IoU scores below 0.5

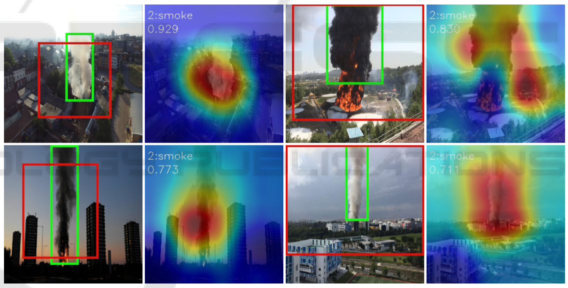


(c) Bounding boxes with IoU scores over 0.5 on false positive images

Figure 9: Bounding boxes generated for fire objects.



(a) Bounding boxes with IoU scores over 0.5



(b) Bounding boxes with IoU scores below 0.5

(c) Bounding boxes with IoU scores over 0.5 on false positive images

Figure 10: Bounding boxes generated for smoke objects.

such as autumn leaves or clouds. To increase the number of correct classifications and the accuracy of the predicted bounding boxes, more images with different object sizes, view angles and similarities to fire and smoke can be added to the training dataset. Using CNNs as an approach for detecting objects brings significant improvement in the performance compared to color and texture based detection (Chino et al., 2015).

The proposed model even achieved only 1% lower F1-score than the fine-tuned AlexNet in Muhammad et al. (2018), for which they reached a 0.89 F1-score. However, they trained their network with ten times more images than the training dataset used in this work. Even though the results in fire classification are surpassed by methods developed in Frizzi et al. (2016) and Mao et al. (2018), but their work could only predict one single object class. The proposed model on the contrary is able to detect two dangerous

(a) "Situation: fire is located TOP of 1 House and is smaller than House. Severity: medium"

(b) "Situation: fire is located TOP LEFT of 2 Person and is twice as big as Person. Severity: medium"

(c) "Situation: fire is located TOP RIGHT of 1 Car and is smaller than Car. Severity: small b"

Figure 11: Situation description for fire images.

(a) "Situation: smoke is located TOP RIGHT of 1 Person and is twice as big as Person. Severity: medium"

(b) "Situation: smoke is located TOP of 1 House and is smaller than House. Severity: medium"

(c) "Situation: smoke is located TOP of 1 House and is twice as big as House. Severity: large"

Figure 12: Situation description for smoke images.

(a) "Situation: fire is located TOP LEFT of 1 Car and is twice as big as Car. Severity: large"

(b) "Situation: smoke is located TOP LEFT of 2 Car and is twice as big as Car. Severity: large"

Figure 13: Example of bad situation descriptions.

objects independently and with much smaller dataset.

The localization performance of the model is highly affected by the classification performance, because it involves segmenting the regions of detected object classes and deriving the bounding box from it. Thus higher confidence scores in the classification part results in higher accuracy in locating objects, which can be seen in the Figure 9a and Figure 10a. On the contrary, the localization results becomes worse when predicting small or large objects. This can be explained through the low resolution of the feature map of the CAM, which originally has 8×8 pixel size. Smaller objects can be easier identified with higher feature map resolution.

In Table 6 the overall detection mAP scores for two mainstream CNN models with COCO dataset are listed: Faster R-CNN and SSD 300. Although the overall mAP score of the modified Inception-v3 with 0.29 is not comparable with any of the listed networks, but the score for one smoke class with 0.42

Table 6: Comparison of the mAP scores of different neural networks in object detection.

Method	mAP (IoU $\geq$ 0.5)
SSD 300 Liu et al. (2015)	0.412
Faster R-CNN Ren et al. (2015)	0.427
Inception-v3 with CAM	**0.285 (fire: 0.23, smoke: 0.42)**

is still competitive. The fact, that the proposed network is trained without using any bounding box annotations, underlines the good performance even more.

The situation description is based on the accuracy of both detection output from the classification and localization. A good object detection leads to a better situation description as can be seen in Figure 11 and Figure 12, otherwise the situation description would not be correct by giving the wrong spatial expression (see Figure 13). Additionally, it is not possible for the model to differentiate, whether the detected objects is positioned in the foreground or background, leading to wrong spatial relationship description. This can be seen in the description in Figure 13b: the smoke should be “BEHIND the car” and not “TOP left of the car”.

In addition, it is not possible for the model to determine the depth information of the objects, because it can not differentiate the foreground from the background in normal planar images. This problem can be seen in the description of the Figure 13b. In order to obtain the depth information of the objects, the drones can be equipped with additional sensors like time-of-flight cameras or LiDAR.

Ultimately, the developed model is meant for detecting situations in still images and, thus, not very suitable for real-time video detection due to the complexity and the large Inception-v3 network. A possible solution to optimize the speed and reduce the complexity is using network pruning (Molchanov et al., 2016) or light-weighted network such as SSD, YOLO for detection and MobileNet vor classification. Typically, a little accuracy is then sacrificed for faster speed.

7 CONCLUSION AND FUTURE WORKS

The results show, that the proposed model is able to recognize, locate and describe fire and smoke with CAM in the modified Inception-v3 network. Compared to other related works, only a small image dataset is required for this model, because the network is retrained only for the last layer. For classification task, the retrained Inception-v3 is able to achieve similar results compared to fully trained networks. The high classification performance allows the model to generate CAM precisely and enabled more than acceptable results in localization task, even outperforms the Faster R-CNN for smoke objects. The performance of the situation description is highly affected by the accuracy of the object classification and localization parts, because they are involved in providing necessary information for situation analyzing. Furthermore, a thorough search of the relevant literature yielded almost no papers, which are able to detect fire and smoke by providing small image-level dataset and describe the underlying dangerous situation in the same time. At this point, the proposed model provides a valuable contribution for solving those different tasks. For future works, the model performance can be improved by a larger image training dataset containing different object classes (e.g. material spills, hazard symbols etc.), sizes, light conditions and view angles. To apply the model on UAV for real-time situation detection tasks, the Inception-v3 needs to be pruned or exchanged with smaller networks like MobileNets. At last, further research can be conducted on the explanatory power of the situation description by evaluating the sentences against human annotated descriptions.

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