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Original Article

Development of an Aerial Fire Identification System Based on Visual Artificial Intelligence

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Abstract: To reduce losses due to fire, it is necessary to extinguish and rescue immediately. However, in the dense area fire trucks were unable to reach the fire site due to narrow road access. In this case, drones that can fly by themselves to the point of fire then release fire-fighting bombs automatically can help fire disaster management. This means it needs a system where it can identify whether there is a fire. This study explores the idea of identifying fire using computer vision approach by making 8 identification models with each dataset of day, night, day, and night, thermal, day filter, night filter, day and night filter, and thermal filter, which had been tested by a set of data that corresponded to each dataset. YOLOv4 algorithm and Google Colaboratory were used, where each model took 8-10 hours to be trained. Results show that the day and night model was the most robust by having the highest average F1-score, 0.37. And will be performing the best on thermal data test with the value of F1-score is 0.6. This can be a representation for exploring new ideas on further study of how to obtain the most suitable dataset and data test.

Keywords: fire, object detection, YOLOv4, F1-score, robustness

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1. Introduction

In the most populous province in Indonesia, DKI Jakarta, there have been around 6,429 fires throughout 2020 based on statistics. This dense area makes the distance between houses very close, which can accelerate the spread of fire from one house to another. To reduce losses due to fire, it is necessary to extinguish and rescue immediately. However, the fire trucks were unable to reach the fire site due to the narrow road access. In this case, drones that can fly by themselves to the point of fire then release fire-fighting bombs automatically can help fire disaster management. This means it needs a system where it can identify whether there is a fire.

This study explores the idea of identifying fire using computer vision approach by making 8 identification models with each dataset of day, night, day and night, thermal, day filtered, night filtered, day and night filtered, and thermal filtered, which had been tested by a set of data that corresponded to each dataset. YOLOv4 algorithm and Google Colaboratory were used, where each model took 8-10 hours to be trained. Each dataset contains 300-450 data in the form of images from the top view in a state of fire and not fire, also at the daylight and night.

2. Materials and Methods

2.1 Confusion matrix

There are four categories in the confusion matrix, which are True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). TP means that the model is capable to identify the desired object in the input image. FP means an error while identifying the input image by considering non-object as objects. FN means that there is an error also while identifying by being unable to identify the object in the input image. TN means that there is no error by identifying nothing where the input image has no object in it.

2.2 Precision and recall

Precision is the ratio of true predictions (true positive) and the total number of predictions. It measures how accurate is the identification model. While the recall is the ratio of true positive and the total desired predictions. It measures how well the model identifies the object in the input image.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

2.3 FI-score

F1-score is the harmonic mean of the precision and recall. The highest possible value is 1 which has the perfect precision and recall.

$$F1 = 2 \cdot \frac{Precision\ .\ Recall}{Precision+Recall} \tag{3}$$

2.4 Mean average precision (mAP)

AP is generally defined as the area under the smoothed precision-recall curve. This metric is commonly used to evaluate object detection models. In this study, COCO AP@0.50 is used, which is the same as Pascal VOC.

3. Results

This study explores the idea of identifying fire using computer vision approach by making 8 identification models tested with 8 data tests also, which the dataset and data test are days, night, day-night, thermal, day filter, night filter, day-night filter, and thermal filter. The images on every data test are different from the datasets to avoid bias for the results.

Images for datasets are collected from Google Images and Instagram consist of 50-day images and 50-night images by each half of it is in the form of fire with no smoke and the others are non-fire images. The images are edited in Photoshop software for the thermal dataset to make thermal images look alike. For filter datasets, the images are filtered in the Google Colaboratory platform using OpenCV library with dehazer, convert BGR2HSV, and inRange filters. In the inRange filter, for day filter, night filter, day-night filter datasets are using range low(0, 100, 200) and for the thermal filter, a dataset using low(10, 100, 200). The range high the dataset being(30, 250, 255) is implemented for the 4 filter datasets. Then the images are annotated and augmented on the Roboflow website with the output for each dataset being 300-450 images.

Data tests are collected from the Kaggle website then annotated with the Roboflow website resulting in each data test consisting of 173 bounding boxes.

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4. Discussion

YOLOv4 algorithm and Google Colaboratory were used in this study, where each model took 8-10 hours to be trained, as presented in Table 1 to Table 8 below.

Table 1. Results of day dataset model testing

	D [a]	N [b]	DN [c]	T [d]	DF [e]	NF [f]	DNF [g]	TF [h]
TP [i]	26	3	12	8	0	1	0	0
FP [j]	168	44	107	14	754	424	550	109
FN [k]	147	170	161	165	173	172	173	173
Precision	0.13	0.06	0.1	0.36	0	0	0	0
Recall	0.15	0.02	0.07	0.05	0	0.01	0	0
F1-Score	0.14	0.03	0.08	0.08	-	0	-	-
mAP@0.50	4.82%	1.06%	2.37%	3.72%	0%	0.01%	0%	0%

[a] Day data test.
[b] Night data test.
[c] Day night data test.
[d] Thermal data test.
[e] Day filter data test.
[f] Night filter data test.
[g] Day night filter data test.
[h] Thermal filter data test.
[I] True positive.
[j] False positive.
[k] False-negative.

Table 2. Results of night dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	11	36	28	52	1	3	8	10
FP	41	85	64	46	6	11	4	8
FN	162	137	145	121	172	170	165	163
Precision	0.21	0.3	0.3	0.53	0.14	0.21	0.67	0.56
Recall	0.06	0.21	0.16	0.3	0.01	0.02	0.05	0.06
F1-Score	0.1	0.24	0.21	0.38	0.01	0.03	0.09	0.1
mAP@0.50	3.14%	11.67%	9.03%	25.55%	0.19%	1.47%	4.79%	6.04%

Table 3. Results of day-night dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	73	55	59	90	24	29	23	52
FP	45	61	40	35	46	31	32	31
FN	100	118	114	83	149	144	150	121
Precision	0.62	0.47	0.6	0.72	0.34	0.48	0.42	0.63
Recall	0.42	0.32	0.34	0.52	0.14	0.17	0.13	0.3
F1-Score	0.5	0.38	0.43	0.6	0.2	0.25	0.2	0.41
mAP@0.50	40.31%	25.18%	32.71%	53.92%	7.20%	10.89%	11.04%	33.99%

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Table 4. Results of thermal dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	10	22	14	90	18	28	26	53
FP	29	44	45	109	153	123	97	176
FN	163	151	159	83	155	145	147	120
Precision	0.26	0.33	0.24	0.45	0.11	0.19	0.21	0.23
Recall	0.06	0.13	0.08	0.52	0.1	0.16	0.15	0.31
F1-Score	0.09	0.18	0.12	0.48	0.1	0.17	0.18	0.26
mAP@0.50	3.29%	8.31%	4.05%	29.21%	2.86%	4.84%	6.64%	12.45%

Table 5. Results of day filter dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	1	0	1	0	16	2	6	6
FP	3	0	5	7	57	41	57	28
FN	172	173	172	173	157	171	167	167
Precision	0.25	0	0.17	0	0.22	0.05	0.1	0.18
Recall	0.01	0	0.01	0	0.09	0.01	0.03	0.03
F1-Score	0.01	-	0.01	-	0.13	0.02	0.05	0.06
mAP@0.50	0.52%	0%	0.39%	0.10%	5.32%	0.55%	1.82%	2.89%

Table 6. Results of night filter dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	15	16	10	37	18	21	28	61
FP	81	68	70	59	100	111	88	85
FN	158	157	163	136	155	152	145	112
Precision	0.16	0.19	0.12	0.39	0.15	0.16	0.24	0.42
Recall	0.09	0.09	0.06	0.21	0.1	0.12	0.16	0.35
F1-Score	0.11	0.12	0.08	0.28	0.12	0.14	0.19	0.38
mAP@0.50	3.73%	4.64%	2.37%	16.76%	3.04%	5.59%	7.02%	23.88%

Table 7. Results of day-night filter dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	9	53	37	86	56	43	42	99
FP	62	136	78	59	53	67	67	40
FN	164	120	136	87	117	130	130	74
Precision	0.13	0.28	0.32	0.59	0.51	0.39	0.39	0.71
Recall	0.05	0.31	0.21	0.5	0.32	0.25	0.25	0.57
F1-Score	0.07	0.29	0.26	0.54	0.4	0.3	0.3	0.63
mAP@0.50	2.24%	18.25%	12.91%	45.94%	28.19%	17.71%	17.71%	52.37%

Table 8. Results of thermal filter dataset model testing

	D	N	DN	T	DF	NF	DNF	TF
TP	1	1	1	0	82	61	73	82
FP	9	18	11	3	466	226	398	140
FN	172	172	172	173	91	112	100	91
Precision	0.1	0.05	0.08	0	0.15	0.21	0.15	0.37
Recall	0.01	0.01	0.01	0	0.47	0.35	0.42	0.47
F1-Score	0.01	0.01	0.01	-	0.23	0.27	0.23	0.42
mAP@0.50	0.21%	0.43%	0.09%	0.07%	21.53%	18.54%	21.72%	30.63%

Tables 1 to 8 show the results of 64 testing cases with 8 datasets and 8 data tests, which are day, night, day-night, thermal, day filter, night filter, day-night filter, thermal filter. The representative of several tested models was also presented in Figure 1.

Figure 1. Model testing results on new input images

Fig. 1 shows the results of several tested models using various new input images. From the figure, it can be seen that the model can identify many spots of fire (true positive), but there are still some spots that are not identified (false negative).

5. Conclusions

In this study, 8 identification models had been built with each dataset of day, night, day and night, thermal, day filter, night filter, day and night filter, and thermal filter, which had been tested by a set of data that corresponded to each dataset model. YOLOv4 algorithm and Google Colaboratory were used, where each model took 8-10 hours to be trained. Based on the results, it can be concluded that the day and night model was the most robust by having the highest average F1-score, which is 0.37. The model is good enough to be implemented on the corresponding data test but

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will be performing the best on the thermal data test with the value of F1-score being 0.6. This result can be a representation for exploring new ideas on further study of how to obtain the most suitable dataset to be trained and data test to be tested. So that the application of fire identification system can use the highest robustness model with the right input tools.

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