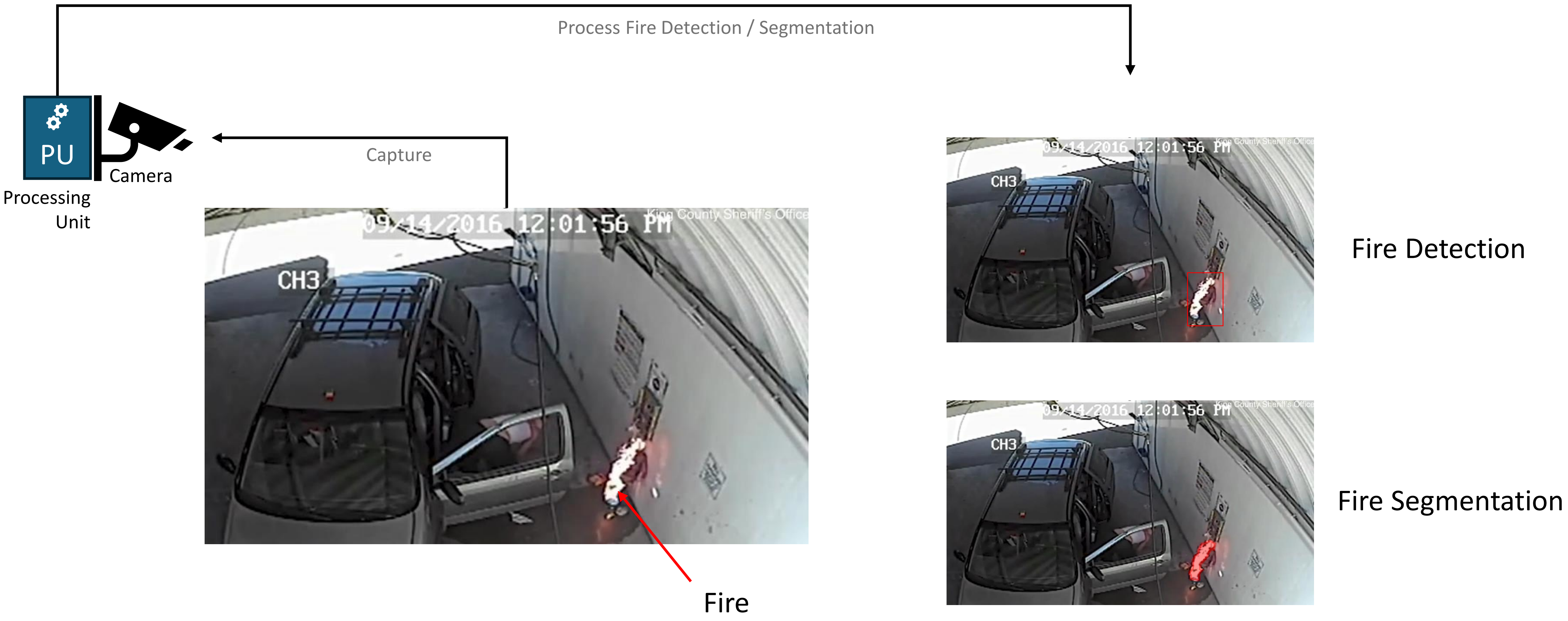
Fire and Smoke Detection

2024/12/09

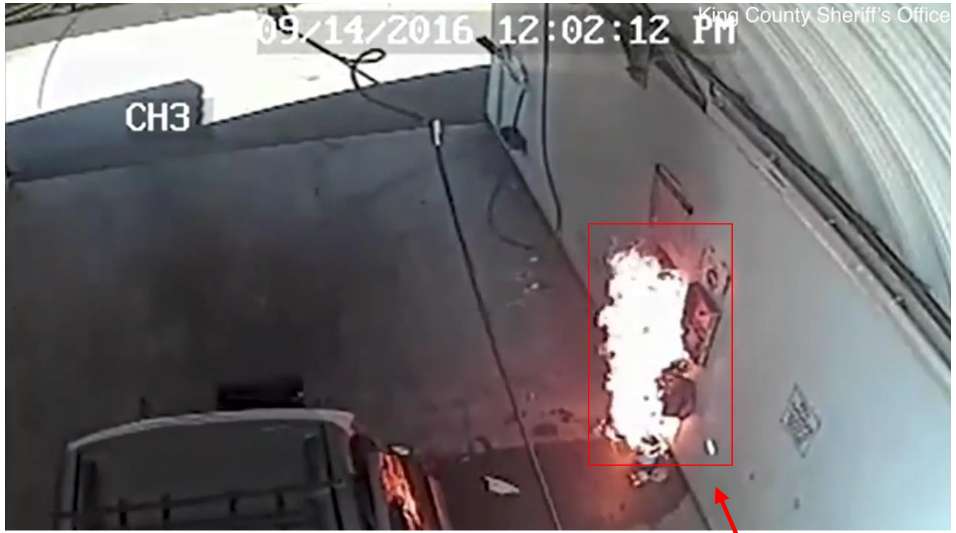
Computer Vision & Pattern Recognition Lab
kit 금오공과대학교
Kumoh National Institute of Technology

Contents

Introduction



Motivation



Burning Stage

Initial Stage

Easier to find using DL models
(existing research)

Difficult to find fire in the initial stages
(limitation)

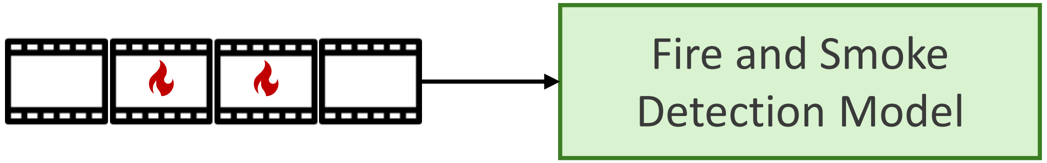
Motivation

Most of the current deep learning-based fire detection models need more resources for Fire detection.

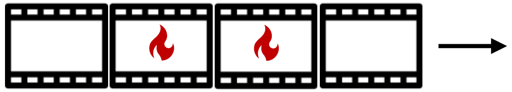
Also, have high inference time

For real time detection, we need lighter model with efficient processing to be able to run on edge devices

Current Models



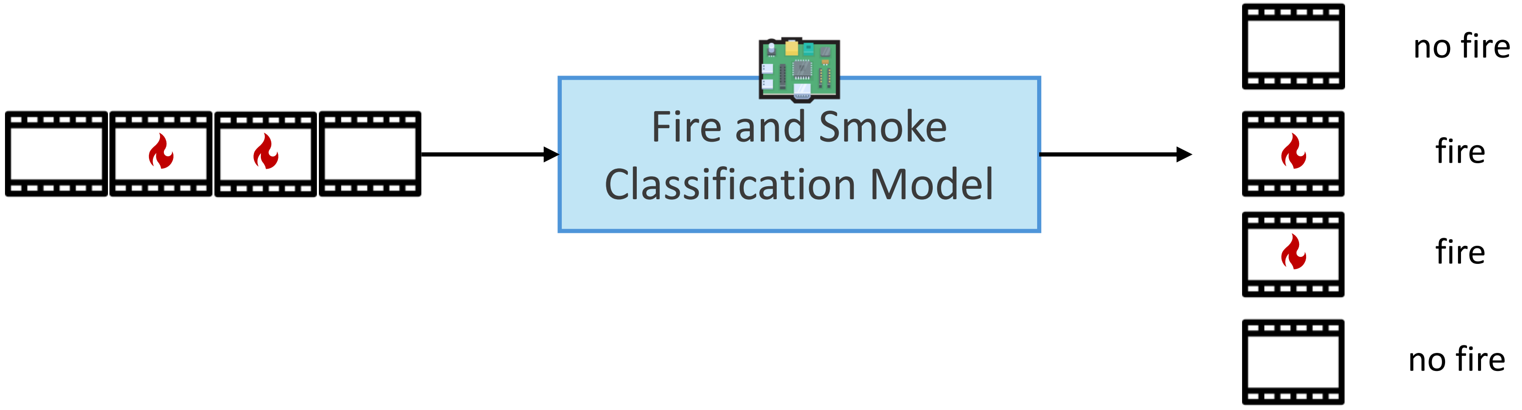
Constantly searching for fire in video feed



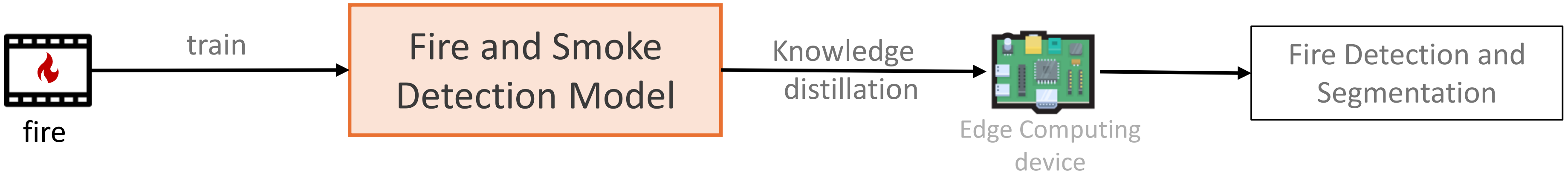
Deploy a classifier to filter video feed (on device) → Use a lightweight detection model to locate fire (on device)

Goal

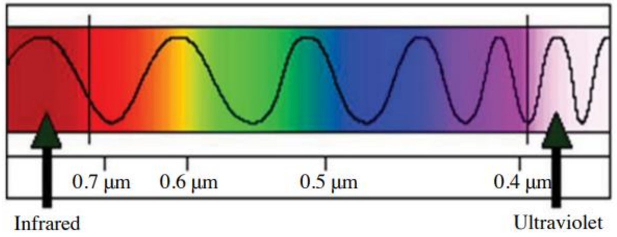
Use a classification model to filter the parts with fire possibility



Use a detection model to locate fire regions



Background



→ Visible light region of the electromagnetic spectrum

→ Generic colors of fire are red and yellow when temperature lies below 1000°C

Low Temperature → Low frequency of visible light

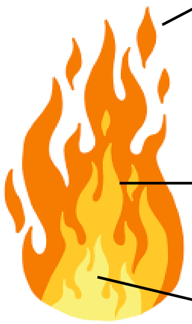
High Temperature → High frequency of visible light

Low temperature fire

High temperature fire

Computer Vision-based Method to Detect Fire Using Color Variation in Temporal Domain

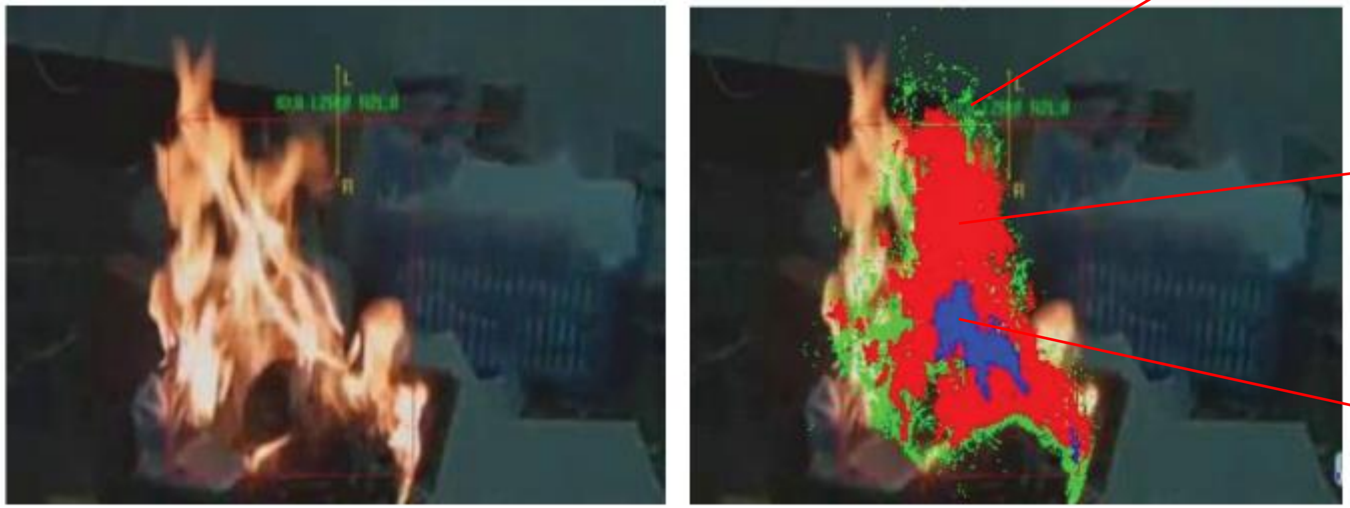
Background



Short term fire part (Blaze)

Flickering fire

Long term fire part



Short term fire

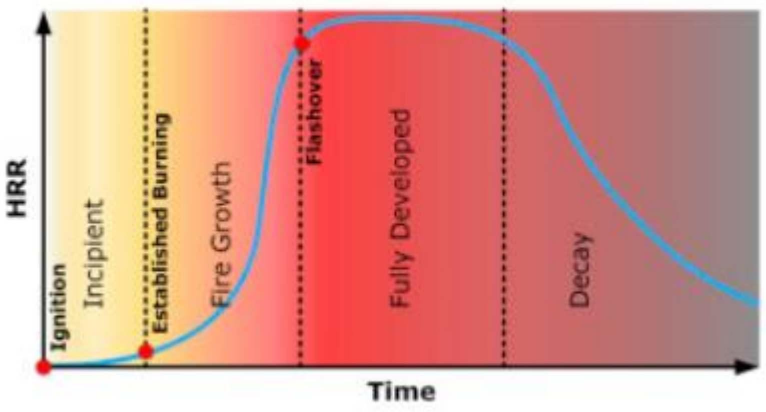
Flickering fire

Long term fire

Computer Vision-based Method to Detect Fire Using Color Variation in Temporal Domain

Background

(Heat release rate)



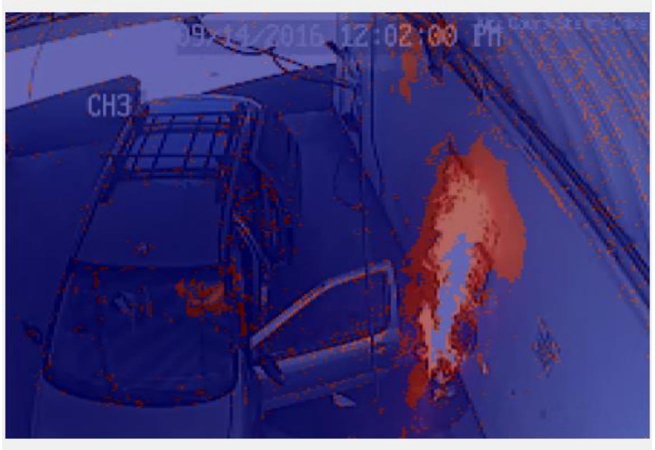
- Ignition → HRR starts at a very low level since the fire is just starting.
- Incipient Stage→ The fire is still small, and HRR begins to increase as it gains strength.
- Established Burning (Growth)→ HRR rises rapidly as the fire spreads and consumes more fuel.
- Flashover→ HRR reaches a peak or very high point, leading to the rapid transition of a room to a fully developed fire.
- Fully Developed Stage→ HRR stabilizes at a high level as the fire consumes maximum available fuel.
- Decay Stage→ HRR begins to decrease as fuel becomes scarce, leading to a reduction in fire intensity until it eventually extinguishes.

Indoor fire detection utilizing computer vision-based strategies

Traditional Methods – Frame Difference

Frame 350

Frame 353



Frame Difference

When the background is fixed, frame difference can help in finding fire regions.

However, might be difficult with movement of vehicles and people.

Frame Difference Method to Detect Fire and Compare the Accuracy and Precision with Vibe Method

Traditional Methods – Gaussian Mixture Models

Fire has distinct color properties, typically in the red, orange, and yellow ranges. GMM can model these colors by clustering pixels based on their RGB or HSV values.

A Gaussian Mixture Model represents a distribution as a mixture of multiple Gaussian distributions.

$$p(x) = \sum_{k=1}^{K} \pi_k \cdot \mathcal{N}(x|\mu_k, \Sigma_k)$$

Where K is the number of gaussian components
π_k is the weight for each component with $\sum_{k=1}^{K} \pi_k = 1$
$\mathcal{N}(x|\mu_k, \Sigma_k)$ is the Gaussian distribution with mean μ_k and covariance Σ_k for the k-th component.

A fire color mapping-based segmentation: Fire pixel segmentation approach

Related previous study on fire detection

a) Fire Detection Using Computer Vision [2018]

Video Feed → Background subtraction → Color Detection → Wavelet Analysis

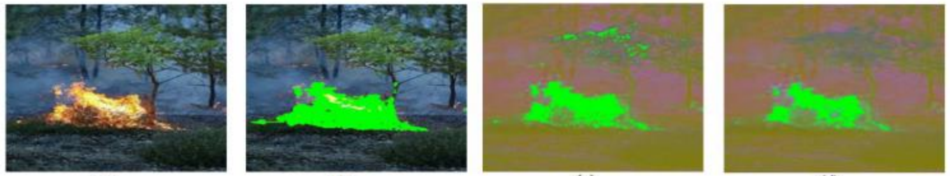
Find regions with motion

Convert to YCbCr color space and run through an ANN to get fire pixels

YCbCr → Y= luminance, Cb = chrominance blue, Cr = chrominance red

Calculate energy using wavlets on moving regions that had fire like color

When the energy > threshold, the patch is treated as fire region



(a) (b) (c) (d)

Fig 2 (a) Original image, (b) Detected using RGB, (c) Detected using YCbCr (d) Detected using ANN

Related previous study on fire detection

b) Advanced Video SmokE Detection for Real-Time Measurements in Antifire Indoor and Outdoor Systems – AdViSED [2020]

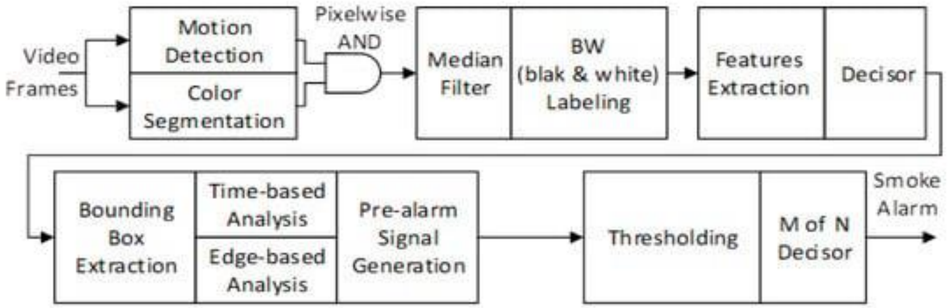


Table 6. Real-time processing in fps for different platforms, without displaying processed output frames.

Platform	Frame Size				
	320 × 480	640 × 480	1280 × 720	1920 × 1080	1920 × 1440
X86 64b PC	29.3 fps	17.5 fps	6.07 fps	N/A	1.81 fps
RPi 3 model B	13.4 fps	4.47 fps	01.38 fps	0.87 fps	N/A

Figure 2. Detection of smoke on a test video. (**a**) Current Frame n; (**b**) motion detection; (**c**) color segmentation; (**d**) logic AND pixelwise; (**e**) median filter; (**f**) feature extraction; (**g**) bounding box extractor; (**h**) bounding boxes applied on the current frame n; and (**i**) final result at runtime with many overlaps and smoke alarm activated.

Related previous study on fire detection

c) Fire and Smoke Detection Using Fine-Tuned YOLOv8 and YOLOv7 Deep Models [2024]

Model	Precision	Recall	mAP:50	mAP:50-95
YOLOv8n	0.919	0.793	0.869	0.658
YOLOv8s	0.929	0.828	0.891	0.721
YOLOv8m	0.935	0.831	0.895	0.745
YOLOv8l	0.949	0.837	0.901	0.753
YOLOv8x	**0.954**	**0.848**	**0.926**	**0.772**
YOLOv7	0.881	0.778	0.854	0.647
YOLOv7-X	0.918	0.817	0.882	0.715
YOLOv7-W6	0.922	0.824	0.887	0.745
YOLOv7-E6	0.937	0.824	0.896	0.748
YOLOv6l	0.582	0.605	0.852	0.496
Faster-RCNN	0.437	0.374	0.471	0.348
DETR	0.443	0.362	0.413	0.291

(a) Detection of smoke and fire at night. (b) Smoke detected with high precision. (c) Fire and smoke detected on the city.

(d) Smoke detection very far away. (e) Smoke and fire detection on the mountain. (f) Smoke detection.

(g) Fire and smoke detection in forest. (h) Fire and smoke detection in the city. (i) Fire detection in industrial zone.

Figure 5. Example of fire and smoke detection by YOLOv8x model.

Related previous study on fire detection

d) A Yolo-based Approach for Fire and Smoke Detection in IoT Surveillance Systems [2024]

Used YOLO v8

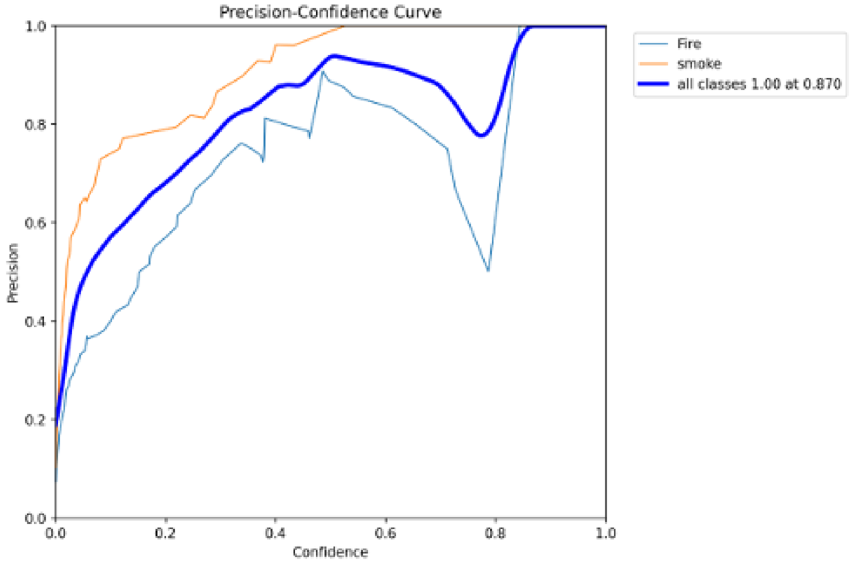


Fig. 5. P-curve of the model.

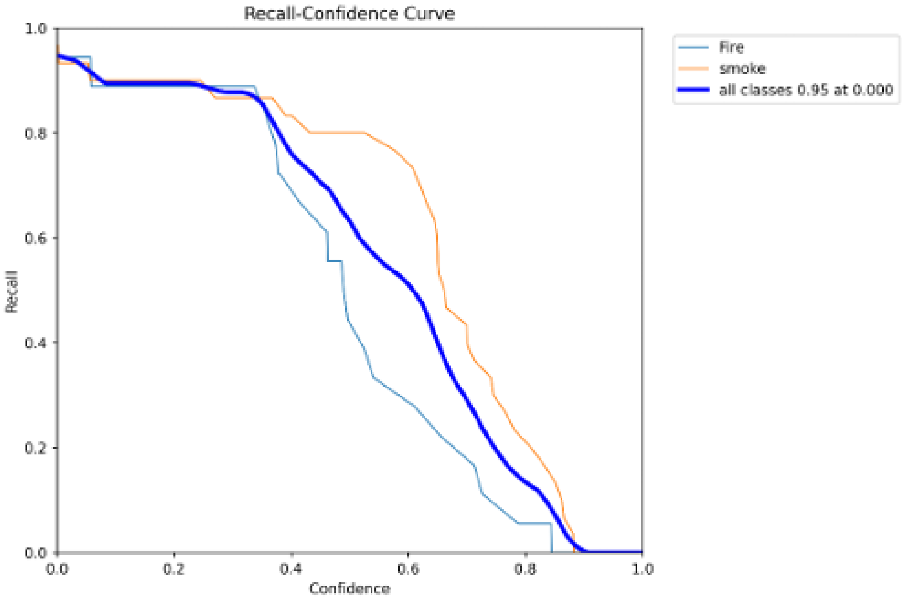
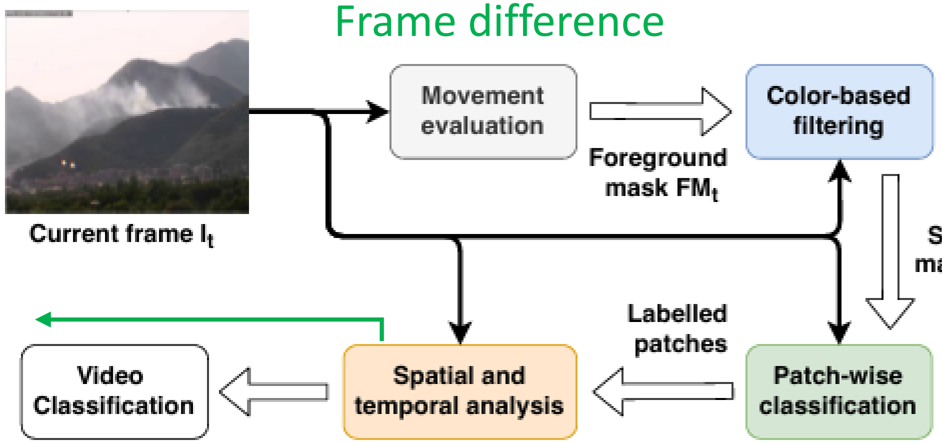


Fig. 6. R-curve of the model.

Related previous study on fire detection

e) A Smart Visual Sensor for Smoke Detection Based on Deep Neural Networks [2024]

Frame difference



Frame difference

CNN

number of patches, frames having smoke > threshold

Figure 3. Overview of the proposed method. The current frame (I_t) is spread to all the stages together with the outcome of each of them. The movement evaluation takes the current frame as input and produces an updated foreground mask FM_t to the color-based filtering module, which performs a further refinement of the binary mask by taking into account the appearance. The output of the latter is a binary mask, namely the smoke mask SM_t, used by the patch-wise classification stage to select the region of the image in which the smoke is expected to be. Finally, the outcome of the classification is provided to the last stage, spatial and temporal analysis, to evaluate the evolution of the smoke over the time and classify the video.

Related previous study on fire detection

e) A Smart Visual Sensor for Smoke Detection Based on Deep Neural Networks [2024]

(a) (b)

Figure 10. Comparison between bounding box (**a**) and polygon labeling (**b**). The image on the left shows an example of bounding box while the one on the right depicts a polygon annotation example. It is clear that polygon labeling is more appropriate and can better capture the smoke shape without including non-smoke areas.

Table 4. Results obtained on the MIVIA-SDD test set in terms of accuracy (A), recognition rate (RR), false positive rate (FPR), false positive videos (FPVs) and false positive events (FPEs). The best results are highlighted in bold.

Method	Patch-Based			Frame-Based			Video-Based				
	A	RR	FPR	A	RR	FPR	A	RR	FPR	FPV	FPE
MobileNet	86.93	94.57	16.89	85.40	74,95	9.61	83.96	88.88	18.57	13	206
VGG-19	86.29	**96.24**	18.69	85.45	75,13	9.62	85.85	**94.44**	18.57	13	211
ResNet-50	86.22	94.38	17.85	85.46	75.09	9.58	85.85	**94.44**	18.57	13	211
Inception v3	**89.87**	94.77	**12.59**	85.55	73.32	**8.61**	**88.68**	**94.44**	**14.28**	**10**	**192**
Xception	88.87	95.29	14.34	**86.11**	**77.90**	9.96	83.96	**94.44**	21.42	15	218

Related previous study on fire detection

f) A lightweight fire detection algorithm for small targets based on YOLOv5s [2024]

For small fire detection

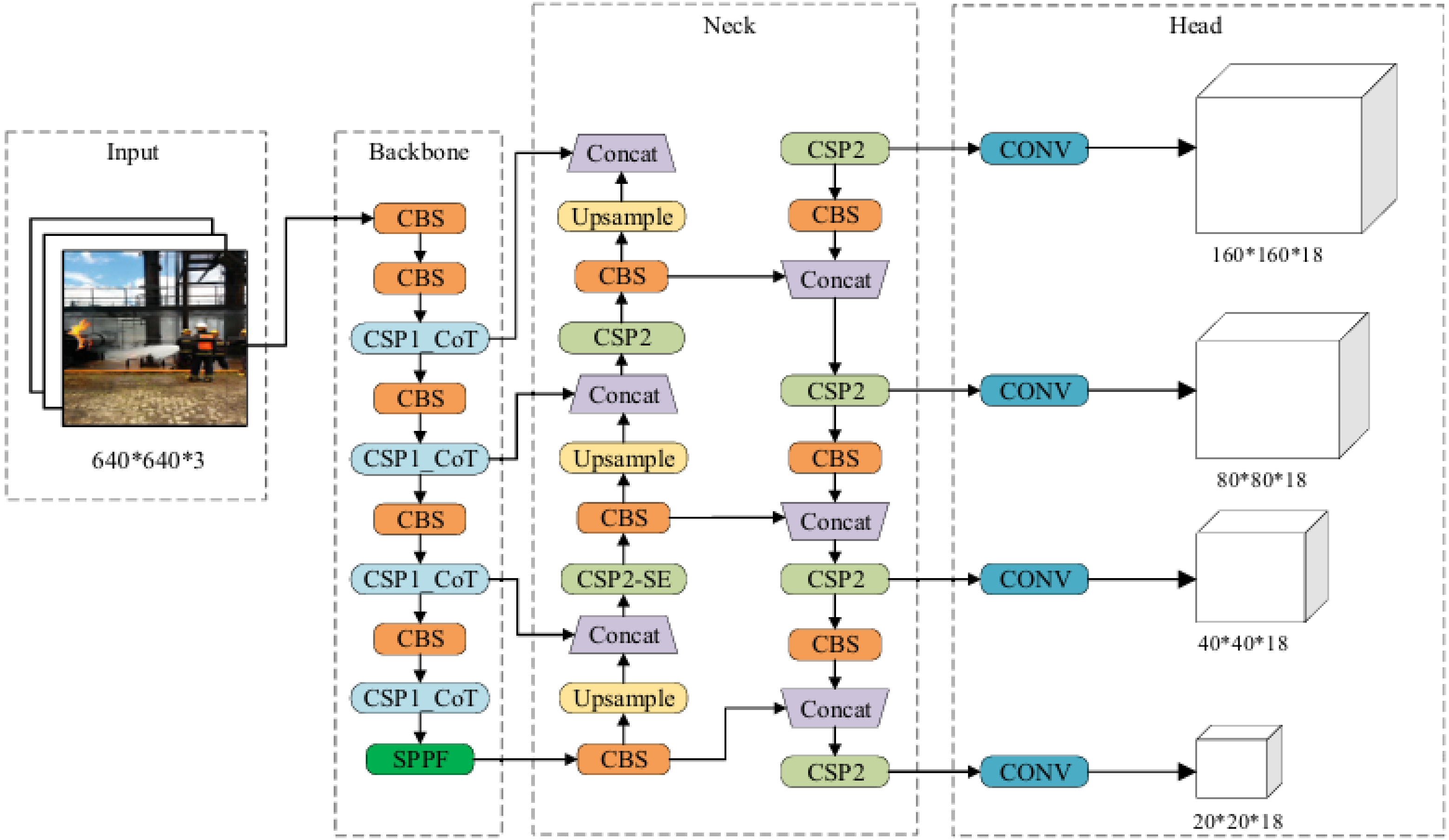


Figure 8. The architecture of the proposed fire detection model based on improved YOLOv5s.

Related previous study on fire detection

f) A lightweight fire detection algorithm for small targets based on YOLOv5s [2024]

Figure 12. The fire image recognition results of the YOLOv5s model.

Model	Precision /%	mAP@0.5/%	Weight Size/MB	FPS	Time/ms
SSD	82.8	78.1	90.6	22	45.5
Faster R-CNN	83.5	87.3	315	32	31.2
YOLOv3-tiny	81.4	82.6	17.4	180	5.6
YOLOv4-tiny	49.6	79.9	23.6	188	5.3
YOLOv5m	86.2	87.4	42.1	66	15.2
YOLOv5l	86.8	87.8	88.5	64	5.6
YOLOv7-tiny	83.7	86.5	11.7	90	11.1
YOLOv5s	85.9	87.2	14.4	105	9.5
YOLOv8s	86.5	86.9	22.5	81	12.3
YOLOv9	85.3	88.8	102.8	62	16.2
Literature[20]	86.3	84.1	14.9	87	11.4
Literature[33]	82.1	78.9	16.9	66	15
Literature[43]	88.9	90.3	49.6	42	23.8
Ours	94.8	96.0	14.6	85	11.7

Related previous study on fire detection

g) Benchmarking Multi-Scene Fire and Smoke Detection [2024]

Table 5: Performance comparison of different models on our miniMS-FSDB. Key metrics include detection accuracy, mAP, Performance (Gflops), and number of parameters (M) for each category. Fire represents the Average Precision (%), Smoke represents the Average Precision (%), and mAP represents the mean Average Precision (%) of fire and smoke. For consistency and comparability, we use small input images for all baseline models. Ours denotes our method.

Model	Fire (%)	Smoke (%)	mAP (%)	Perf (Gflops)	Params (M)
YOLOv5s [28]	66.3	81.3	73.8	15.8	7.0
YOLOv5x [28]	67.5	81.6	74.5	203.8	86.2
YOLOv5n [28]	72.4	78.2	75.3	4.1	**1.8**
YOLOv5l [28]	71.5	79.7	75.6	107.7	46.1
YOLOv5m [28]	69.6	84.1	76.8	47.9	20.9
SSD [22]	71.2	84.4	77.8	731.5	23.9
RetinaNet [23]	80.4	89.4	84.9	**1,715.3**	36.4
FasterRCNN [26]	98.0	93.0	95.5	504.3	41.4
FCOS [27]	94.1	95.9	95.0	1,289.9	32.1
Ours	**98.3**	**99.3**	**98.8**	1,290.5	33.3

(a) False results of general detection

(b) Correct results of our method

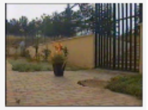
Figure 3: For ordinary fire and smoke, some of the difficulties encountered in detection are addressed using our method. (a) represents the false results of the general detection. (b) represents the correct results of our method. In the diagram, blue boxes represent ground truth, and red boxes represent predicted results.

Fire and Smoke datasets

1. MIVIA Fire Detection dataset

This collection of videos has been used in order to test our methods for fire and smoke detection. It is composed by 31 videos both acquired in real environments. The dataset can be seen as composed by two main parts: the first 14 videos characterized by the presence of the fire and the last 17 videos which do not contain any event of interest; in particular, this second part contains critical situations traditionally recovered as fire, such as red objects moving in the scene, smokes or clouds.

Sample

VIDEO	RESOLUTION	FRAME RATE	FRAMES	FIRE	EXAMPLE
Fire1	320×240	15	705	Yes	
Fire2	320×240	29	116	Yes	
Fire3	400×256	15	255	Yes	
Fire4	400×256	15	240	Yes	
Fire5	400×256	15	195	Yes	
Fire6	320×240	10	1200	Yes	
Fire7	400×256	15	195	Yes	
Fire8	400×256	15	240	Yes	

Fire and Smoke datasets

2. Firenet Dataset

Firenet dataset is a fire dataset that is provided by Arpit et al. from fire and non fire videos that are captured and obtained. The dataset is comprised of 46 videos consisting fire scenes, 16 videos consisting of non fire scenes and an additional 160 images consisting of non fire scenes. In total the dataset consists of 62 videos and 160 images.

Sample

Fire and Smoke datasets

3. Fire Flame Dataset

A comprehensive image dataset for fire and smoke detection is given by Deep Quest AI. The dataset consists of images of 3 classes: Fire, Smoke and Neutral. Each of the classes have 1000 images split as 900 images for training and 100 images for testing. Thus, there are a total of 3000 images in the dataset. Figure 3 shows few sample images from this dataset.

Sample

Fire and Smoke datasets

4. Video Smoke Detection Dataset

A video smoke detection dataset consisting of smoke images and videos is released by Dr Feiniu Yuan. The dataset website consists of 3 smoke videos and 3 non smoke videos. There is a database of smoke and non smoke images with 4 sets of data with Set 1 consisting of 552 smoke and 831 non smoke images, Set 2 consisting of 668 smoke and 817 non smoke images, Set 3 consisting of 2201 smoke and 8511 non smoke images and Set 4 consisting of 2254 smoke and 8363 non smoke images. In addition to these image datasets there are an additional 648 black and white smoke images and two sets of non smoke datasets each consisting of 27707 and 28760 images respectively.

Sample

Fire and Smoke datasets

5. State Key Laboratory of Fire Science (SKLFS) Dataset

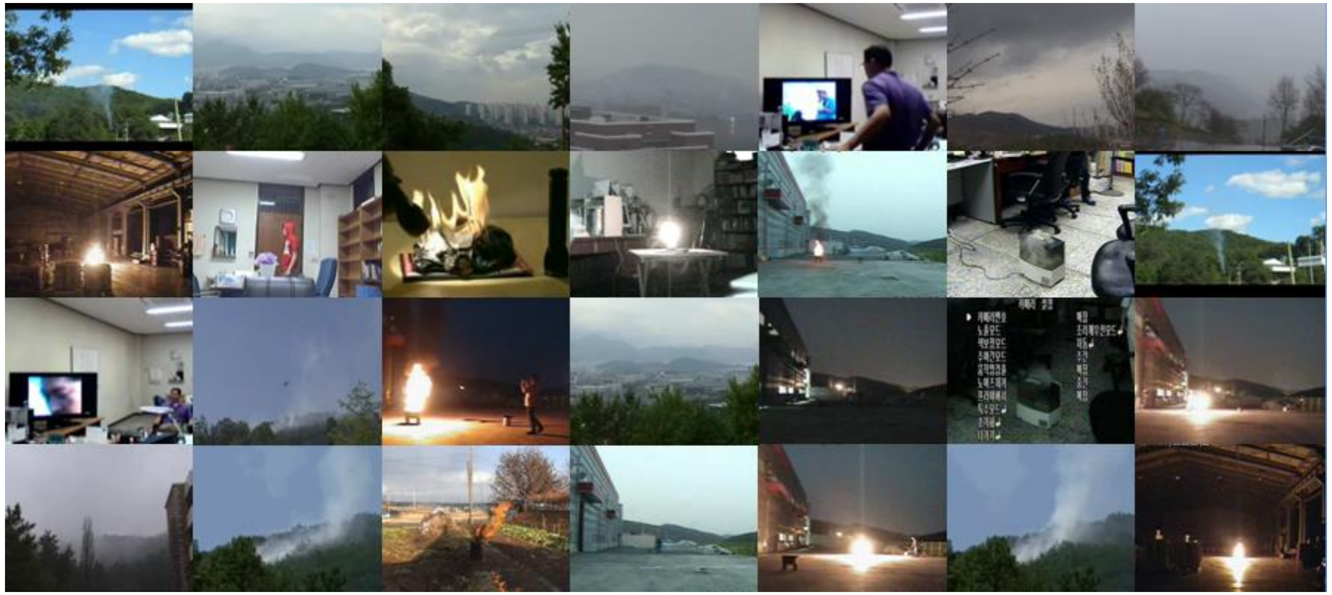
A comprehensive image and video dataset for fire and smoke detection is given by State Key Laboratory of Fire Science. The dataset consists of 36104 smoke and non-smoke images, with block labels and textures. There are 30000 synthetic image and video datasets and 3578 real image and video datasets on which the deep learning models are trained and developed. The synthetic smoke and non-smoke images have different parameters of rendering, lighting and wind being set randomly in a certain range for diversity. Since different sets of the parameters influence directly the appearance of synthetic smoke images, these images will be realistic or non-realistic.

Sample

Fire and Smoke datasets

6. KMU Fire and Smoke Dataset

A video dataset for fire and smoke detection is given in KMU Fire and Smoke Database. A publicly available sample dataset consists of video clips of 4 classes: indoor & outdoor (short distance flame), indoor & outdoor (short distance smoke), wildfire smoke, and smoke or flame-like moving object. Totally there are 308.1 MB video sequences in these four categories.



Sample

Fire and Smoke datasets

7. Kaggle Fire Dataset

The dataset was created by my team during the NASA Space Apps Challenge in 2018, the goal was using the dataset to develop a model that can recognize the images with fire. Data was collected to train a model to distinguish between the images that contain fire (fire images) and regular images (non-fire images). Data is divided into 2 folders, fire_images folder contains 755 outdoor-fire images some of them contains heavy smoke, the other one is non-fire_images which contain 244 nature images (eg: forest, tree, grass, river, people, foggy forest, lake, animal, road, and waterfall).

Sample

Preliminary Experiments

1) Using Gaussian Mixture Model (GMM)

Select a region to calculate GMM parameters for fire

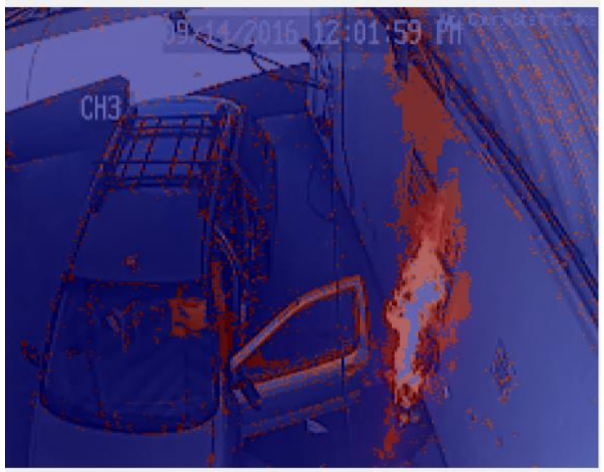
Use GMM to predict new frames

Preliminary Experiments

1) Using Frame Difference

Frame - 345

Frame - 346



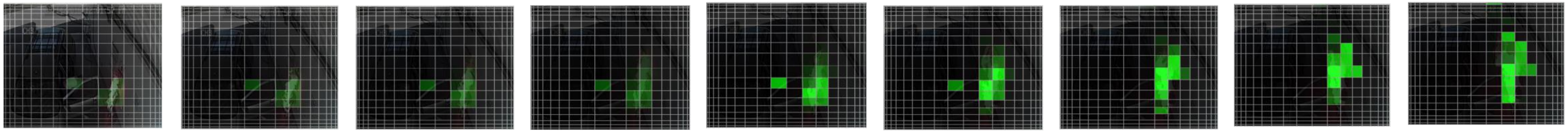
Frame Difference

Preliminary Experiments

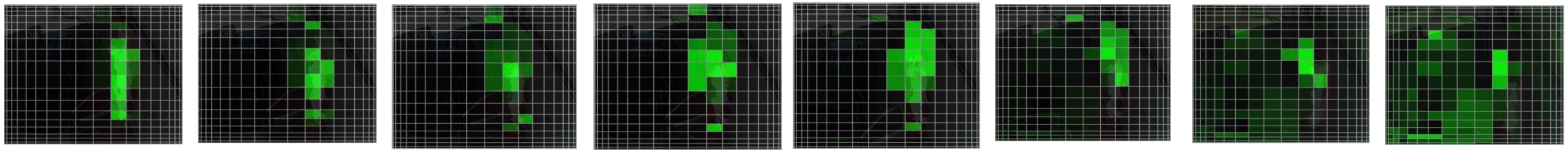
3) Using adaptive contrast-based smoke and fire detection

344 345 346 347 348 349 350 351 352

353 354 355 356 357 360 365 370



344 345 346 347 348 349 350 351 352



353 354 355 356 357 360 365 370