Fire defender

“Computer Vision Project”

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1-Introduction

Fire detection is a critical problem in computer vision with applications in safety, disaster prevention, and surveillance. This project aims to detect fire in images using a combination of classical image processing techniques and modern deep learning models. We explore multiple approaches including grayscale processing, histogram-based thresholding (Otsu's method), region growing segmentation, and feature-based methods like Harris Corner Detection, HOG (Histogram of Oriented Gradients), and SIFT (Scale-Invariant Feature Transform). Finally, we implement YOLO (You Only Look Once) for real-time object detection to identify fire.

2. Dataset Preparation

We use a dataset containing two classes: "fire" and "no fire." These images are collected from a public dataset on Kaggle. The images are initially in color and are converted to grayscale to facilitate classical processing techniques.

Steps:

* Separated images into fire and no_fire folders.
* Converted all images to grayscale using OpenCV.
* Resized grayscale images to 224x224 for uniformity.
* Augmented "no fire" images using flipping, blurring, noise addition, and brightness adjustment.

3-Image Processing Techniques

3.1 Histogram Analysis:

We computed histograms for both "fire" and "no fire" grayscale images to understand intensity distribution. Fire images typically have more high-intensity pixels.

3.2 Otsu’s Thresholding:

Used to automatically find the optimal threshold that separates background and foreground (fire regions). The best threshold is determined by maximizing inter-class variance.

3.3 Region Growing Segmentation:

This technique starts from seed points and grows a region based on pixel intensity similarity. Applied on both fire and no-fire images using a fixed threshold.

4. Feature-Based Detection

4.1 Harris Corner Detection:

Detected corner features in grayscale images. Fire regions usually generate high-corner responses due to flames' texture.

4.2 HOG (Histogram of Oriented Gradients):

Extracted gradient orientation features from fire and no fire images and evaluated their discriminative power using precision, recall, F1-score, and accuracy.

4.3 SIFT (Scale-Invariant Feature Transform):

Detected keypoints and computed descriptors. Fire images usually contain more keypoints. Classification performance was evaluated based on presence and density of keypoints.

5. Deep Learning-based Detection:

5.1 YOLOv5/YOLOv8:

Used a pre-trained/custom-trained YOLO model to detect the presence of fire. Each image is passed through the model, and if a fire label is detected, it is classified as a "fire" image.

Evaluation metrics:

1. Precision
2. Recall
3. F1-score
4. Accuracy

YOLO provided the best performance in terms of speed and accuracy compared to classical methods.

6. Evaluation Summary:

Method	Precision	Recall	F1-Score	Accuracy
Otsu	0.77	0.20	0.31	0.42
Region Grow	0.64	0.87	0.73	0.58
HOG	0.67	1.00	0.80	0.67
SIFT	0.67	0.99	0.80	0.66
YOLO	0.9095	0.4457	0.5982	0.6009
Harries	0.67	1.00	0.80	0.67

7. Conclusion:

This project demonstrates how combining classical techniques and deep learning can offer comprehensive insights into fire detection. While classical methods offer interpretability and simplicity, YOLO excels in real-time and robust detection. Future work could include expanding the dataset, adding temporal data (video), and optimizing classical parameters dynamically.

8. References:

- OpenCV Documentation
- Kaggle Fire Detection Dataset
- Ultralytics YOLOv5
- Scikit-learn Metrics
- Academic papers on image segmentation and feature extraction