# Fire defender

## "Computer Vision Project"

## **Team Members:**

<ul> <li>Nermeen Kamal El Din</li> </ul>	42110428
<ul> <li>Hadeer Gamal Fayad</li> </ul>	42110427
<ul> <li>Menna Tallah Sayed Ghallab</li> </ul>	42110247
<ul> <li>Alaa Hussein Ibrahim</li> </ul>	42210367

## **Supervised By:**

Dr. Wael Zakaria

Eng. Nora Tarek

## 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				
Region Grow				
Grow				
HOG				
SIFT				
YOLO				

## 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