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Smart Fire Safety: Real-Time Segmentation and Alerts Using Deep Learning

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Fires are the major causes of property damage, injuries, and death worldwide. The ability to avoid or reduce the effects of fires depends on their early identification. The accuracy and responsiveness of conventional fire detection systems, such as smoke detectors and heat sensors, are constrained. Computer vision-based fire and smoke detection systems have been suggested as a replacement for conventional systems in recent years. To tackle the challenges a robust real-time framework has been proposed, whereby, images are taken from cameras and using a custom train YOLOv8 object segmentation model smoke and fires are localized in the image which are then fed to an expert system for alert generation. The expert system makes decisions on the fire status based on its size and growth across multiple frames. Furthermore, A new dataset was meticulously curated and annotated for the segmentation task, to assess the efficacy of the proposed system, comprehensive benchmarking was conducted on the proposed dataset using a suite of benchmarks. The proposed system achieved an mAP score of 74.9% on the benchmark dataset. Furthermore, it was observed that employing segmentation for localization as opposed to detection, resulted in system accuracy improvement. The system can immediately identify fires and smoke and send accurate alerts to emergency services.

Keywords: Yolo-v8; Instance Segmentation; Fire and Smoke detection; Fire size; Fire spread; Emergency alert message; Arduino Uno.

Introduction:

Fire has played a major role in the advancement of human society, but uncontrolled fires can lead to a significant loss of human life and property, so it is essential to prevent such types of fires because they can be widespread and result in huge losses. The National Fire Protection Association (NFPA) estimates that over 350,000 house-structure fires nationwide require the help of fire departments annually, with direct damages estimated to be around $7 billion. In addition, there are 12,300 civilian fire injuries and about 2,500 civilian fire fatalities per year [1]. In Pakistan, fire has caused hundreds of casualties and infrastructural damage totaling billions of rupees. One of Pakistan's most damaging fire disasters is thought to be the Baldia Town fire incident. However, the relevant government officials have not drawn any lessons from the situation [2]. Recently, a terrible fire in Lahore's renowned Hafeez Center destroyed hundreds of shops and caused traders to suffer severe losses [3]. A strong communication network is essential for the efficient operation of firefighting services. Today, many buildings have built-in smoke detectors and fire alarm systems as the most common fire detection method. These systems are activated when smoke from a fire rises and triggers sensors, usually located in the ceilings of the buildings. These sensors then activate the fire alarm and fire suppression systems however in 2018, 38% of fire alarms failed to sound when there was a fire, and 45% of these incidences were due to improper system positioning, according to the Home Office of the United Kingdom [4]. While this method is generally effective, there can be a delay between the smoke rising and hitting the sensor, which can allow the fire to spread quickly [5]. This delay should be minimized to prevent fires from getting out of control so traditional fire detection methods, including smoke detectors and heat sensors, may not provide the level of accuracy and speed necessary to quickly and effectively detect and respond to fires. In light of this, there has been a recent surge in the development of Deep Learning and computer vision-based fire and smoke detection systems as an alternative approach. These systems utilize cameras to gather visual data about the environment and apply machine learning techniques to analyze and detect fires and smoke. These Deep-learning techniques have been a major asset in the extraction of relevant features that best represent fires. Such methods have been applied to a wide range of fields, including image classification, autonomous vehicles, speech recognition, pedestrian detection, facial recognition, and cancer detection among others, showcasing their effectiveness in detecting and segmenting various object classes [6]. In this research, we propose a real-time fire and smoke segmentation detection system that uses the YOLO-v8 [7] object detection algorithm and an emergency alert and danger level warning system. The proposed system is designed to detect fires and smoke in real time, providing accurate and timely alerts to emergency services. The YOLO-v8 algorithm is trained on a custom-segmented dataset of fires and smoke to identify these phenomena in real-world environments. Additionally, the system employs color and texture-based features for segmenting and identifying the fire and smoke regions in the image. The system also includes a danger level warning and emergency alert that utilizes the size, location, and intensity of the fire or smoke to determine the level of emergency. The system can communicate the alerts to emergency services through email and push notifications. The results of the experiments demonstrate that the proposed system can detect fires and smoke in real time with high accuracy and provide accurate and timely emergency alerts. The system also can segment the fire and smoke regions in the image, providing more detailed information about the emergency. We believe that the proposed system has the potential to significantly reduce the impact of fires on people and property. It serves as a valuable tool for emergency response and building safety.

Literature Review:

Advances in AI, machine learning, and deep learning have fueled the widespread use of these technologies in fire and smoke detection. Souidene Mseddi et al. [8] proposed a fire detection model, combining YOLOv5 and U-net, achieving 99.6% accuracy. Ge Zhang et al.[9]

enhanced YOLOv5 with a Swin transformation, improving feature fusion and achieving a 0.7% accuracy boost. Chen et al.[10] introduced a mixed Gaussian algorithm and YOLOv5-based smoke detection with 94.7% accuracy and 66.7 FPS speed. Sun et al.[11] addressed instance segmentation drawbacks with a semi-supervised technique and a lightweight SOLOv2 network, improving accuracy. Solorzano et al. [12] researched gas sensors for fire detection, demonstrating persistent predictive calibration models. Feiniu et al. [13] proposed a smoke segmentation model using CNN with VGG16 architecture. Jiao et al. [14] utilized Yolo v3 for UAV-based forest fire detection, achieving 83% accuracy at 3.2 frames per second. Hao Xu et al. [15] Innovative algorithm which was built using YOLOv5n. A SepViT Block was used to replace the model's final layer to strengthen the connection between the backbone network and the global information. A self-designed Light-BiFPN was also used to strengthen and lighten the network, reduce information loss, and improve accuracy and training convergence speed. Lastly, the Mish activation function was employed. For real-time fire detection on mobile devices, the Light-YOLOv5 significantly decreases the number of parameters and computations while increasing detection accuracy. Bhanumathi. M et al. [16] proposed image-based techniques for fire detection using surveillance cameras. They employ a background subtraction technique to detect fire using an RGB color pattern and motion detection technology. The technique seeks to spot fire quickly to protect people and property from its danger. The proposed system makes use of CCTV cameras to detect environmental changes brought on by a fire. Fatma M. Talaat et al.[17] proposed a Smart Fire Detection System (SFDS), which is based on the YOLOv8 algorithm, is a transformative approach to fire detection in smart cities achieving a precision of 97.1%. One disadvantage in this is the possibility of including unnecessary items within the bounding box, making it difficult to identify the seriousness of a detected incident. This ambiguity might cause difficulties in discerning between circumstances that require immediate attention due to risk and those that may be less critical. SN Saydirasulovich et al.[18] presents an improved YOLOv8 model for UAV-based wildfire smoke detection, which addresses obstacles such as sluggish recognition and accuracy issues. The model includes Wise-IoU v3, Ghost Shuffle Convolution, and the BiFormer attention mechanism, resulting in a 3.3% improvement in average precision. Despite its success, the model is highly sensitive to atmospheric conditions, which can lead to false positives. Wahyono et al.[19] analyses Faster RCNN, Yolov4, and Yolov5 for fire detection in surveillance footage using datasets including FireNet, VisiFire, and FireSense. Yolov5 scores the best on the FireSense dataset, whereas Yolov4 excels with the highest TPR (84.62%) on VisiFire. However, including undesired background implies that more factors should be investigated in the future for better accuracy, particularly taking into account real-world camera constraints. Leibiao Hu et al.[20] proposed a novel YOLOv8 algorithm FSD-YOLOv8, trained on the FASDD dataset. Specifically designed for accurate flame and smoke detection. It incorporates a de-hazing stage for improved precision and uses dilated convolutions to extract complex features. FSDYOLOv8 works better than traditional techniques. however, its accuracy is reduced in dynamic lighting and continuously smoke-filled environments. De Venancio et al.[21] presented a low-power automatic fire detection system utilizing YOLOv4. The suggested method reduces computational costs and memory consumption by up to an astounding 83.86%, respectively. The model achieved a f1 score of 72% and a map of 73.9% using the D-Fire dataset during training. X Xie et al.[22] Propose a YOLOv5-based real-time flame detection system for firefighting drones. A coordinate attention method, enhanced small-target recognition, and a novel loss function were introduced in the model to enhance the performance of the model. The experimental findings reveal an average precision of 96.6%, which is 5.4% higher than the original. The lightweight structure of the algorithm makes it suitable for firefighting drones and allows for fast identification. how every its accuracy reduces in detection at night, indicating potential directions for further study. Chayma Bahhar et al. [23] suggests a novel method for detecting forest fires in real-time by combining a classifier to increase precision and using an ensemble of two YOLO architectures (Yolov5s and Yolov5l). The FLAME dataset was used to train the model. The model performs better than the others, as evidenced by the trial results, which show 0.87% recall and 0.8% precision. The model is more resilient in a variety of forest fire conditions thanks to the ensemble architecture which reduces false positives.

In summary, this work uses an organized approach. Our technique is described in Section III; the experimental setting is described in Section IV; the dataset used and evaluation measures are covered in Section V. Section VI presents the findings and debates, while Section VII wraps up this work.

Methodology:

The proposed system attempts to improve building fire safety by installing a fire and smoke detection and alert system. To assess visual data from cameras mounted in the building, the system used the most recent fire detection algorithms. The YOLO-v8 segmentation detection algorithm is the central element of the suggested system which is used to examine visual data from the cameras. The alarm is activated by Arduino setup when fire or smoke is successfully detected in real-time through cameras. The alarm's activation notifies the building's residents of the fire emergency and begins the water spray, both of which aid in containing the fire's progress. The system also had a smoke sensor coupled to the Arduino setup. If there is smoke in the building, the sensor will detect it, which will cause the buzzer to sound and the water spray to begin. As a result of the smoke sensor's integration, the system has a backup method of spotting fires. A danger level warning system that gives real-time updates on the severity of the fire emergency is another component of the planned system. Building occupants and emergency services can react to the fire emergency in an informed way thanks to the warning system, which is based on the size of the fire, the spreading of the fire, and the 1-minute time if the fire is still detected by the YoloV8 model. The proposed system sends emergency notifications to emergency services and building inhabitants via email. The notification gives emergency services vital details about the location and severity of the fire, enabling them to react to the emergency swiftly and effectively. It is crucial to remember that the effectiveness and accuracy of the suggested approach depend on the camera's accurate calibration. The whole methodology is shown through a block diagram in Figure 1.

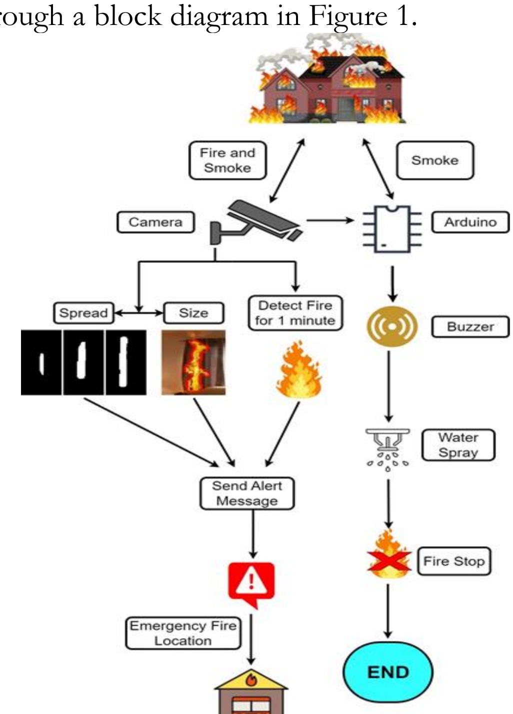

Figure 1: Methodology through block diagram

YOLO-v8 Instance Segmentation:

YOLOv8-seg (You Only Look Once version 8) is a cutting-edge object detection system that utilizes deep learning to achieve real-time results. It uses a unique network architecture to perform instance segmentation. The structure of yolo-v8 instance segmentation can be seen in Figure 2. YOLOv8-Seg is a significant improvement in the YOLO family, designed primarily for segmentation jobs. This model differs from its predecessors with an improved backbone structure that includes a 3 x 3 convolution, a C2f module, and an SPPF module. The C2f module replaces the basic 6 x 6 convolution, resulting in a lightweight architecture and improved gradient flow with skip connections and split operations. Notably, YOLOv8-Seg deviates from the traditional C3 module by incorporating improved cross-stage partial networks (CSP) for better residual connections. The head module demonstrates complicated feature fusion algorithms that include PANet and FPN, with major performance enhancements applied.

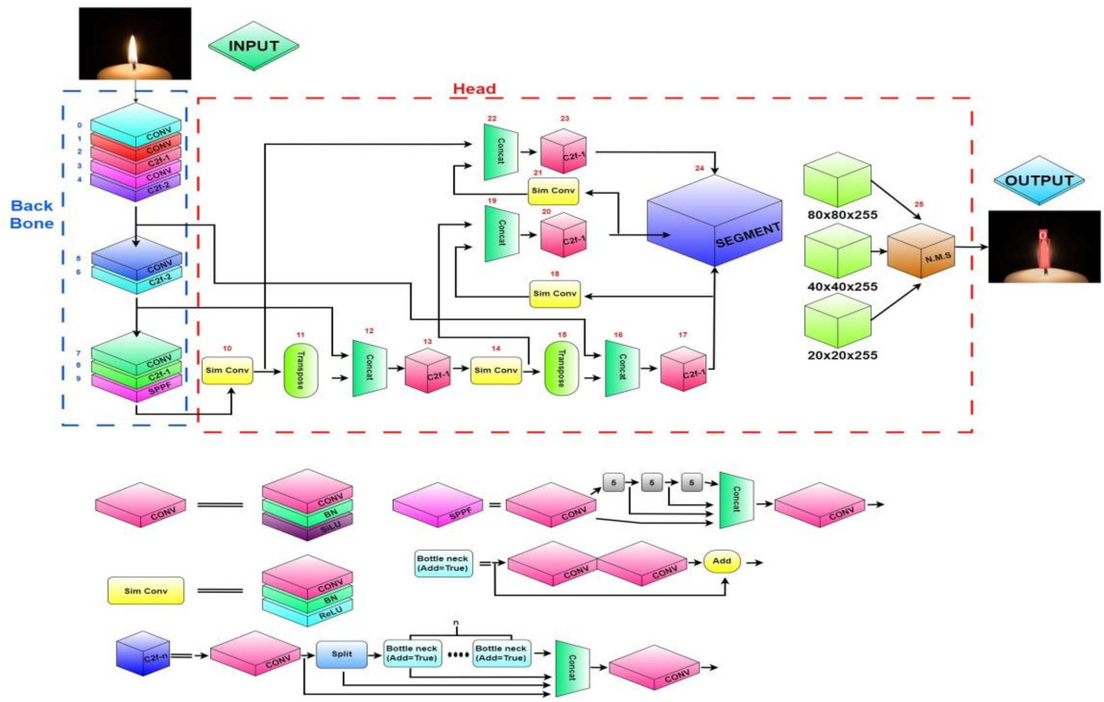

Figure 2: Represents all the layers present in the Yolo-v8 instance segmentation Architecture

Experimental Setup:

Experimental Environment:

The Experiment was conducted using the Google Colab platform.

Training:

The training parameters for the fire and smoke detection model are shown in Table 1. The fire and smoke data set used in the study was divided into a training set and a validation set, with the proportion being 80:20.

Table 1: Training Parameter.

Parameter	Details
Picture size	640 x 640
Epochs	300
Batch size	16
Optimizer	SGD
Learning rate	0.01
Early stopping Patience	40
Multi-scale	50%
Momentum	0.937

System Deployment:

The Arduino Setup used in this paper is shown in Figure 3. Arduino UNO will receive information from both the camera and the MQ2 Gas Sensor. When fire or smoke is detected by the camera or smoke is sensed by the MQ2 sensor, Arduino will turn on the red light and buzzer.

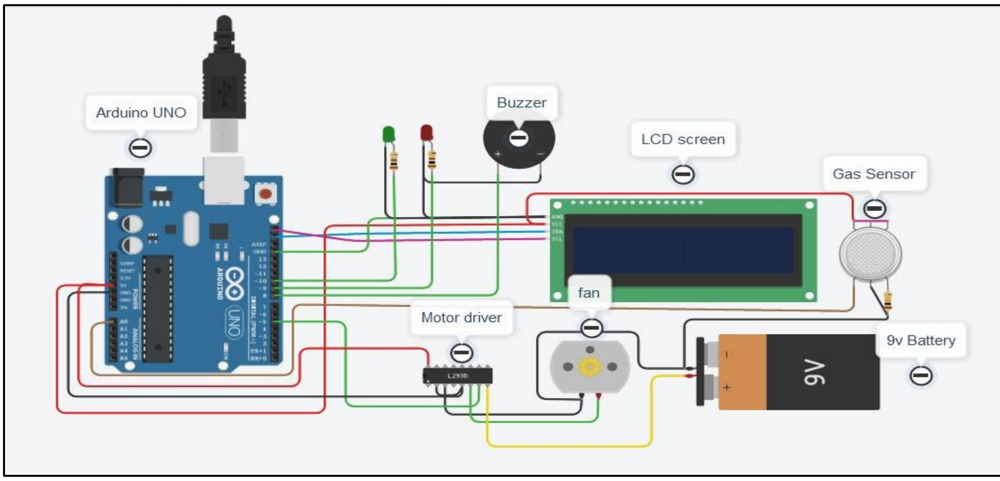

Figure 3: Represent the Experimental Setup

The primary components that have been used in this setup are i. Arduino Uno ii. MQ2 Gas Sensor iii. I2C LCD Display Driver iv. 16x2 LCD display
v. Passive Piezo Buzzer vi. Light-Emitting Diodes

Employed Dataset and Evaluation Metrics:

Dataset:

In this paper, we proposed a novel data set for fire and smoke gathered from images and videos. The data set contains 892 pictures in total, divided into three groups fire, fire-smoke, and smoke. A wide variety of locations, including both indoor and outdoor scenes were represented in the data set. The instance segmentation task was performed on the data set using the Label-Me tool and the annotation files were saved in JSON format. To make the data set compatible with the Yolov8 framework, we wrote a code to convert the JSON format to a text format. This data set can be utilized for a variety of tasks, such as object detection, semantic segmentation, and fire and smoke instance segmentation, thanks to its accurate annotations and wide set of photos depicting various situations. The data-set high quality and diversity made it easier to create more sophisticated algorithms and models for analyzing fire and smoke. Random samples from the data set are shown in Figure 4.

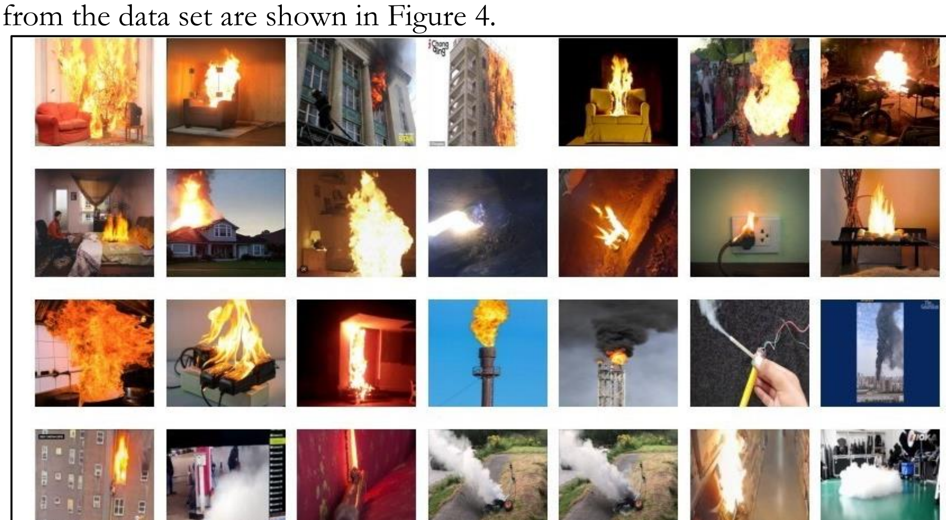

Figure 4: Illustrate fire and smoke images from over data-set

Evaluation Metrics:

We assess the effectiveness of over model through:

- **F1-Score:**

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (1)$$

- **Precision:**

$$P = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

- **Recall:**

$$R = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

- **mAP50:**

$$mAP50 = \frac{1}{|X|}\sum_{i=1}^{|X|} AvgP(z_i) \quad (4)$$

Where:
  - $|X|$: Number of queries in the dataset.
  - z_i: i-th query in the dataset.
  - AvgP(z_i): Average precision for the i-th query, using the first 50 items in the ranked list.

- **mAP50-90:**

$$mAP50 - 90 = \frac{1}{|Q|}\sum_{i=1}^{|Q|} AvgP(q_i) \quad (5)$$

Where:
  - $|Q|$: is the total number of queries in the dataset.
  - q_i: represents the i-th query in the dataset.
  - AvgP(q_i): Average precision for the i-th query, using only the top 50 to 90 ranked items.

Results and Discussion:

Table 2: Results of the Bounding Boxes

Model	Performance Evaluation Metrics				
	F1 score	Precision	Recall	mAP-50	mAP50-90
YOLOv5n	73.4%	82.3%	66.3%	72.0%	44.8%
YOLOv5-s	76.5%	**90.2%**	66.5%	74.8%	51.1%
YOLOv5-m	75.4%	85.5%	67.5%	74.0%	51.2%
YOLOv5-l	76.0%	84.5%	69.1%	75.6%	54.1%
YOLOv7	76.9%	86.0%	69.7%	**77.9%**	55.3%
YOLOv8-n	73.4%	85.0%	64.6%	72.5%	49.3%
YOLOv8-s	73.7%	86.0%	64.6%	72.4%	50.8%
YOLOv8-m	76.2%	86.1%	68.4%	76.5%	**56.1%**
YOLOv8-l	**77.4%**	86.4%	**70.2%**	76.8%	55.8%

The training outcomes of different models on the proposed dataset of fires and smoke are shown in Tables 2 and 3. The training's outcomes revealed that the system achieved an f1-Score of 77.4% for Boxes and 75.7% for Masks. Every model performed well but YOLOv8 Large was particularly noteworthy as it produced the greatest results for masks in terms of mAP50 and map50-90 achieving 74.9% and 51.0% respectively. Figure 5 shows the model's performance on some test images. The results of map50 for Masks of all models are shown in Figure 6. The precision and recall results for boxes and masks were 86.4%, 70.2%, 85.7%, and 67.9% respectively. The fine-tuned YOLOv8 large model was incorporated into the system due to its better results in detecting fire and smoke masks. The real-time performance of the system can be seen in Figures 7, and 8, showing an excellent result in detecting fire and smoke. The emergency alert system was successfully implemented in the model and can send emergency messages if any of the three danger level conditions are satisfied as shown in Figure 9.

Table 3: Results of the Masks

	Performance Evaluation Metrics				
Model	**F1 score**	**Precision**	**Recall**	**mAP-50**	**mAP50-90**
YOLOv5-n	70.8%	79.4%	63.9%	68.7%	39.8%
YOLOv5-s	74.5%	**87.9%**	64.7%	72.5%	43.6%
YOLOv5-m	73.9%	83.9%	66.1%	72.2%	44.3%
YOLOv5-l	74.3%	87.3%	64.8%	72.7%	44.4%
YOLOv7	74.7%	86.9%	65.6%	70.7%	41.7%
YOLOv8-n	73.3%	84.9%	64.5%	72.6%	47.5%
YOLOv8-s	73.5%	85.7%	64.4%	72.3%	48.1%
YOLOv8-m	75.0%	84.7%	67.4%	**74.9%**	48.9%
YOLOv8-l	**75.7%**	85.7%	**67.9%**	**74.9%**	**51.0%**

Figure 5: Results of the trained model on some test images

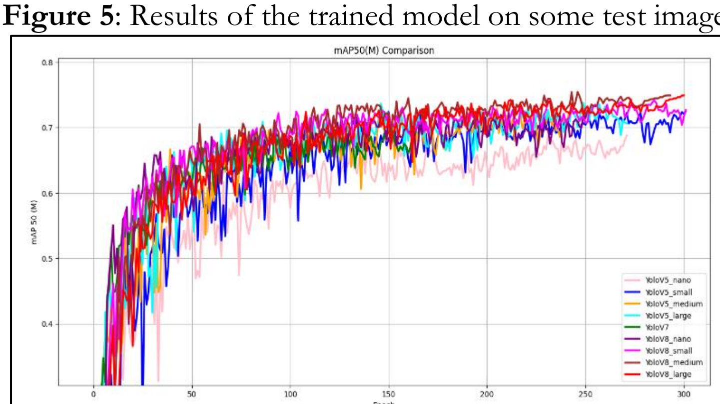

Figure 6: Model training curves of mAP0.5 metric for segmentation masks

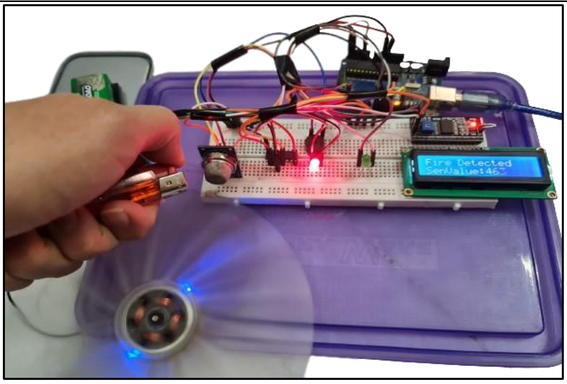

Figure 7: Show that when the smoke sensor detects smoke it starts the alarm and water spray

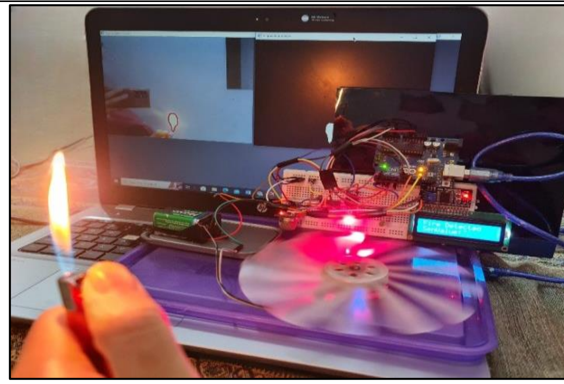

Figure 8: Show that when the camera detects fire and smoke it starts the alarm and water spray

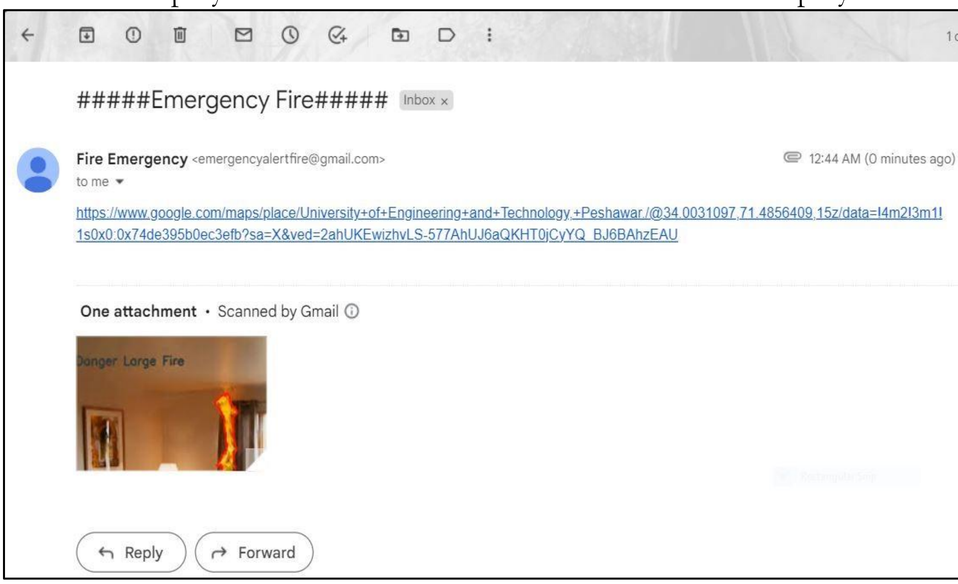

Figure 9: Show that when any danger level condition is satisfied an emergency alert message is sent

Conclusion:

To ensure public and building safety we proposed and implemented a system that uses the YOLO-v8 object segmentation detection technique for real-time fire and smoke detection. The system was created to instantly detect fire and smoke and send precise, timely alerts to emergency services and building occupants. The system was fitted with a hazard level warning system that was based on the size of the fire, spreading of fire, and 1 minute perennially detection of fire. The YOLO-v8 algorithm was trained on a novel instance-segmented data set. The trained algorithm achieves f1-Score of 75.7% and mAP50 of 74.9% for the Masks. The study's findings demonstrated that the suggested system could accurately and promptly provide emergency notifications while detecting fires and smoke in real time with high precision. The suggested system showed excellent potential in lessening the damage caused by fires to people and property, and it might be an important aid in emergency response and building safety. The novel instance segmented data set, the hazard level warning system, and the emergency alert system are the main contributions to this research. In the future, the system performance can be further enhanced by training the YOLO-v8 algorithm on a larger and more diverse data set. The system for alerting of danger levels and emergency alerts can be further improved by including more complex algorithms to forecast how the fire or smoke will develop as well as interacting with emergency response systems.

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