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Real-Time Fire Detection Using YOLOv8 and Twilio SMS Alerts

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Abstract:
Fire alarm systems are essential components of modern safety infrastructure, playing a critical role in mitigating risks to human life, property, and the environment. Despite their necessity, traditional sensor-based methods—such as smoke and heat detectors—often struggle with significant limitations, including delayed response times and high rates of false alarms. These issues are particularly prevalent in large industrial warehouses or open-air environments where environmental variables can impede the accuracy of physical sensors.
To address these challenges, this study presents a real-time fire detection system that integrates the YOLOv8 deep learning architecture with the Twilio SMS communication service. The system utilizes the YOLOv8 (You Only Look Once) algorithm, which is highly regarded for its ability to perform high-speed and accurate object detection in video streams. The model was trained using a diverse and comprehensive dataset consisting of 11,263 annotated images from Roboflow, ensuring reliable detection across various lighting and environmental conditions.
The platform continuously analyzes live video feeds to identify the visual signatures of fire. Upon confirmed detection, it automatically triggers an instantaneous SMS alert via the Twilio API to pre-defined emergency recipients. Quantitative evaluation demonstrates the model's high efficacy, achieving a mean Average Precision (mAP@.5) of 95%, with a precision of 95.4% and a recall of 76%. With an average confidence level of 0.58%, this system offers a robust, automated solution that bridges the gap between detection and emergency notification.

Keywords: Artificial Intelligent, YOLOv8, Fire Detection, Twilio SMS, Real-Time Monitoring.

الكشف عن الحرائق في الوقت الفعلي باستخدام YOLOv8 وتنبيهات الرسائل القصيرة Twilio

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الملخص
تُعد أنظمة إنذار الحريق ضرورة حتمية للحد من المخاطر الجسيمة التي تهدد الأرواح، والبنى التحتية، والنظم البيئية على حد سواء. ومع ذلك، فإن المنهجيات التقليدية المعتمدة على المستشعرات المادية (مثل كواشف الدخان والحرارة) تعاني غالباً من استجابة بطيئة ومعدلات مرتفعة من الإنذارات الكاذبة، ولا سيما في البيئات المفتوحة أو المساحات الشاسعة حيث تواجه تلك المستشعرات صعوبة في الاكتشاف المبكر قبل تفاقم الحريق.
في هذا العمل البحثي، تم تصميم نظام متطور للكشف عن الحرائق في الوقت الفعلي من خلال دمج نموذج التعلم العميق **YOLOv8**مع خدمة التنبيه عبر الرسائل النصية القصيرة (**SMS**) المقدمة من منصة **Twilio.** تهدف هذه المنصة الذكية إلى تحليل تدفقات الفيديو المباشرة بدقة متناهية لتحديد البدايات المرئية لاندلاع الحريق فور حدوثها. يعتمد النظام في جوهره على خوارزميةYOLOv8 ، التي تم تدريبها باستخدام قاعدة بيانات ضخمة ومتنوعة تحتوي على **11,263صورة** مشروحة تم استخلاصها من منصة **Roboflow**، مما منح النموذج قدرة فائقة على تمييز الإشارات البصرية للحريق في ظروف بيئية مختلفة.
وعند تأكيد عملية الاكتشاف، يقوم النظام تلقائياً بتفعيل واجهة برمجة تطبيقات Twilio لإرسال إشعارات نصية فورية إلى مستلمين محددين مسبقاً، مما يضمن سرعة الاستجابة للطوارئ. وقد أثبت التقييم الكمي للنظام فاعلية استثنائية؛ حيث حقق

النموذج متوسط دقة (**mAP@.5**) بنسبة **95%**، مع دقة (**Precision**) بلغت **95.4%** ومعدل استدعاء (**Recall**) بنسبة **76%**، وبمتوسط درجة ثقة تصل إلى **0.58**. تؤكد هذه النتائج أن النظام يمثل حلاً تقنياً واعداً يتجاوز ثغرات الأنظمة التقليدية ويوفر حماية ذكية وموثوقة.

الكلمات المفتاحية: الذكاء الاصطناعي، YOLOv8، اكتشاف الحرائق، Twilio SMS، المراقبة في الوقت الحقيقي.

Introduction

One of the most important challenges for public security and environmental stability from fire hazards is especially in light of urbanization and faster climate change. Whether in residential areas, industrial areas, or forest ecosystems, fire causes sufficient human and economic losses in the fire. It is necessary to detect fast and reliable fire to enable initial intervention and reduce potential losses.

Traditional fire detection systems—such as smoke alarms, thermistors, and infrared sensors—have been placed a lot. However, their dependence on physical signals often limits the effectiveness of dynamic or large environments. These systems trigger the alarm only when the fire increases significantly, which causes limited time. In addition, they are unsafe for false alarms and environmental interventions.

Progress in artificial intelligence (AI), especially within data vision, has given rise to the visually based fire detection system like Video Fire Detection Systems (VFD) capable of analyzing live video feeds to detect early visual signs of fire, such as smoke and flames. The most prominent detection in real time is YOLO in framework (You Only Look Once). The latest version gives significant improvements in both YOLOv8 accuracy and efficiency, including a modern spine, anchor-free detection, and attention-based module [1, 2].

Complementing detection, timely communication is necessary for the placement of the real world. Cloud communication platforms such as Twilio offer programmable message interfaces that allow the system to immediately send SMS [3] and improve emergency reaction skills. Integration of deep learning with cloud message infrastructure introduces a hybrid solution with capacity for wide distribution.

Even though deep learning-based fire detectors have gotten much smarter, few setups tie fast, accurate spotting with dependable alerts that go out the moment flames are seen. Most research either sharpens the detection side or works on passing warnings, leaving a hole where a combined system should be, one that guarantees quick and useful response to real fires [4]. This paper steps into that space by uniting the deep-learning fire detector—YOLOv8—with a speedy SMS alert service from Twilio, giving communities a practical tool that boosts public safety.

The system integrates real-time fire detection with instant notification by combining YOLOv8 and Twilio. YOLOv8 continuously analyzes live video feeds to detect early signs of fire. Upon surpassing a confidence threshold, the system automatically triggers Twilio's API to send SMS alerts to pre-defined recipients, enabling immediate response. The proposed system aims to achieve high identification accuracy and immediate vigilance in both indoor and outdoor scenarios.

Background

You Only Look Once (Yolo) Algorithm

YOLO is an innovative method for real-time detection of several objects within a picture, delineating them with bounding boxes. The image is processed by the CNN algorithm a single time to obtain the output, hence the designation.

In comparison with the traditional convolutional neural network (CNN), the "You Only Look Once" (YOLO) methodology portrays object discovery as a regressive challenge by identifying spatially defined boundary boxes along with the probabilities of the associated classes, which are predicted by a single neural network architecture. YOLO first proposed this unified network architecture, which combines the computation of class probability and bounding box prediction.

The architectural structure of YOLO demonstrates features comparable to those of a traditional convolutional neural network, deriving its conceptual framework from the GoogLeNet model employed in image classification endeavors. The initial layer of the network is responsible for the extraction of features inherent to the image, while the fully connected layers are tasked with the prediction of output probabilities and spatial coordinates. Comprising 24 convolutional layers, two fully connected layers, as well as 1x1 reduction layers and 3x3 convolutional layers, the comprehensive YOLO network model has been established. [5].

Unified Detection of YOLO

The components involved in object detection are unified into a single neural network by the YOLO architecture. All bounding boxes are simultaneously projected from the entire image, which means that the network can handle the entire image with all its objects.

Unified detection in YOLO divides the input image into S × S size grids. The grid cell attempts object detection on itself if the object's center is positioned inside it. As a result, each grid cell attempts to estimate a bounding box

and the confidence scores for each class that has been trained to make predictions. The expected confidence ratings will show the degree of assurance in assigning each object a label and a bounding box.
The confidence score is mathematically formulated as the product of the probability of an object being present, and the Intersection over Union (IOU) between the predicted and the ground truth bounding boxes expressed as

$$confidence = \mathbf{Pr}\ (\mathbf{Object}) \times \mathbf{IOUpredtruth}$$

$$\text{Where:} \quad \text{IOU} = \frac{\text{Intersection Area}}{\text{Union Area}}$$

In cases where an object is correctly localized within a grid cell, the confidence score reflects the degree of overlap between the predicted and actual object regions, as measured by the IOU.
Conversely, when no object is present in the cell, the confidence score is assigned to a value of zero, indicating the absence of any object detected within that region. [6].

YOLOv8 Overview
YOLOv8 is the one of advanced versions in the YOLO family of object detection model. Although it retains the fundamental architectural principles of its predecessors, as shown in Fig.1, this version introduces several significant enhancements over earlier implementations, such as a new neural network architecture that utilizes both Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) and a new labeling tool that streamlines the annotation process [4]. The labeling tool provides a range of practical features like auto labeling, labeling shortcuts, and customizable hotkeys. all of which simplify and accelerate image preparation for model training. The FPN works by gradually reducing the spatial resolution of the input image while increasing the number of feature channels. This results in the creation of feature maps that are capable of detecting objects at different scales and resolutions. In contrast, PAN architecture enhances feature propagation by aggregating information from multiple layers through skip connections, thereby improving the model's ability to detect objects with diverse shapes and scales more accurately [7].

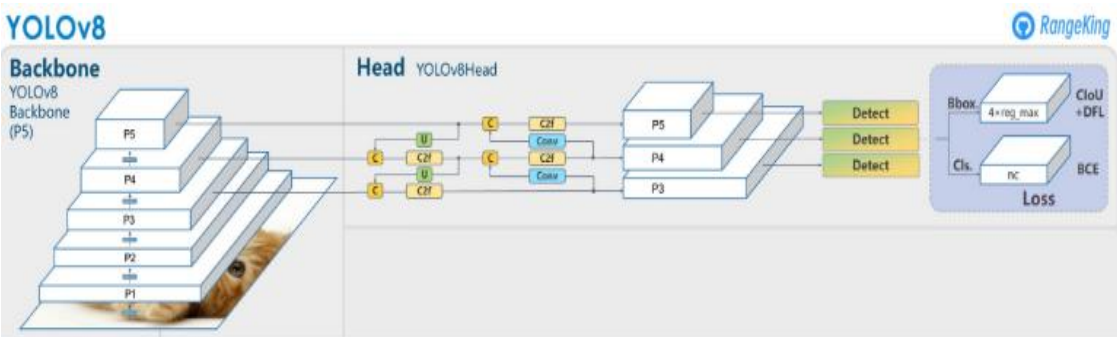

Figure 1. YOLOv8 Architecture [4]

Related Work
Fire-detection tools have come a long way, especially since deep learning burst onto the scene. Many researchers have pushed the limits and reported impressive results, yet some questions and practical hurdles still linger; this paper aims to tackle those. quick recap of key earlier studies can be found in TABLE I.

TABLE 1. ASUMMARY OF PRIOR RESEARCH ON FIRE DETECTION.

Study/Authors	Model Used	Dataset/ Context	Accuracy / mAP	Unique Contribution
Liu et al. (2023)	YOLOv5n (lightweight)	Forest fire scenes	Accuracy: ~92%	Lightweight deployment in edge devices
Zhao et al. (2023)	Fire-YOLO (YOLOv3 + EfficientNet)	Smoke/ fire dataset	Improved small-object detection	Feature enhancement for small flames/smoke
Chetoui and Akhloufi (2024)	YOLOv8	11,132 images (smoke /fire)	Precision: 83.7%, Recall: 95.2%	Baseline YOLOv8 performance on smoke/fire

Zhang et al. (2024)	YOLOv8-FEP (Improved)	Custom fire dataset	+3.1% mAP, +5.8% accuracy	EMA + PAN-Bag modules for improved contextual awareness
Yang et al. (2024)	YOLOv8 + attention	Indoor surveillance footage	F1-score: 95%, Recall: 90.34%	Multi-scale attention for enclosed environments
Vimala et al. (2024)	YOLOv8 + Twilio	Real-time web system	Not specified	Twilio integration with Node.js, MongoDB, React

Focus on finding without immediate warning:
Many studies, such as Zhang et al. [1], Yang et al. [2], and Chetaui and Akhloufi [8], focus on increasing the accuracy of the Fire Detection Model (eg, Yolov 8 and its variants) mainly. While these functions contribute significantly to the identity component, they often ignore or inadequate the important need for a reliable and immediate alert system. This is the result of a major interval in broad fire reaction systems, as the authorizes related to effective detection alone are not sufficient without early notification.
Lack of quantitative evaluation of integrated systems:
Some studies, such as Vimala et al. [3] and Sheeba et al. [12], have detected integration of fire detection with mechanisms (eg, twilio or web API); they often lack extensive quantitative evaluation of the performance of the integrated system. For example, Vimala et al. [3] does not report accuracy for its system or any metrics, making it difficult to assess its real effectiveness in real -world scenarios. This deficiency of quantitative data limits the ability to compare such systems.

Focus on specific scenarios or deployment limitations:
Much of the recent research targets narrow use-cases. Liu et al. [9] designed a lightweight system for spotting forest fires, while Mohapatra et al. [11] pilot detection on flying drones. These efforts shine in their settings but offer little guidance for mixed indoor-outdoor scenarios and still stumble once operators try to roll them out across a wide area.

Challenges of false alarms and slow response:
Although latest deep-learning pipelines promise greater precision, mistaken alerts still flood dashboards, and older hardware outlined in the introduction reacts only after critical seconds are lost. This paper therefore blends YOLOv8s accuracy with a direct-notification engine, aiming to slash lag time, cut cancellations, and give end users two reasons to trust every ping they receive. In contrast to previous works that focus separately on detection or alerting, or that lack quantitative evaluation of integrated systems, this paper offers:

Methodology
This study implements a real-time fire detection system by integrating IP Webcam for video streaming, YOLOv8 for deep learning models trained on a custom dataset-based detection, and Twilio for emergency alerts. The methodology consists of four main phases:
1. Data Acquisition and Preprocessing
2. Model Training, Optimization and Evaluation
3. Real-Time Fire Detection
4. Twilio Alert System Integration

Each phase is described in detail below. Fig.2. shows the flowchart for this study.

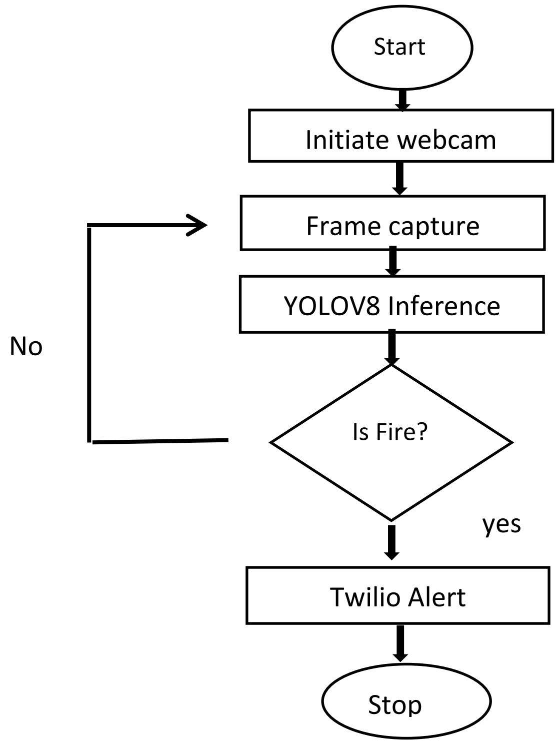

Figure 2. System flowchart

Data Acquisition and Preprocessing (Roboflow)

The Fire Detection Dataset (Version 7) from Roboflow (Workspace: vision-zz6rk, Project: fire_detector-g4lir) was used, which contains 11,263 annotated images of fire and smoke scenes. The dataset was split into 9,855 training images (87%), 938 validation images (8%), and 470 test images (4%). Preprocessing included auto-orientation and resizing (stretched to 640×640 pixels). To enhance model generalization, Roboflow's built-in augmentations were applied as shown in the TABLE II below. These augmentations simulate real-world variability and improve robustness. The dataset was downloaded in YOLOv8 format via the Roboflow Python API [14].

Table 2. Augmentations Characteristics

Flip	Horizontal, Vertical
Crop	0% Minimum Zoom, 20% Maximum Zoom
Rotation	Between -15° and +15°
Shear	±10° Horizontal, ±10° Vertical
Noise	Up to 0.54% of pixels
90° Rotate	Clockwise, Counter-Clockwise, Upside Down

Webcam Integration Methodology for Google Colab

The study employed Google Colab's JavaScript bridge to access local hardware peripherals, enabling direct webcam acquisition despite Colab's cloud-based execution environment. This approach circumvents traditional browser security restrictions through a three-stage process: (1) JavaScript-based media device initialization, (2) Base64-encoded frame transmission via IPython kernel messaging, and (3) OpenCV-compatible image conversion.

Model Training and Optimization (YOLOv8)

The YOLOv8 model was trained using a dataset sourced from Roboflow, pre-annotated in YOLOv8 format. Google Colab with a Tesla T4 GPU was used to accelerate training. The model architecture chosen was YOLOv8s (small version), initialized with pre-trained weights (yolov8s.pt) to enhance feature extraction. Training was conducted over 50 epochs with a batch size of 16, an initial learning rate of lr=0.002, and an input image resolution of 640×640 pixels. The optimizer employed was AdamW with momentum=0.9 and default YOLOv8 hyperparameters. To prevent overfitting, as mentioned previously, the dataset was applied to Roboflow's built-in augmentations.

Model Evaluation

Training progress was monitored using metrics such as box loss, classification loss, precision, recall and mAP (mean Average Precision).

Precision: It is also known as the positive predictive value made by the model. It answers the question: Of the instances predicted as positive, how many are actually positive? Equation (1) is used to calculate the precision

Recall (**Sensitivity)**: is a measure of the ability of the model to capture all the positive instances. It answers the question: Of all the actual positive instances, how many did the model correctly predict as positive? Equation (2) is used to calculate recall.

The mean Average Precision (mAP): is a widely utilized evaluation metric in object detection tasks that integrates the precision and recall curves across various categories and computes the average value, thereby assessing the model's detection performance across multiple categories and serving as a benchmark for the overall efficacy of target detection algorithms. mAP50 is the mAP value at the 50% loU threshold. mAP50-95 is a stricter way to measure that finds the mAP values between 50% and 95% loU thresholds and then averages them. Equation (3) is used to calculate mAP.

$$Precision = \frac{(True\ Positive)}{(True\ Positive\ + False\ Positive)} \quad (1)$$

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

$$mAP = \frac{1}{C} \sum_{i=1}^{C} Ap_i \quad (3)$$

Where Ap_i denotes the average precision of a single category, and C denotes the number of all categories.

Twilio Alert System Integration

The system leverages Twilio's cloud communication API platform (Twilio Inc., 2023) to enable real-time SMS notifications. Specifically, Twilio’s Programmable SMS API was integrated to automate emergency alerts when the YOLOv8 model detects fire with a confidence threshold exceeding 50%. Upon positive identification, a Python-based middleware initiates a secure API call to Twilio’s cloud infrastructure, transmitting incident details (including location and confidence level) to pre-registered responders. This implementation ensures timely alerts while maintaining compliance with data protection standards through AES-256 encryption of all sensitive communications. [15].

Discussion and Experimental Results

We first trained the model on Google Collab, the results of the training of the model with the dataset from Roboflow show that fire images can be found with 96% precision and 95% recall. It has an mAP50 of 96.9 % and mAP50-95 of 70% when the last epoch is finished in 1.467 hours. The lightweight pretrained file is 22.5 MB. TABLE III shows the results after training the model. Fig.3 depicts the overall training outcomes of the model, including loss train, loss classification and other metrics. Additionally, Fig.4 shows the confusion matrix revealed minimal misclassifications.

Table 3. Results After Training the Model.

Parameter	**mAP@50**		**Precision**	**mAP@50-95**	**Recall**
Value	0.969		0.964	0.704	0.958

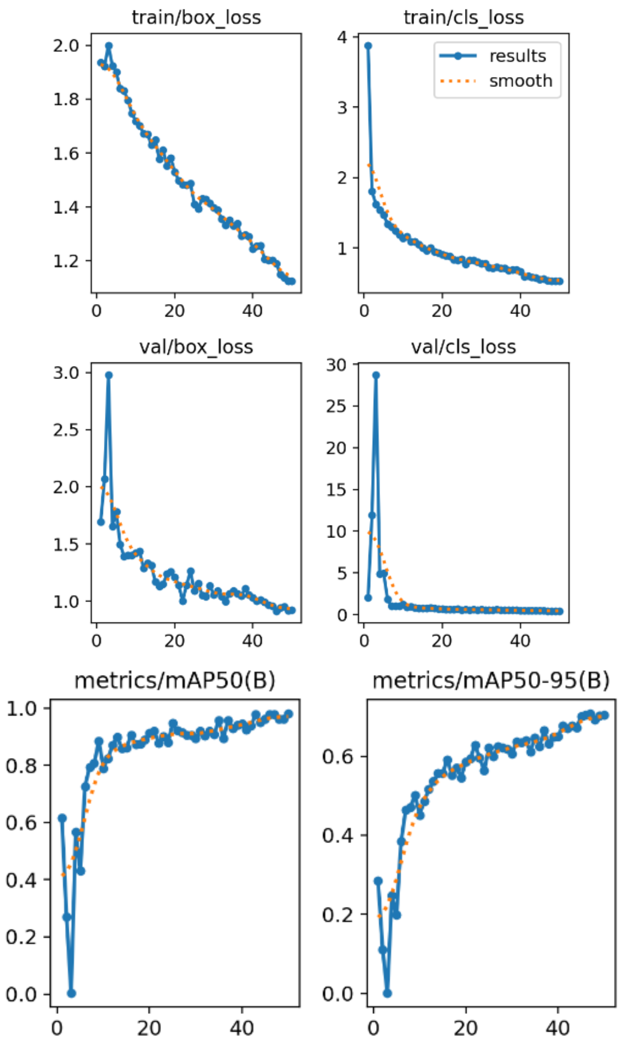

Figure 3. Training and validation performance metrics for fire detection model.

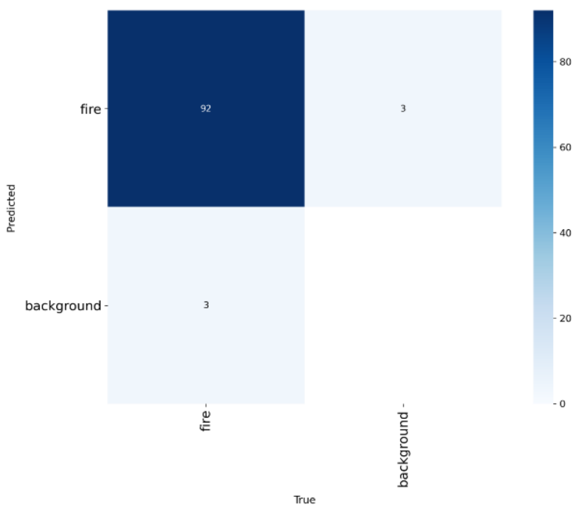

Figure 4. Confusion matrix

Results of the Evaluation of the Model

After training the model, a test on a sample of 470 images was conducted, and the evaluation results were obtained, as shown in Fig. 5 and TABLE IV. The result of the test images is the presence of the fire class, which is identified and annotated within its frame.

Figure 5. Sample testing results of th emodel for fire detection

Table 4. Results After Testing the Model.

Parameter	mAP@50	Precision	average confidence	Recall
Value	95%	95.4%	0.58%	76%

Final result of real-time detection using trained model

The implemented real-time fire detection system successfully processes video frames from a camera feed (webcam) and identifies objects using the YOLOv8 deep learning model. When fires are detected with sufficient confidence (above 50%), the system triggers an SMS alert to the mobile phone via Twilio, notifying the recipient immediately. The detection results are displayed in real-time with bounding boxes and labels around detected fire, allowing for visual verification. Results of fire detection and immediate alert using YOLOV8 and Twilio shown in Fig.6.

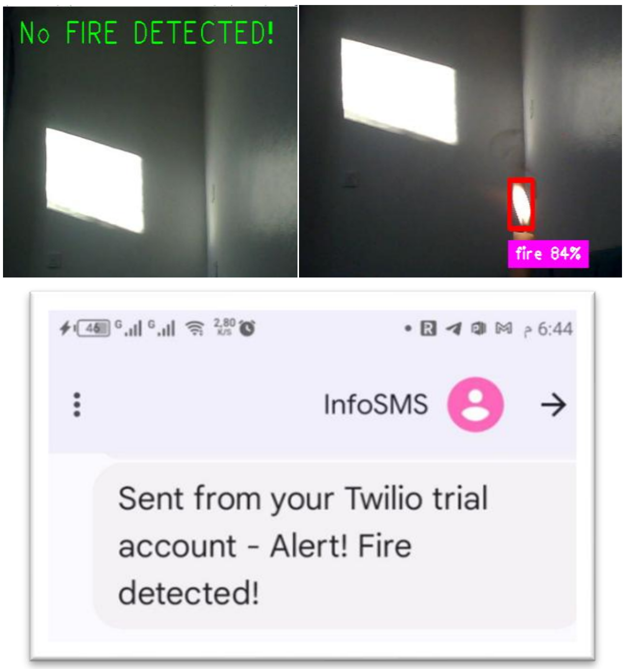

Figure 6. Results of immediate alert using YOLOV8 and Twilio

Existing studies such as Zhang et al. [1], Yang et al. [2], and Chetaui and Akhloufi [8] primarily concentrate on improving the accuracy of fire-detection models like YOLOv8, yet they provide little attention to the equally critical need for an immediate and reliable alerting mechanism. Other works, including Vimala et al. [3] and Sheeba et al. [12], explore integrating detection models with communication tools such as Twilio or web APIs but lack comprehensive quantitative evaluation of their integrated systems, making real-world effectiveness difficult to assess. Additionally, several studies focus on highly specific scenarios—such as forest fire monitoring or drone-based detection—which limits their applicability to mixed indoor-outdoor environments or large-scale deployment. Persistent challenges related to false alarms and delayed responses further highlight the gaps in prior research. In contrast, the present study integrates YOLOv8 with a real-time notification engine and provides clear quantitative performance metrics, offering a more complete and deployable solution than previous works that addressed detection and alerting in isolation.

Conclusions

This paper implements a fire detection system that uses deep learning and the YOLOv8 architecture to make sure that fire detection and alerting stakeholders via Twilio SMS are both very accurate. The system works great. It has an average accuracy (mAP@.5) of 95%, a precision of 95.4%, and a recall of 76% with an average confidence 0.58% . These result show that the model can find fires both inside and outside with great accuracy and dependability. Current fire response systems often lack either built-in accuracy or a way to quickly and effectively alert people. The combination of accurate detection and real-time alerting fills a major gap in these systems. By providing automated and reliable alerts, this system ensures that fire detection is quickly followed up with immediate action, significantly reducing response time and enhancing public safety.

Limitations

The proposed system demonstrates that real-time fire detection using YOLOv8 in combination with Twilio SMS messages is viable, despite several limitations that must be acknowledged. First, the accuracy and resilience of the detection are significantly influenced by the diversity and quality of the training dataset. The current model faces difficulties and generates false positive and false negative results in complex scenarios with large illumination variations, smoke, reflections or visual objects such as flashes.

Second, network and hardware conditions have an impact on real-time system performance. Frame rates and inference speeds may drop in systems with high processing loads or limited resources, which could impact detection speed. Additionally, because Twilio uses SMS messaging, the delivery of notifications depends on a reliable cellular network and a robust internet connection, which may cause message errors or delays in an emergency.

Third, the alert system only supports SMS messages. This channel does not provide sufficient contextual information (such as photos or short videos of the incident) that would help users assess the severity and validity of the alert. Furthermore, there is currently no direct integration with local emergency response systems or automatic escalation to other alert channels.

Recommendations

For future work, several directions are proposed for improving and expanding this system:

Advanced alert features: The Twilio alert system could be expanded to include multiple alert options, such as automated voice calls or even integration with local emergency systems for direct access to emergency services. The ability to send short video clips or images of the event to recipients for better documentation could also be added.

Improved User Interface: Developing a more intuitive graphical user interface (GUI) for monitoring and controlling the system, allowing users to easily define monitoring areas, configure alert settings, and review detection logs remotely.

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