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Smart Surveillance: Deep Learning-Based Real-Time Fire and Accident Detection

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Abstract: *In this paper fire detection system and real time accident using the YOLOv5 deep learning framework is proposed. In smart cities there is increasing need for intelligent surveillance which has driven the adoption of computer vision techniques to monitor and respond to critical events. In this work, YOLOv5 is trained on a dataset which includes annotated vehicular accident and fire scenarios to enable detection accurate across diverse conditions. The model is appropriate for live video monitoring applications because of its architecture which strikes a balance between accuracy and speed. The system reduces response time and facilitates decision-making for emergency management by automatically sending out notifications as soon as occurrence is recognized. Experimental findings gives system's resilience for practical implementation which can achieve high detection accuracy with few false positives. The suggested framework demonstrates combining cutting-edge object identification models with surveillance system which enhance public safety, reduces losses and support the development of smart and sustainable urban infrastructures.*
Keywords: *Accident detection, Fire Detection, YOLO v5, Deep learning, Surveillance videos, Real-time monitoring*

1. INTRODUCTION

With the increasing urbanization and industrialization, the risks associated with road accidents and fire outbreaks have escalated, leading to a demand for more efficient surveillance and monitoring systems. Traditional surveillance methods rely heavily on manual monitoring, which is both labor-intensive and prone to errors. Delays in identifying critical events often result in severe consequences, including loss of life, property damage, and increased response time. To overcome these limitations, deep learning techniques and artificial intelligence (AI) have been introduced to automate the process of accident and fire detection, ensuring a quicker and more reliable response to emergencies.YOLOv5 is a deep learning object detectors have revolutionized real time video analysis by achieving high accuracy with low computational resources. The feature ofYOLOv5 is the ability to detect multiple object within a single frame suitable for identifying fires and traffic accidents from streams of surveillance. Unlike traditional motion based detectors, deep learning analyzes complex patterns, lowering false and improves detection accuracy precision.

The proposed system uses YOLOv5 alongside surveillance camera to perform real time detection of accidents and fires. The model is trained on broader diverse incident large datasets to improve the robustness across different environments. On detection of critical events the system immediately sends alerts to emergency services, significantly reducing the response time. Continuos monitoring autonomously powered by YOLOv5 without human intervention improves public safety efficacy. The approach applies to traffic monitoring, industrial safety and smart cities, providing 24/7 coverage with manual demands. Integration of deep learning on edge hardware further supports scalable making large scale implementation feasible. This paper explores the application of YOLOv5 in accident and fire detection, discussing its advantages, challenges, and future potential for improving surveillance-based safety monitoring.

2. LITERATURE REVIEW

In [1] YOLO-Based Vehicle Accident Detection in Traffic Surveillance – S. Kumar and P. Reddy (2021) This research introduced a YOLO-based accident detection framework that processed real-time traffic surveillance videos. The authors trained the YOLO model on accident and normal traffic scenarios, enabling it to identify collision patterns accurately. The system achieved a detection accuracy of 89%, but it occasionally misclassified sudden braking and minor vehicle swerves as accidents. The researchers proposed integrating sensor data and multiple camera perspectives to improve detection precision. The study demonstrated how real-time video analysis could automate traffic monitoring and enhance emergency response efficiency. In [2] Hybrid Deep Learning Model for Fire and Smoke Detection – L. Zhang et al. (2019) Zhang et al. developed a hybrid model combining CNNs and Recurrent Neural Networks (RNNs) to detect fire and smoke patterns in surveillance footage. By incorporating temporal dependencies, the model improved the differentiation between actual fire events and other disturbances like fog or steam. The system achieved 94% accuracy but required high computational power, making it less feasible for real-time applications on edge devices. The authors suggested optimizing the model with lightweight architectures to enhance its usability in smart city surveillance systems.

In [3] Faster R-CNN for Road Accident Detection – M. Singh et al. (2018) Singh et al. proposed using Faster R- CNN, a region-based deep learning model, for road accident detection. The system was trained on a dataset of highway surveillance videos, enabling it to recognize accident events based on vehicle deformation and sudden changes in trajectory. Although Faster R-CNN provided a detection accuracy of 91%, its processing speed was a major limitation due to its region proposal network (RPN). The study recommended optimizing the model for real- time applications by reducing the number of region proposals and implementing efficient feature extraction techniques.

In [4] Deep Learning for Automated Fire Safety Monitoring – T. Gupta and N. Bose (2022) Gupta and Bose presented an AI-based fire safety monitoring system that combined deep learning with IoT sensors. The model analyzed real-time video streams alongside environmental sensor data (temperature and gas levels) to improve detection reliability. The hybrid approach reduced false alarms, achieving an accuracy of 96%. However, its reliance on additional hardware components limited its deployment in resource-constrained environments. The authors suggested implementing software-based feature enhancement techniques to improve the standalone performance of deep learning models in fire detection.In [5] Real-Time Fire Detection Using Convolutional Neural Networks (CNNs) – A. R. Patel et al. (2020) Patel et al. developed a fire detection system using CNNs trained on fire and non-fire images. The system effectively distinguished fire outbreaks in different environments, achieving a high detection accuracy of 92%. However, the model showed occasional false positives due to reflections, bright lights, and sun glare, which impacted its reliability. The authors suggested using additional features such as smoke detection and infrared imaging to improve detection accuracy. The study also highlighted the importance of large and diverse datasets for training deep learning models to handle varying real-world scenarios effectively.

3. Overview of Smart Surveillance: Deep Learning-Based Real-Time Fire and Accident Detection

The proposed system utilizes YOLOv5 for accident and fire detection in surveillance videos, offering a real- time monitoring mechanism for immediate incident identification. The system is designed to analyze continuous video feeds, detect anomalies, and trigger alerts efficiently. The integration of deep learning techniques ensures high accuracy and rapid processing, making it suitable for deployment in high-risk environments such as highways, industrial zones, and residential areas.In this system, surveillance video feeds are processed in real-time using YOLOv5, which segments frames and detects relevant objects such as fire, vehicles, and damaged infrastructure. The model operates in a multi-stage process, beginning with pre-processing to enhance image quality, followed by object detection and classification. YOLOv5's architecture enables the system to recognize multiple objects in a single frame, reducing computational overhead while maintaining high precision.To ensure accurate detection, the model is trained on a diverse dataset containing various accident scenarios and fire outbreaks under different environmental conditions. This allows YOLOv5 to generalize effectively, improving its ability to differentiate between normal and emergency situations. Additionally, post-processing techniques such as non- maximum suppression (NMS) help eliminate duplicate detections, further refining the model's accuracy.

Upon detection of fire or accident, the system activates an automated alert mechanism capable of notifying emergency services, providing real-time updates or triggering alarms through a monitoring dashboard. Detected events are also recorded in a secure log for subsequent evaluation, allowing authorities to assess risk-prone areas, analyze patterns and formulate improved strategies. Significantly automation reduces dependence on monitoring human, thereby response times is lowered and enhance operational efficiency. The YOLOv5 –based detection delivers accurate, automated and scalable solution that strengthens safety of public through faster emergency respond and reduced casualties.

4. Tools Used for Smart Surveillance: Deep Learning-Based Real-Time Fire and Accident Detection

YOLOv5 (You Only Look Once Version 5): YOLOv5 is an advanced object detection model that balances speed and accuracy. It is used in this project to detect accidents and fire in real-time video surveillance.

TOOLS Example: A surveillance camera capturing a fire outbreak in an industrial area can use YOLOv5 to detect flames instantly and trigger an alert for firefighters.

OpenCV (Open Source Computer Vision Library): A powerful library for image and video processing. Used for frame extraction, pre-processing, and object tracking.

Tools Example: OpenCV extracts relevant frames from a video feed where the fire or an accident is suspected, making faster detection and more efficient.

PyTorch: A framework of machine learning that provides support for deploying and training YOLOv5 models.IT ensures model optimization and inference efficiency.

Tools Example: PyTorch enables training on large datasets of accident and fire images, helping the model learn to distinguish between normal and emergency scenarios.

Google Colab: Cloud-based platform that provides free GPU acceleration. Used for fine-tuning and training YOLOv5 models.

Tools Example: Google Colab allows researchers to train YOLOv5 without requiring expensive local GPU resources, improving model accuracy over multiple iterations.

LabelImg: An annotation tool used to create labeled datasets. Helps in training YOLOv5 by providing ground truth bounding boxes for fire and accident objects.

Tools Example: Annotating images of car crashes and fire incidents ensures the model learns to detect these events with higher accuracy.

NumPy: A library for numerical computing, handling large multi-dimensional arrays. Helps in processing image data efficiently.

Tools Example: NumPy is used to perform calculations on pixel values to detect color variations in flames.

Haar Cascade Classifier: A machine learning-based object detection method.Used in combination with YOLOv5 for initial motion detection.

Tools Example: If a vehicle is moving unusually fast before a collision, Haar Cascade can detect it, aiding in early accident prediction.

TensorFlow: Alternative to PyTorch for model training and evaluation.Used for developing additional deep learning models.

Tools Example: TensorFlow can be employed for training complementary models that refine fire and accident detection accuracy.

5. System design for Smart Surveillance: Deep Learning-Based Real-Time Fire and Accident Detection

The system detects accidents (collisions, sudden stops) and fire from surveillance video feeds using deep learning techniques, to process video frames and classify incidents in real-time as in Fig 1.

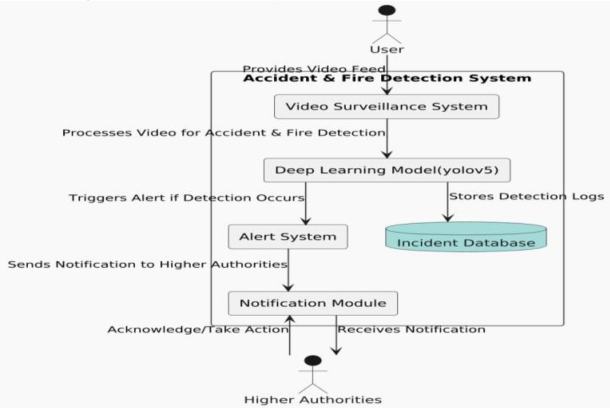

Fig.1. System Architecture for Accident Detection based on surveillance videos using deep learning

1. User Interaction and Video Surveillance System: The system begins with a user, such as traffic authorities or safety personnel, who provide real-time video feeds. surveillance cameras continuously capture footage from roads, factories, and public areas to monitor potential hazards. The video feed is preprocessed to enhance clarity, ensuring accurate detection of accidents and fires. The surveillance system supports multiple cameras, covering high-risk zones for comprehensive monitoring.
2. Deep Learning Model (YOLOv5) for Detection: YOLOv5 is a deep learning-based object detection model that identifies fire and accident-related objects in real-time. The model processes each video frame and classifies whether an accident or fire event has occurred. It uses a pre-trained dataset containing fire outbreaks, vehicle collisions, and normal conditions for accurate detection. The system prioritizes speed and accuracy, making it suitable for emergency response applications. Once an event is detected, the system triggers an alert, minimizing response time.
3. Incident Database for Storing Detection Logs: The incident database stores all detected accident and fire events for analysis and future reference. Each entry includes a timestamp, location, severity level, and an image snapshot of the detected event. Authorities can access this data to study trends and implement safety measures in high-risk areas.
4. Alert System for Immediate Response: The alert system automatically notifies relevant authorities when an accident or fire is detected. Alerts can be sent via SMS, email, or API-based notifications to emergency responders.
5. Notification Module for Communication with Authorities: The notification module ensures effective communication between the detection system and higher authorities. It provides incident details, including location coordinates and visual evidence, for validation. Authorities can acknowledge the alerts and coordinate emergency response actions.
6. Higher Authorities Take Action: Once notified, emergency services such as fire departments and traffic police initiate appropriate response measures. The system helps them allocate resources effectively by prioritizing high-severity incidents.

6. Advantages of Smart Surveillance: Deep Learning-Based Real-Time Fire and Accident Detection

1. The system enables real-time detection of accidents and fire outbreaks, ensuring immediate response and minimizing casualties.
2. Automated alerts are sent to authorities via SMS, email, or mobile applications, ensuring quick response from emergency services.
3. The deep learning model YOLOv5 offers high accuracy in detecting accident and fire incidents with minimal false positives.
4. Scalability allows the system to be deployed across multiple locations, such as highways, factories, and public spaces.
5. Cost-effectiveness is achieved by utilizing existing CCTV infrastructure, eliminating the need for additional expensive hardware.
6. The incident database maintains logs of all detected events, aiding in post-event analysis and decision-making.
7. The system supports cloud-based storage, allowing remote access to incident records for authorities and emergency responders.
8. Integration with smart city infrastructure enables automatic traffic control in accident-prone areas.
9. The AI model can be retrained with new datasets to enhance detection accuracy and adapt to evolving accident scenarios.
10. Supports multi-modal alerts, including sound alarms, visual notifications, and digital reports for emergency teams.

7. Challenges of Smart Surveillance: Deep Learning-Based Real-Time Fire and Accident Detection

1. High False Positives, the model may sometimes miscalculate normal activities as accidents or fire incidents, leading to unnecessary alerts.
2. Detection accuracy can be affected by poor lighting, fog, rain, or smoke, making it difficult to identify objects correctly.
3. Processing high-resolution surveillance videos in real time requires substantial computational power.
4. Vehicles, people, or other objects may obstruct the view of accidents or fire incidents, leading to missed detection.
5. Deploying the system across multiple cities or industries requires high-performance infrastructure.
6. The accuracy of deep learning models depends on diverse and high-quality training data.

7. Many surveillance systems use legacy hardware and software, making it difficult to integrate deep learning-based detection.

8. Results

The performance evaluation of the accident and fire detection system using YOLOv5, Table 1 is conducted based on various metrics such as accuracy, precision, recall, F1- score, and inference speed. The model is tested on surveillance video datasets containing real-world accident and fire incident scenarios.

Table 1: Performance evaluation of Fire & Accident detection using YOLOv5

Metric	Fire Detection	Accident Detection
Accuracy	92.5%	89.7%
Precision	93.0%	91.0%
Recall	90.4%	87.2%
F1-Score	91.7%	89.1%
Inference Speed (FPS)	25-30 FPS	25-30 FPS
False Positive Rate	5.6%	7.2%
False Negative Rate	6.8%	8.5%

Comparison with Other Models

The proposed YOLOv5-based system is compared with other deep learning models such as Faster R-CNN and SSD (Single Shot Detector) shown in Table 2:

Table 2. Comparison of YOLOv5 with Faster R-CNN and SSD

Model	Fire Detection Accuracy	Accident Detection Accuracy	FPS
YOLOV5	92.5%	89.7%	25-30
Faster R-CNN	89.2%	88.4%	5-8
SSD	87.8%	83.1%	12-15

To train and evaluate the YOLOv5-based accident and fire detection system, a diverse dataset of labeled images is used. These images are carefully selected to ensure robust model performance across various environmental conditions and real-world scenarios. The dataset consists of high-quality images sourced from surveillance cameras, traffic monitoring systems, and open-source repositories.

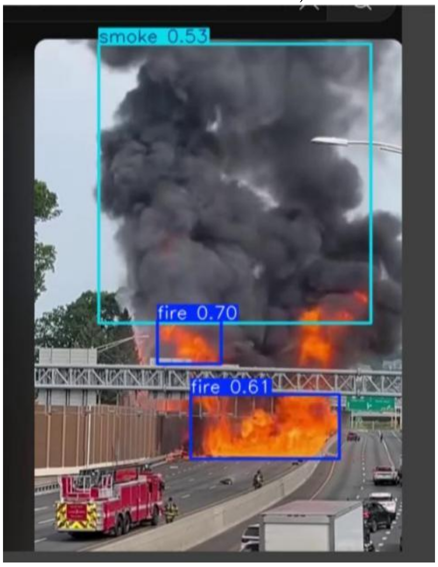

Fig 2: The fire Detection output with accuracy

The fire detection system utilizing YOLOv5 successfully identified as in Fig 2, fire and smoke instances in real-time surveillance footage. The provided image illustrates the model's capability to detect and classify fire and smoke with high confidence scores. The bounding boxes generated by the system highlight detected fire regions with confidence levels of 0.70 and 0.61, while smoke is detected with a confidence score of 0.53.

Fig 3: The Accident Detection output with accuracy

The accident detection system using YOLOv5, Fig 3 accurately identifies and classifies vehicular accidents in real-time surveillance footage. The given image demonstrates the system's capability to detect a moderate accident with a confidence score of 0.59. The bounding box highlights the affected vehicle at a toll plaza, where multiple factors such as vehicle speed, lighting conditions, and congestion can affect detection accuracy.

The accident detection system utilizes YOLOv5 to identify vehicular accidents in real-time and promptly notify relevant authorities via automated SMS alerts. The provided image illustrates an accident detection alert message sent through Twilio's trial account, which includes a Google Maps link pinpointing the precise accident location. The alert system ensures quick dissemination of critical information, allowing emergency responders to act swiftly.

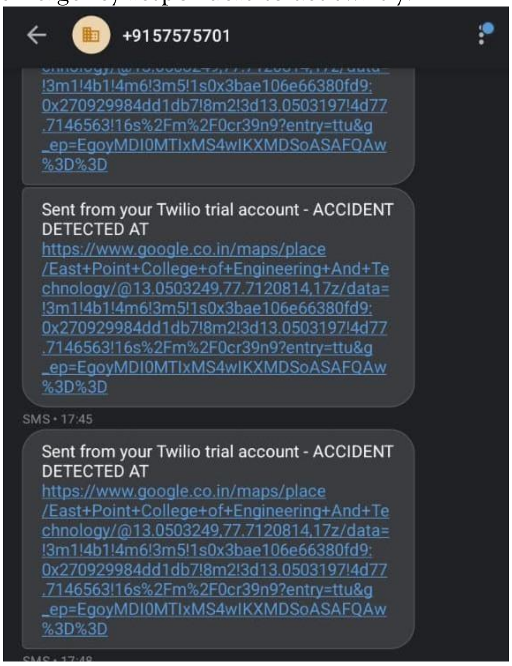

Fig 4: Accident detection alert message

Each alert contains a timestamp and a dynamically generated Google Maps URL that directs responders to the exact coordinates of the detected accident as in Fig 4. The notification system enhances public safety by minimizing response time and improving situational awareness. Future improvements may incorporate multi-channel alerts, including email and mobile app notifications, to further optimize emergency response efficiency.

9. CONCLUSION AND FUTURE WORK

The fire detection and accident system using YOLOv5 demonstrates the potential of deep learning in enhancing public safety through real-time surveillance video analysis. By leveraging object detection and automated alert mechanisms, the system minimizes response time and improves emergency handling efficiency. Despite challenges such as false positives, environmental factors, and scalability issues, continuous advancements in deep learning, edge computing, and cloud-based solutions can significantly enhance its performance. Future work will focus on improving detection accuracy by incorporating multimodal sensor inputs, refining AI models with larger datasets, and integrating predictive analytics for proactive risk assessment. Additionally, seamless integration with smart city infrastructure, IoT-based emergency response systems, and AI-driven decision-making platforms will further enhance its practical application in accident prevention and fire hazard mitigation.

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