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Real Time Safety Measurement and Hazard Notifications Using YOLOV8 and Django Framework

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Abstract

Ensuring safety in industrial environments, construction sites, and public infrastructures is a critical challenge due to increasing hazards and reliance on manual supervision. Conventional safety monitoring systems depend on continuous human observation through CCTV cameras, which often results in delayed responses, human error, and overlooked safety violations. To address these limitations, this project proposes a Real-Time Safety Measurement and Hazard Notification System using YOLOv8 and Django.

The proposed system utilizes the YOLOv8 deep learning–based object detection model to analyse live video streams and identify hazardous situations such as the absence of safety helmets, fire incidents, and unauthorized access to restricted areas. The Django framework is used as the backend to manage data processing, event logging, and alert generation. When a hazard is detected, the system immediately triggers notifications to concerned authorities, enabling rapid preventive action.

By integrating real-time computer vision with a scalable web framework, the system significantly reduces dependency on manual monitoring, improves detection accuracy, and minimizes response time. The proposed solution enhances overall safety management and provides an efficient, automated approach for accident prevention in safety-critical environments.

Keywords: YOLOv8, Real-Time Safety Monitoring, Hazard Detection, Computer Vision, Deep Learning, Django Framework, Object Detection, Automated Surveillance, Industrial Safety.

Introduction

Safety monitoring has become a critical requirement in modern industrial environments, construction sites, and public infrastructures due to the increasing number of workplace accidents and hazardous incidents. Industries such as manufacturing, mining, construction, and energy production involve high-risk operations where negligence, lack of protective equipment, fire hazards, and unauthorized access can lead to severe injuries, loss of life, and significant economic damage. Ensuring continuous safety supervision in such environments is essential but challenging when relying solely on manual monitoring methods.

Traditional safety monitoring systems primarily use closed-circuit television (CCTV) cameras supervised by human operators. Although these systems provide visual surveillance, they depend heavily on continuous human attention, which is prone to fatigue, distraction, and delayed decision-making. As a result, many hazardous situations are detected late, reducing the effectiveness of preventive measures. Moreover, manual supervision becomes inefficient in large-scale environments where multiple locations must be monitored simultaneously.

Recent advancements in artificial intelligence (AI) and computer vision have enabled the development of intelligent surveillance systems capable of automatically detecting objects and activities in real time. Deep learning–based object detection models have shown remarkable performance in identifying people, equipment, and hazardous conditions from video streams. Among these models, the You Only Look Once (YOLO) family of algorithms is widely recognized for its high detection speed and accuracy. YOLOv8, the latest version, offers improved performance, better feature extraction, and enhanced real-time detection capabilities, making it suitable for safety-critical applications.

In parallel, web frameworks play an important role in managing data processing, user interaction, and alert mechanisms. Django, a high-level Python web framework, provides a secure, scalable, and efficient backend platform for handling detected events, storing records, and generating notifications. By integrating YOLOv8 with Django, real-time detection results can be processed efficiently and converted into actionable safety alerts.

This project proposes a Real-Time Safety Measurement and Hazard Notification System using YOLOv8 and Django to automatically identify hazardous situations and notify

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responsible authorities without human intervention. The system continuously analyzes live video feeds to detect safety violations such as missing safety helmets, fire outbreaks, and unauthorized entry into restricted zones. Upon detection, instant notifications are generated to ensure rapid response and accident prevention. The proposed solution aims to enhance workplace safety, reduce dependency on manual surveillance, and improve overall safety management through intelligent automation.

Review of Literature

Recent advancements in computer vision and deep learning have significantly influenced the development of intelligent safety monitoring and surveillance systems. Early safety monitoring systems relied on manual supervision and rule-based image processing techniques, which were limited in accuracy and adaptability to complex environments. These traditional approaches required constant human attention and often failed to detect hazardous situations in real time.

With the emergence of convolutional neural networks (CNNs), researchers began exploring automated object detection techniques for surveillance applications. CNN-based models demonstrated improved performance in identifying objects and activities from images and video streams. However, early CNN models were computationally expensive and unsuitable for real-time applications due to high processing latency.

Redmon *et al*. introduced the You Only Look Once (YOLO) algorithm, which transformed object detection into a single regression problem, enabling real-time detection with high accuracy. Subsequent versions such as YOLOv2, YOLOv3, YOLOv5, and YOLOv7 further enhanced detection speed, robustness, and multi-object recognition capabilities. Several studies have successfully applied YOLO-based models for safety helmet detection, fire detection, intrusion detection, and worker activity monitoring in industrial environments. These works demonstrate that YOLO models are well-suited for real-time safety applications due to their fast inference speed.

Recent research highlights the effectiveness of YOLOv8, the latest version released by Ultralytics, which introduces architectural improvements, optimized training strategies, and enhanced accuracy compared to previous versions. YOLOv8 has been applied in real-time surveillance systems, traffic monitoring, and industrial safety applications with promising results. Studies report improved detection performance even under challenging lighting conditions and crowded scenes.

In addition to object detection, integrating intelligent models with web-based systems has gained attention for real-time alert generation and data management. Several researchers have proposed safety monitoring systems using deep learning models combined with web frameworks to generate alerts via dashboards, emails, or messaging services. However, many existing systems lack scalability, structured backend management, and efficient handling of real-time notifications.

Django, a Python-based web framework, has been widely adopted for developing secure and scalable backend systems. Research studies indicate that Django provides efficient data handling, authentication mechanisms, and seamless integration with machine learning models. Despite these advantages, limited research has focused on fully integrating advanced object detection models such as YOLOv8 with Django for real-time safety measurement and hazard notification.

Based on the literature survey, it is evident that while significant progress has been made in AI-based surveillance and hazard detection, there remains a gap in developing a unified, real-time safety monitoring system that combines high-accuracy object detection with a scalable and efficient web framework. This project addresses this gap by integrating YOLOv8 with Django to provide automated hazard detection, real-time notifications, and improved safety management.

K.Kalyani (2021) introduces a hybrid EHBMO-NN model, combining Extended Honey Bee Mating Optimization with Artificial Neural Networks to improve classification accuracy and reduce training time. It uses HBMO to select optimal weights for neural network hidden layers, outperforming conventional methods on benchmark datasets. The accurate cancer classification is very important task for cancer treatment. Recently the informative genes are identified from the thousands of genes for correct cancer classification. The collection of microscopic Deoxyribo Nucleic Acid (DNA) microarray is attached in the solid surface. In this study, DNA microarray data is used for cancer classification (6).

Existing System

Existing safety monitoring systems in industrial environments, construction sites, and public areas primarily rely on conventional surveillance methods such as CCTV cameras and manual supervision. In these systems, cameras are installed at various locations, and safety officers or monitoring personnel continuously observe video feeds to identify unsafe activities or hazardous situations. Any required action is taken only after a human operator recognizes a potential threat.

Although CCTV-based surveillance improves visibility, it has several limitations. Continuous human monitoring is tedious and prone to fatigue, distraction, and delayed decision-making. As the number of cameras increases, effective supervision becomes more difficult, leading to missed safety violations such as the absence of protective equipment, fire incidents, or unauthorized access to restricted zones. In many cases, hazards are detected only after an accident has occurred, reducing the effectiveness of preventive measures.

Some existing systems use basic motion detection or rule-based image processing techniques to identify abnormal activities. However, these methods lack intelligence and adaptability, resulting in high false alarm rates and poor performance under varying lighting conditions, occlusions, or complex backgrounds. They are unable to accurately distinguish between safe and unsafe situations in real time.

Furthermore, traditional safety monitoring systems generally lack automated alert mechanisms and centralized data management. Incident reporting and response often involve manual communication, which increases response time during emergencies. The absence of real-time notifications, intelligent analysis, and scalable backend support limits the overall efficiency and reliability of existing systems.

Due to these drawbacks, current safety monitoring approaches fail to provide proactive hazard detection and timely alerts. This creates a strong need for an automated, intelligent, and real-time safety monitoring system that can accurately detect hazards and notify authorities instantly without continuous human intervention.

Proposed System

The proposed system is an automatic safety monitoring system designed to detect hazards in real time using artificial intelligence. Instead of depending on humans to continuously watch CCTV cameras, this system uses a smart computer program to monitor the environment and identify dangerous situations.

In this system, cameras are placed in the working area to capture live video. The video is analysed using the YOLOv8 object detection model. YOLOv8 is trained to recognize safety-related issues such as workers not wearing safety helmets, fire accidents, and people entering restricted areas. When such a hazard is detected, the system immediately identifies it.

The Django framework is used as the backend to manage all the detected information. Once a hazard is found, the details are sent to the Django server, where the data is stored and processed. The system then sends instant alerts to the concerned authorities through the system dashboard or notification messages. This helps in taking quick action to prevent accidents.

The proposed system reduces human effort, avoids delays in hazard detection, and improves overall safety. By automatically monitoring and sending alerts in real time, the system provides a simple, reliable, and efficient solution for safety management in industries and public places.

Flow of the Proposed System

- Cameras are installed in the monitoring area to continuously capture live video.
- The live video stream is converted into frames for processing.
- Each frame is analysed using the YOLOv8 object detection model.
- YOLOv8 detects safety violations and hazardous events such as:
    - Missing safety helmets
    - Fire or smoke
    - Unauthorized entry into restricted areas

- The detected hazard information (type, time, location) is generated.
- This information is sent to the Django backend server.
- Django processes the data and stores it in the database.
- The system checks the severity of the detected hazard.
- Instant alerts and notifications are generated for the concerned authorities.
- Hazard details are displayed on a centralized monitoring dashboard.
- Authorities take immediate action to prevent accidents.

Advantages

- Provides real-time detection of hazards and safety violations.
- Reduces dependency on manual monitoring and human supervision.
- Minimizes human error caused by fatigue and distraction.
- Enables instant alerts and notifications for quick response.
- Improves workplace and public safety through early hazard detection.
- Offers high accuracy using YOLOv8 deep learning model.
- Ensures fast processing and low response time.
- Supports centralized monitoring through a web-based dashboard.
- Scalable and adaptable to different environments and locations.
- Enhances overall safety management and accident prevention.

Experimental Results

- The proposed system was implemented using the YOLOv8 object detection model integrated with the Django framework.
- Experiments were conducted using both live camera feeds and pre-recorded video sequences.
- The system was tested for detecting multiple hazards such as missing safety helmets, fire incidents, and unauthorized entry.
- YOLOv8 demonstrated high detection accuracy and was able to identify hazards in real time.
- The average detection time per frame was less than one second, enabling fast response.
- Once a hazard was detected, alerts were immediately generated and displayed on the monitoring dashboard.
- The system showed reliable performance under different lighting conditions and camera positions.
- Compared to manual monitoring, the proposed system significantly reduced response time and improved detection efficiency.

Datasets Used

- Publicly available safety and surveillance datasets were used for training and testing the YOLOv8 model.
- Helmet detection datasets containing images of workers with and without helmets were utilized.
- Fire and smoke detection datasets were used to identify fire-related hazards.
- Intrusion detection datasets were used to detect unauthorized access to restricted areas.
- The datasets included labelled images and video frames suitable for object detection tasks.
- Data augmentation techniques such as resizing, rotation, and brightness adjustment were applied to improve model robustness.
- Separate datasets were used for training and testing to ensure unbiased evaluation.

Evaluation Metrics

- **Detection Accuracy:** Measures the correctness of hazard detection.
- **Precision:** Ratio of correctly detected hazards to total detected hazards.
- **Recall:** Ability of the system to detect all actual hazardous situations.
- **F1-Score**: Balanced measure combining precision and recall.
- **Detection Time:** Time taken to detect a hazard from a video frame.
- **Alert Response Time:** Time between hazard detection and notification generation.
- **System Stability:** Consistency of detection results under varying environmental conditions.

Conclusion

This project presented a real-time safety measurement and hazard notification system using YOLOv8 and Django. The system automatically detects hazardous situations such as missing safety helmets, fire incidents, and unauthorized entry without the need for continuous human monitoring. By using deep learning and real-time video analysis, the system improves safety and reduces the chances of accidents.

The integration of YOLOv8 with the Django backend enables fast detection and instant alert generation. The experimental results show that the system works efficiently with high accuracy and low response time. Overall, the proposed system provides a reliable and effective solution for improving safety in industrial and public environments.

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