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Safety Vision: A YOLOv8-Based Real-Time Personal Protective Equipment Compliance Monitoring System for Industrial Workplace Safety

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Abstract: *Safety compliance is a critical requirement in industrial and construction environments where workers are exposed to various occupational hazards. Ensuring that workers consistently wear Personal Protective Equipment (PPE), such as helmets, safety vests, and face masks, is essential for reducing workplace accidents and complying with industrial safety regulations. Traditional methods of PPE monitoring rely heavily on manual supervision, which is time-consuming, labour-intensive, and susceptible to human error. To address these challenges, this study presents* ***SafetyVision****, a real-time artificial intelligence-based workplace safety monitoring system that automatically detects PPE compliance using the YOLOv8 object detection framework. The proposed system analyses live video streams captured from webcams or CCTV cameras to identify workers and determine whether mandatory safety equipment is being worn. An intelligent instance-tracking mechanism groups consecutive non-compliant detections into a single violation event, applies a configurable grace period to minimize false alarms, and automatically captures timestamped evidence for future auditing. The application is developed using the Flask web framework, Flask-SocketIO for real-time communication, OpenCV for video processing, and SQLite for persistent storage of violations and evidence. A browser-based dashboard enables supervisors to monitor live video feeds, receive instant alerts, review historical violations, and configure system parameters without interrupting operation. The proposed system also incorporates configurable detection modes, runtime settings management, and automated snapshot recording to enhance operational flexibility and reliability. Experimental implementation demonstrates that SafetyVision performs continuous PPE monitoring with high responsiveness while significantly reducing dependence on manual inspection. By integrating deep learning, computer vision, and real-time web technologies into a unified platform, the system offers an efficient, scalable, and cost-effective solution for improving workplace safety, ensuring regulatory compliance, and supporting evidence-based industrial safety management in construction sites, manufacturing industries, and other hazardous work environments.*

Keywords: YOLOv8, Personal Protective Equipment (PPE) Workplace Safety Computer Vision Real-Time Monitoring Object Detection Flask Framework Industrial Safety Monitoring

I. INTRODUCTION

Objectives

The specific objectives are:

- To develop a real-time PPE monitoring system using the YOLOv8 object detection model.

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- To automatically detect workers wearing or missing safety helmets, reflective vests, and face masks.
- To implement an instance-tracking mechanism that converts repeated frame detections into unique violation events.
- To reduce false alarms through a configurable non-compliance grace period.
- To capture and store timestamped snapshot evidence for every confirmed safety violation.

II. PROBLEM STATEMENT

Industrial organizations face significant challenges in maintaining continuous compliance with workplace safety regulations. Although the use of Personal Protective Equipment (PPE) is mandatory in hazardous environments, monitoring worker compliance is typically performed through manual inspections by safety officers. Such inspections are periodic rather than continuous, allowing many safety violations to remain undetected between inspections. Manual supervision also becomes impractical in large industrial sites where hundreds of workers operate simultaneously across multiple locations.

III. RESEARCH GAP

A review of existing literature indicates that numerous studies have applied deep learning algorithms such as Faster R-CNN, SSD, YOLOv5, and YOLOv7 for PPE detection. While these approaches demonstrate satisfactory object detection accuracy, most research is limited to frame-level classification and does not address the operational challenges encountered in real industrial environments.

Several existing systems generate repeated alerts for every detected frame, resulting in excessive false notifications and alert fatigue among supervisors. Many solutions also lack intelligent violation tracking, configurable grace periods, automated evidence capture, historical violation management, and real-time web-based monitoring interfaces. Furthermore, most research prototypes emphasize detection performance while overlooking practical deployment features such as runtime configuration, violation auditing, browser-based dashboards, and persistent database management.

IV. REVIEW OF LITERATURE

Workplace safety monitoring has attracted significant attention due to the rapid advancement of Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV). Researchers have increasingly focused on automated Personal Protective Equipment (PPE) detection systems to reduce workplace accidents and improve compliance with occupational safety regulations.

Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville established the theoretical foundations of deep learning, demonstrating how convolutional neural networks (CNNs) achieve superior performance in image recognition tasks. Their work has become the basis for modern object detection systems used in industrial safety applications.

Joseph Redmon introduced the YOLO (You Only Look Once) object detection algorithm, which revolutionized real-time object detection by treating detection as a single regression problem. Compared with traditional region-based detectors, YOLO significantly improved inference speed while maintaining high detection accuracy, making it suitable for real-time surveillance applications.

Subsequent improvements including YOLOv5, YOLOv7, and YOLOv8 further enhanced detection precision, computational efficiency, and model scalability. YOLOv8 introduced anchor-free detection, improved feature extraction, and optimized training procedures that enable accurate detection of small objects such as helmets, safety vests, and face masks in complex industrial environments.

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V. RESEARCH METHODOLOGY

The research follows a design and implementation methodology for developing an intelligent workplace safety monitoring system. The methodology consists of system analysis, model selection, software development, testing, and performance evaluation.

Initially, workplace safety requirements were studied by examining PPE compliance practices followed in industrial and construction environments. Common safety equipment including helmets, reflective safety vests, and face masks was identified as mandatory protective equipment for monitoring.

The system adopts YOLOv8 as the primary object detection model because of its high detection accuracy and real-time processing capability. Live video frames captured through webcams or CCTV cameras are continuously processed using OpenCV. Each frame is analysed to identify workers and determine the presence or absence of required PPE.

VI. SYSTEM ARCHITECTURE

Safety Vision follows a layered architecture that integrates computer vision, artificial intelligence, database management, and web technologies into a unified monitoring platform.

The Capture Layer acquires continuous video frames from a webcam or CCTV camera using OpenCV. These frames are transmitted to the Detection Layer, where the YOLOv8 deep learning model performs object detection to identify workers and PPE items including helmets, safety vests, and masks.

The detected objects are forwarded to the Instance Tracking Layer, which evaluates PPE compliance based on configurable safety rules. This layer groups repeated detections into unique violation instances, applies configurable grace periods, manages violation lifecycles, and determines when evidence snapshots should be captured.

The Persistence Layer stores violation records, timestamps, detected PPE information, missing PPE items, and snapshot images using SQLite. This database maintains complete historical records for future auditing and reporting.

VII. IMPLEMENTATION

The Safety Vision system is implemented using Python and modern open-source technologies suitable for real-time computer vision applications.

The backend application is developed using Flask, which manages routing, API services, user requests, and communication between software modules. Flask-Socket IO provides bidirectional real-time communication for live monitoring dashboards and instant safety alerts.

YOLOv8 serves as the core object detection engine, processing live video frames captured through OpenCV. The model identifies workers and PPE items with high accuracy while maintaining real-time inference speed suitable for continuous monitoring.

An intelligent Instance Detector module converts raw frame-level detections into meaningful violation events by applying configurable delay thresholds and lifecycle management. The Compliance Checker verifies whether all mandatory PPE items are present before determining compliance status.

VIII. RESULTS AND DISCUSSION

The developed Safety Vision system was successfully implemented and evaluated using live webcam video under various workplace monitoring scenarios. Experimental testing confirmed that the system accurately detected workers wearing mandatory PPE and successfully identified non-compliance involving missing helmets, safety vests, and face masks.

The YOLOv8 object detection model demonstrated fast inference speed, allowing continuous real-time monitoring without significant latency. The intelligent instance-tracking mechanism effectively eliminated repeated alerts by grouping consecutive detections into single violation instances. This significantly reduced alert fatigue compared with conventional frame-by-frame detection systems.

The configurable grace period further minimized false alarms caused by temporary occlusions, rapid worker movement, and brief detection interruptions. Automated snapshot capture created timestamped visual evidence for every confirmed violation, improving accountability and facilitating safety audits.

IX. CONCLUSION

The SafetyVision system demonstrates the effectiveness of integrating Artificial Intelligence, computer vision, and web technologies to automate workplace safety monitoring. By utilizing the YOLOv8 object detection model, the proposed system continuously monitors live video streams and accurately detects whether workers are wearing mandatory Personal Protective Equipment (PPE), including helmets, safety vests, and face masks. Unlike conventional monitoring systems that rely on manual inspections or generate repetitive frame-level alerts, Safety Vision introduces an intelligent instance-tracking mechanism that consolidates repeated detections into meaningful violation instances, thereby reducing false alarms and improving the overall reliability of safety monitoring.

The implementation of configurable grace periods, automatic evidence captures, real-time browser notifications, and persistent database storage significantly enhances the practical usability of the system in industrial environments. The Flask-based web application and Flask-Socket IO framework provide supervisors with a responsive dashboard for live monitoring, reviewing historical violations, and configuring system parameters without interrupting system operation. SQLite ensures lightweight yet reliable storage of violation records and captured snapshots, making the solution suitable for deployment on standard workstation hardware.

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