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PPE AND INDUSTRIAL SAFETY VIOLATION DETECTION USING YOLO

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Abstract

Industrial workplaces such as manufacturing plants, construction sites, warehouses, and factories contain various safety hazards that can cause serious injuries or accidents. Personal Protective Equipment (PPE), including helmets, safety vests, gloves, safety shoes, and protective masks, plays an important role in reducing workplace risks. However, manually monitoring PPE compliance across large industrial areas is difficult and time-consuming. The PPE and Industrial Safety Violation Detection Using YOLO system is proposed as an automated computer-vision solution for detecting workers and identifying PPE-related safety violations in real time.

The proposed system uses the YOLO (You Only Look Once) object-detection algorithm to analyze images and live video streams captured from CCTV or surveillance cameras. YOLO processes frames and identifies multiple objects simultaneously by generating bounding boxes, class labels, and confidence scores. The model can be trained to detect workers, helmets, safety vests, gloves, safety shoes, masks, and other safety-related objects depending on the requirements of the industrial environment.

The system compares detected workers with the required PPE conditions and identifies violations such as a worker without a helmet, missing safety vest, absence of gloves, or failure to wear other required protective equipment. Each detected violation can be assigned a confidence score and severity level according to predefined safety rules. When a serious violation is identified, the system can generate a real-time alert for authorized safety personnel along with the camera location, timestamp, and visual evidence.

A centralized dashboard can display live camera feeds, detected workers, PPE compliance rates, violation counts, severity levels, and historical safety statistics. The system can maintain records of detected violations for further analysis and reporting. Safety managers can use these records to identify frequently occurring violations, monitor safety compliance, and determine areas where additional training or corrective action may be required.

Overall, the proposed system provides an efficient and scalable method for AI-assisted industrial safety monitoring. By combining YOLO-based object detection, PPE verification, rule-based violation analysis, real-time alerts, and dashboard visualization, the system can reduce dependence on continuous manual observation. It is designed to support safety teams rather than replace human judgment, and future

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versions can incorporate additional capabilities such as restricted-area detection, fall detection, fire and smoke detection, worker-machine proximity monitoring, and advanced safety analytics.

I. Introduction

Industrial safety is a major concern for organizations operating manufacturing plants, construction sites, warehouses, workshops, and other workplaces. Workers may be exposed to hazards such as heavy machinery, falling objects, electrical equipment, chemicals, vehicles, and unsafe working conditions. Proper use of Personal Protective Equipment is one of the important measures used to reduce the risk of workplace injuries. Therefore, organizations need effective methods for continuously monitoring whether workers are following required safety procedures.

Traditional PPE monitoring is generally performed by supervisors or safety officers who visually inspect workers and work areas. Although human supervision is valuable, continuously observing a large number of workers across multiple locations is difficult. Safety violations can occur between inspection periods or may be overlooked when supervisors are responsible for monitoring several areas at the same time. Manual monitoring can also require significant manpower and may result in inconsistent observations.

Computer vision provides an opportunity to automate parts of industrial safety monitoring. Surveillance cameras can continuously capture workplace activities, while artificial-intelligence models can analyze the captured video to identify workers and safety equipment. Deep-learning object-detection algorithms can recognize multiple objects within individual frames and determine their locations. This makes computer vision suitable for detecting PPE items and identifying situations where workers may not be following safety requirements.

YOLO (You Only Look Once) is a popular family of real-time object-detection algorithms designed to detect multiple objects efficiently. Unlike approaches that process object proposals through several stages, YOLO performs object detection in a unified framework. Its ability to provide fast inference makes it suitable for applications where safety violations need to be identified quickly from live video streams.

The proposed PPE and Industrial Safety Violation Detection Using YOLO system uses YOLO-based detection to identify workers and their required protective equipment. The system analyzes the detected objects according to predefined safety rules and identifies possible violations. Alerts and visual evidence can then be provided to authorized safety personnel. The main objective is to improve safety visibility, reduce repetitive manual monitoring, and enable faster responses to potential PPE violations.

II. Literature Survey

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Traditional industrial safety monitoring systems have primarily depended on safety officers, manual inspections, checklists, and CCTV surveillance. Safety personnel visually inspect workers to determine whether they are wearing required protective equipment. Although manual inspection allows human judgment and contextual understanding, it is difficult to perform continuously across large facilities. The increasing number of workers and surveillance cameras has created a need for automated monitoring techniques.

Early computer-vision approaches used image-processing methods such as background subtraction, edge detection, contour analysis, and handcrafted features to identify workers and safety equipment. These approaches were useful in controlled environments but often struggled with complex industrial backgrounds. Changes in illumination, worker poses, shadows, camera angles, and object occlusion could significantly affect detection performance.

Machine-learning approaches improved object classification by learning patterns from labeled training data. Traditional classifiers could be trained to distinguish PPE items from other objects using extracted visual features. However, feature engineering was often required, and separate processing stages could make the system slower and more difficult to maintain. These limitations encouraged researchers to explore deep-learning-based object detection.

Convolutional Neural Networks significantly improved computer-vision applications by automatically learning visual features from training images. Modern object-detection models can simultaneously identify multiple objects and provide their locations. YOLO-based architectures became particularly useful for real-time applications because they offer a practical balance between detection speed and accuracy. YOLO models have therefore been explored for detecting helmets, safety vests, workers, masks, and other PPE equipment.

Recent research has focused on detecting multiple PPE categories and identifying safety violations by analyzing relationships between workers and protective equipment. Instead of simply detecting whether a helmet exists somewhere in an image, a safety system needs to determine whether the detected helmet belongs to a particular worker. This requires appropriate detection logic, spatial association, confidence thresholds, and carefully designed safety rules.

Modern industrial safety-monitoring systems increasingly combine object detection with real-time alerts, dashboards, historical analytics, and edge or cloud deployment. Such systems can provide continuous monitoring and help organizations identify recurring safety violations. However, challenges such as occlusion, low-light conditions, crowded workplaces, camera placement, small PPE objects, and domain-specific differences remain important. The proposed system addresses these requirements using YOLO-based detection combined with PPE verification, violation classification, alert generation, and centralized monitoring.

III. System Analysis

The proposed system is designed to automatically monitor industrial video and identify PPE-related safety violations. The system receives live video streams or images from authorized CCTV and surveillance cameras installed across industrial areas. Video frames are extracted and passed through an image-preprocessing module to resize and normalize the input. A trained YOLO model analyzes each frame and detects workers and relevant PPE objects such as helmets, safety vests, gloves, masks, and safety shoes. The detection model generates bounding boxes, class labels, and confidence scores for each detected object. A PPE-association module determines which protective equipment is associated with each detected worker. The safety-rule engine compares the detected PPE against the requirements defined for the particular workplace or work zone. When required PPE is missing, the system identifies the corresponding safety violation. A confidence threshold is applied to reduce unreliable detections and false alerts. Each violation can be assigned a severity level according to organizational safety policies. Critical violations can trigger immediate notifications to authorized safety personnel. The system stores violation information, timestamps, camera identifiers, and evidence images in a centralized database. A dashboard presents live detections, PPE compliance statistics, violation counts, and historical safety trends. This provides continuous AI-assisted safety monitoring while allowing human safety personnel to verify and respond to important events.

Existing System

Existing PPE monitoring systems mainly depend on safety officers who manually observe workers and verify compliance with workplace safety regulations. Supervisors may inspect workers at regular intervals or monitor CCTV feeds to identify missing protective equipment. Although this approach can be effective in small workplaces, it becomes difficult to scale across large industrial facilities. Continuous monitoring requires significant manpower and can be affected by fatigue, workload, and limited visibility. CCTV systems can record workplace activities but generally do not automatically understand whether a worker is wearing the required PPE. Traditional computer-vision systems may use image-processing techniques to identify helmets or other objects, but their performance can be affected by lighting, shadows, occlusion, and complex backgrounds. Some systems detect PPE objects without determining whether the equipment belongs to a particular worker. Existing approaches may also lack automated severity classification and real-time alert mechanisms. Historical violation data may require manual recording and analysis. Different safety-monitoring tools may operate independently, making centralized analysis difficult. As industrial facilities become larger and more complex, manual PPE monitoring becomes increasingly challenging. These limitations demonstrate the need for an automated real-time system that can detect workers, identify PPE, associate equipment with workers, and report violations. The proposed YOLO-based solution is designed to address these requirements.

Disadvantages of Existing System

- Heavy dependence on manual safety inspections.
- Continuous CCTV observation requires significant manpower.
- Safety violations may be missed during busy periods.

- Manual inspection is time-consuming.
- Human observation can be affected by fatigue.
- Traditional image-processing methods may be sensitive to lighting.
- Shadows and reflections can cause incorrect detections.
- Occlusion can make PPE difficult to identify.
- Some systems cannot detect multiple PPE categories.
- Limited automatic association between workers and PPE.
- Limited real-time violation alerts.
- Manual recording of safety violations is repetitive.
- Historical safety analysis may require manual effort.
- Difficult to scale monitoring across large industrial facilities.

Proposed System

The proposed system uses the YOLO object-detection algorithm to provide automated real-time PPE and industrial safety violation detection. The system accepts live video or image input from authorized CCTV cameras and surveillance devices. Incoming frames are extracted and preprocessed before being passed to a trained YOLO detection model. The model identifies workers and PPE categories such as helmets, safety vests, gloves, masks, and safety shoes according to the selected project configuration. Bounding boxes, class labels, and confidence scores are generated for detected objects. A worker-PPE association module analyzes the spatial relationship between detected workers and protective equipment. The safety-rule engine determines which PPE items are mandatory for a specific work area or activity. If a required item is missing, the system identifies a potential safety violation. A confidence threshold helps filter low-confidence predictions and reduce unnecessary alerts. Detected violations can be classified into low, medium, or high severity according to predefined organizational rules. High-priority violations can generate real-time notifications containing the event type, camera, timestamp, and visual evidence. The system stores detection results in a centralized database for historical analysis and reporting. A dashboard provides live video, PPE compliance rates, violation counts, risk levels, and historical trends. The system can also be extended to detect restricted-area entry, unsafe worker-machine proximity, falls, fire, smoke, and other industrial safety conditions.

Advantages of Proposed System

- Provides real-time PPE detection using YOLO.
- Automatically identifies multiple PPE categories.
- Reduces dependence on manual monitoring.
- Supports continuous CCTV-based surveillance.
- Provides bounding boxes and confidence scores.
- Identifies missing or incorrectly worn PPE.
- Supports worker-PPE association.
- Generates real-time safety violation alerts.
- Provides configurable safety rules.
- Supports severity classification.
- Maintains centralized violation records.

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- Provides historical safety analytics.
- Offers dashboard-based visualization.
- Can monitor multiple industrial areas.
- Can be extended with additional safety-detection modules.

IV. Methodology

The methodology of the proposed system consists of several stages beginning with data collection and ending with real-time violation reporting. The first stage is **dataset collection**, where industrial images and video frames containing workers and PPE items are collected from suitable sources. The collected images are annotated with bounding boxes and class labels for workers, helmets, safety vests, gloves, masks, safety shoes, and other required categories. The annotated dataset is divided into training, validation, and testing subsets. During preprocessing, images are resized and normalized according to the input requirements of the selected YOLO model. Data augmentation techniques can be applied to improve model robustness against different lighting conditions, poses, and camera angles. The YOLO model is trained using the prepared dataset to detect workers and PPE objects. During inference, live video frames are passed through the trained model to obtain object detections and confidence scores. A worker-PPE association process determines whether the required protective equipment is present for each detected worker. The safety-rule engine compares the detected PPE against the required PPE configuration for the relevant workplace area. If an expected PPE item is missing, the system generates a violation event. The violation is assigned a severity level and can trigger an alert when it meets predefined conditions. Detection results and evidence are stored in a database and displayed through a monitoring dashboard. Finally, model performance is evaluated using precision, recall, F1-score, mAP, inference speed, and false-alert rate to determine the effectiveness of the system.

System Architecture

The system architecture consists of several interconnected modules including the Camera/Input Layer, Video Processing Layer, YOLO Detection Model, PPE Verification Module, Safety Rule Engine, Violation and Severity Classification Module, Alert System, Database, Analytics Engine, and Monitoring Dashboard. The process begins with authorized CCTV or surveillance cameras capturing live video from industrial work areas.

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The video-processing module extracts individual frames and performs preprocessing such as resizing and normalization. The processed frames are passed to the trained YOLO model, which detects workers and PPE objects within each frame. The detection model generates bounding boxes, class labels, and confidence scores for each detected object. The PPE verification module associates detected protective equipment with individual workers based on spatial relationships and configured detection logic. The safety-rule engine checks whether each worker is wearing the PPE required for the corresponding workplace or work zone. When required PPE is missing, the violation module creates a safety event and determines its severity level. High-priority violations are transferred to the alert system, which sends notifications to authorized safety personnel. Detection results and evidence are stored in a centralized database for future analysis. The analytics engine calculates PPE compliance rates, violation frequencies, category distributions, and historical safety trends. The monitoring dashboard displays live camera feeds, detected PPE, violation alerts, compliance statistics, and historical reports. The complete architecture follows the flow **CCTV/Camera Input → Frame Processing → YOLO Detection → Worker & PPE Identification → Worker-PPE Association → Safety Rule Verification → Violation & Severity Classification → Alert Generation → Database → Analytics Dashboard → Human Safety Response**.

V. Result and Output

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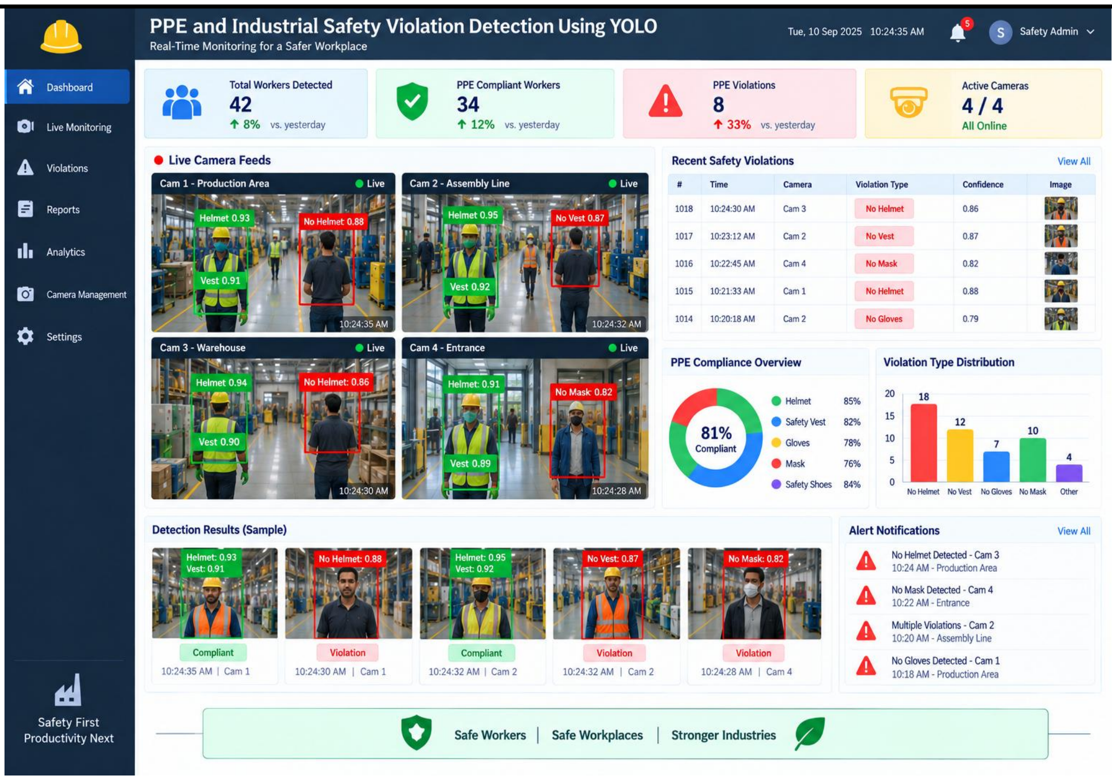

VI. Conclusion

The PPE and Industrial Safety Violation Detection Using YOLO system provides an efficient and automated solution for monitoring workplace safety compliance. By using YOLO-based object detection and computer vision, the system can identify workers and detect essential PPE items such as helmets, safety vests, gloves, masks, and safety shoes in real time.

The proposed system reduces the dependency on continuous manual supervision and enables safety teams to identify violations more quickly. By comparing detected PPE with predefined safety rules, the system can recognize violations such as missing helmets, missing safety vests, or missing gloves. Real-time alerts can help authorized safety personnel respond promptly to important safety incidents.

The system also provides a centralized dashboard containing live camera feeds, detected violations, PPE compliance statistics, violation categories, confidence scores, and historical records. These analytical features help organizations identify frequently occurring safety violations and take appropriate corrective or preventive measures.

Overall, the project demonstrates how Artificial Intelligence, Computer Vision, and YOLO can be effectively applied to industrial safety monitoring. The system can contribute to safer working environments while reducing monitoring effort and improving compliance visibility. Future enhancements can include fall detection, restricted-area monitoring, fire and smoke detection, worker-machine proximity detection, advanced PPE recognition, mobile alerts, and integration with IoT-based industrial safety systems.

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