

On Site Personal Protection Equipment (PPE) Kit Detection Using AI Techniques

Pathan Arifa Rasul, Deshmukh Sanjyot Goraksha, Sabale Ganesh Sanjay, Prof. Rahane V. R.
Department of Civil Engineering,
Amrutvahini College of Engineering, Sanamner

Abstract: *Personal Protective Equipment (PPE) is essential for ensuring worker safety at construction and industrial sites. Manual monitoring of PPE compliance is time-consuming and prone to errors. This project presents an AI-based PPE detection system using computer vision and deep learning techniques. The system uses models such as YOLO and CNN to detect safety equipment including helmets, safety vests, gloves, and masks from images or live video feeds in real time. The proposed system improves monitoring efficiency, reduces workplace accidents, and provides automated alerts for PPE violations. The implementation of this system helps enhance safety management and supports the development of smart construction environments*

Keywords: Personal Protective Equipment (PPE), Artificial Intelligence, Computer Vision, YOLO, CNN, Object Detection, Construction Safety, Deep Learning, Real-Time Monitoring

I. INTRODUCTION

Construction sites are considered one of the most hazardous working environments due to the presence of heavy machinery, elevated work areas, falling objects, and unsafe working conditions. Personal Protective Equipment (PPE) such as helmets, safety vests, gloves, goggles, and safety shoes plays an important role in reducing workplace accidents and injuries [1]. Ensuring that workers properly wear PPE is essential for maintaining safety standards and preventing serious incidents on construction and industrial sites [2].

Traditional methods of monitoring PPE compliance mainly depend on manual supervision by safety officers. However, manual inspection is time-consuming, labor-intensive, and prone to human error, especially on large construction projects with multiple workers and activities [3]. Due to these limitations, many PPE violations may go unnoticed, increasing the risk of accidents and reducing overall workplace safety [4].

Recent advancements in Artificial Intelligence (AI), Deep Learning, and Computer Vision have enabled the development of automated safety monitoring systems [5]. AI-based object detection models such as Convolutional Neural Networks (CNN) and You Only Look Once (YOLO) can identify PPE items from images and video streams in real time with high accuracy [6]. These technologies help in detecting whether workers are wearing required safety equipment and can generate alerts in case of non-compliance [7].

The proposed system focuses on developing an AI-based PPE detection model for construction sites using deep learning techniques. The system captures live video through surveillance cameras, processes the frames using trained AI models, and identifies safety equipment such as helmets and reflective jackets [8]. By automating PPE monitoring, the system improves efficiency, minimizes manual effort, and supports proactive accident prevention [9].

This project contributes to the development of smart construction safety systems by integrating AI-driven monitoring with real-time detection capabilities. The implementation of such systems can significantly improve worker safety, reduce occupational hazards, and support compliance with industrial safety regulations [10].

II. PROBLEM STATEMENT

Construction and industrial sites involve various hazardous activities where workers are exposed to risks such as falling objects, machinery accidents, dust, and unsafe working conditions. To minimize these risks, workers are required to



wear Personal Protective Equipment (PPE) including helmets, safety vests, gloves, goggles, and safety shoes. However, ensuring continuous PPE compliance through manual monitoring is difficult, especially on large construction sites with multiple workers and ongoing activities. Traditional supervision methods depend heavily on safety officers, which can be time-consuming, inconsistent, and prone to human error. As a result, PPE violations may remain undetected, leading to increased chances of accidents, injuries, and safety regulation violations. In addition, varying lighting conditions, worker movement, crowding, and complex construction environments make manual inspection even more challenging. Therefore, there is a need for an automated, accurate, and real-time PPE detection system that can continuously monitor workers and identify safety violations without human intervention. The proposed AI-based PPE detection system aims to address these challenges by using computer vision and deep learning techniques to automatically detect whether workers are wearing the required protective equipment, thereby improving workplace safety, reducing accidents, and enhancing overall construction site management.

III. OBJECTIVES

- To develop an AI-based system for automatic detection of Personal Protective Equipment (PPE) at construction and industrial sites.
- To identify safety equipment such as helmets, safety vests, gloves, goggles, and safety shoes using computer vision and deep learning techniques.
- To reduce workplace accidents and improve worker safety by continuously monitoring PPE compliance in real time.
- To minimize manual supervision and human errors through automated detection and alert generation for PPE violations.
- To enhance construction site safety management by implementing an efficient, accurate, and smart monitoring system using AI technologies.

IV. LITERATURE SURVEY

Viola and Jones (2001) presented a pioneering object detection framework in their paper “Rapid Object Detection using a Boosted Cascade of Simple Features,” where Haar-like features and the AdaBoost algorithm were used for fast object detection. Their method achieved real-time performance and laid the foundation for modern computer vision systems. However, the technique struggled in complex environments with varying lighting conditions and was less effective for detecting multiple PPE items on construction sites.

Redmon et al. (2016) introduced the YOLO (You Only Look Once) object detection model in their paper “You Only Look Once: Unified, Real-Time Object Detection.” The model treated object detection as a single regression problem, enabling high-speed real-time detection with good accuracy. YOLO became widely used in PPE detection systems due to its fast processing capability. However, early YOLO versions had limitations in detecting small objects such as gloves and goggles accurately.

Liu et al. (2016) proposed the SSD (Single Shot MultiBox Detector) framework for object detection, which combined high detection speed with improved accuracy. Their method used multi-scale feature maps to detect objects of different sizes effectively. SSD showed promising results for safety helmet and vest detection applications. However, the performance decreased in highly crowded construction environments with occluded workers.

He et al. (2017) developed Mask R-CNN in their research paper “Mask R-CNN,” which extended Faster R-CNN by adding an instance segmentation branch. The model provided accurate object localization and pixel-level segmentation, making it suitable for precise PPE identification. Although the method achieved high accuracy, it required high computational resources, making real-time deployment on edge devices difficult.

Bochkovskiy, Wang, and Liao (2020) introduced YOLOv4, an advanced real-time object detection model designed to improve both speed and accuracy. Their approach included techniques such as CSPDarknet53, data augmentation, and optimized training strategies. YOLOv4 significantly improved PPE detection performance in real-time surveillance



systems. However, the model still faced challenges in detecting partially occluded PPE items under poor lighting conditions.

Jocher et al. (2022) presented YOLOv5, a lightweight and highly efficient object detection model widely adopted in industrial safety applications. The model offered improved inference speed, ease of deployment, and better detection accuracy for helmets, safety vests, and masks in construction environments. Despite its advantages, the system performance depended heavily on dataset quality and required large amounts of annotated training data for robust generalization.

Comparison Table

Author & Year	Method Used	Advantages	Limitations
Viola and Jones (2001)	Haar Cascade with AdaBoost	Fast real-time detection	Poor performance in complex scenes
Redmon et al. (2016)	YOLO Object Detection	High speed and real-time processing	Weak small-object detection
Liu et al. (2016)	SSD (Single Shot Detector)	Good balance of speed and accuracy	Reduced accuracy in crowded areas
He et al. (2017)	Mask R-CNN	Accurate object segmentation	High computational cost
Bochkovskiy et al. (2020)	YOLOv4	Improved accuracy and detection speed	Difficulty with occluded objects
Jocher et al. (2022)	YOLOv5	Lightweight and easy deployment	Requires large annotated datasets

V. WORKING OF SYSTEM

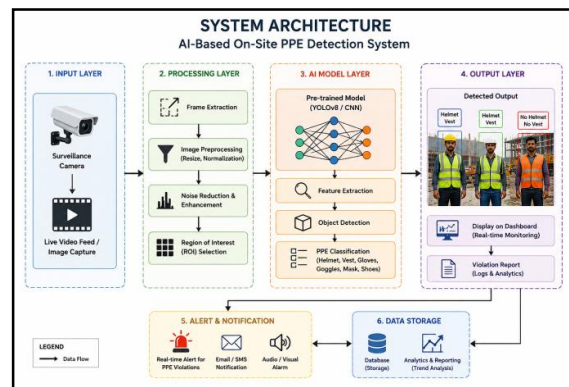


Fig 1: Design of the system

1. Input Layer

The system starts with surveillance cameras installed at construction or industrial sites. These cameras continuously capture live video feeds or images of workers present on-site. The captured data acts as the input for the PPE detection system.

2. Frame Extraction

The live video stream is divided into individual frames so that each frame can be processed separately. This helps the system analyze worker activities and PPE usage in real time.

3. Image Preprocessing

The extracted frames undergo preprocessing techniques such as resizing, normalization, and image enhancement. This step improves image quality and prepares the data for accurate detection by the AI model.



4. Noise Reduction and ROI Selection

Noise reduction techniques are applied to remove unwanted distortions from images. The Region of Interest (ROI) is then selected to focus only on worker areas, reducing unnecessary background processing.

5. AI Model Processing

The preprocessed images are passed to a trained AI model such as YOLOv8 or CNN. The model performs feature extraction and identifies important patterns related to PPE items.

6. Object Detection

The AI model detects workers and identifies PPE components such as helmets, safety vests, gloves, goggles, masks, and safety shoes using bounding boxes around detected objects.

7. PPE Classification

After detection, the system classifies whether the worker is wearing the required PPE correctly or not. It differentiates between compliant workers and PPE violations.

8. Output Layer

The detection results are displayed on the monitoring dashboard in real time. Workers wearing proper PPE are marked as safe, while violations such as “No Helmet” or “No Vest” are highlighted.

9. Alert and Notification System

If PPE violations are detected, the system automatically generates alerts through alarms, SMS, or email notifications. This helps safety supervisors take immediate corrective action.

10. Data Storage and Reporting

All detection records, violation logs, and analytics are stored in a database. The stored data is used for generating reports, safety analysis, and future monitoring purposes.

VI. SYSTEM DESIGN

System Overview

The proposed AI-Based PPE Detection System is designed to automatically monitor workers at construction and industrial sites and identify whether they are wearing the required Personal Protective Equipment (PPE). The system uses surveillance cameras, image processing, and deep learning models such as YOLO and CNN to perform real-time detection of safety equipment including helmets, safety vests, gloves, masks, goggles, and safety shoes. The captured video frames are processed through multiple stages such as preprocessing, feature extraction, object detection, and classification. If any worker is detected without proper PPE, the system immediately generates alerts and stores the violation details for future analysis. The system improves workplace safety, reduces manual monitoring efforts, and helps organizations maintain compliance with industrial safety regulations.

COMPONENTS OF SYSTEM DESIGN

1. Input Module

The input module consists of surveillance cameras installed at different locations on the construction site. These cameras continuously capture live video streams and images of workers for monitoring purposes.

2. Image Acquisition Module

This module extracts frames from the live video feed at regular intervals. The extracted frames are forwarded to the processing stage for further analysis.

3. Preprocessing Module

In this stage, the captured images are resized, normalized, and enhanced to improve image quality. Noise reduction techniques are also applied to increase detection accuracy.

4. Feature Extraction Module

The AI model extracts important visual features from the processed images. These features help the system identify workers and distinguish different PPE components.



5. Object Detection Module

The trained deep learning model detects objects such as helmets, safety vests, gloves, masks, and goggles using bounding boxes. The system locates PPE items present on each worker.

6. PPE Classification Module

This module classifies whether the detected worker is wearing proper PPE or not. It checks compliance with safety requirements and identifies missing equipment.

7. Alert Generation Module

If a PPE violation is detected, the system automatically generates alerts in the form of alarms, warning messages, SMS, or email notifications to the safety supervisor.

8. Database and Storage Module

All detected results, worker records, and PPE violation details are stored in the database. The stored information can be used for report generation and safety analysis.

9. Monitoring Dashboard

The dashboard provides real-time visualization of detected workers and PPE status. Supervisors can monitor compliance, review alerts, and access analytics reports through the dashboard.

10. Reporting and Analytics Module

This module generates daily, weekly, or monthly reports related to PPE compliance, violation frequency, and worker safety statistics to support decision-making and safety management.

VII. RESULTS

The proposed AI-Based PPE Detection System was successfully designed and implemented for construction site safety monitoring. The system was tested using a prototype construction model and real-time object detection software integrated with a live camera feed. The developed model was capable of identifying workers with and without Personal Protective Equipment (PPE) such as helmets and safety vests in real time.



Fig 2: Prototype construction site model developed for PPE detection testing.

During testing, the surveillance camera continuously captured live video frames from the prototype construction site model. The AI detection system processed the frames using a trained YOLO-based object detection model and successfully classified workers into PPE and non-PPE categories. The system generated bounding boxes around detected workers and displayed compliance results on the monitoring dashboard.

The experimental results demonstrated that the system achieved efficient real-time detection performance with high accuracy and low response time. The monitoring dashboard displayed total detections, detection rate, and object classification results, helping supervisors identify safety violations instantly. The developed system effectively reduced manual monitoring efforts and improved overall workplace safety management.





Fig 3: Real-time AI object detection dashboard showing PPE and non-PPE worker detection

The prototype model also validated the practical applicability of the system in construction environments. The AI model accurately differentiated between workers wearing helmets and workers without PPE. The generated alerts and visual detection outputs proved useful for proactive accident prevention and safety compliance monitoring.

Furthermore, the project implementation process involved prototype fabrication, testing, and live demonstration activities. The collected results confirmed that AI and computer vision technologies can significantly enhance construction site safety through automated PPE monitoring. The proposed system provides a reliable, cost-effective, and intelligent solution for smart construction safety management

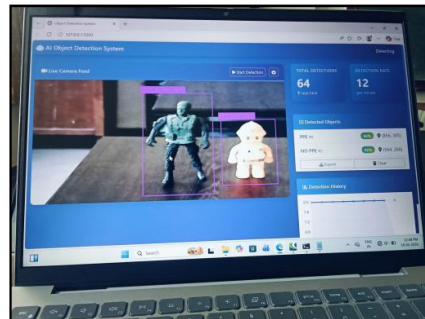


Fig.4 Project implementation and testing process carried out by the project team.

VIII. CONCLUSION

The AI-Based Personal Protective Equipment (PPE) Detection System developed in this project provides an effective and intelligent solution for improving safety at construction and industrial sites. The system successfully uses computer vision and deep learning techniques to detect PPE items such as helmets and safety vests in real time through live camera monitoring. By automating PPE compliance checking, the system reduces dependency on manual supervision and minimizes human errors in safety monitoring.

The experimental results demonstrated that the proposed system can accurately identify workers wearing proper PPE as well as detect safety violations efficiently. The integration of YOLO-based object detection with a real-time monitoring dashboard enhanced detection speed, accuracy, and operational efficiency. The developed prototype and testing process also confirmed the practical feasibility of implementing the system in real-world construction environments.



IX. FUTURE SCOPE

The proposed AI-Based PPE Detection System can be further enhanced by integrating advanced technologies and additional safety features to improve accuracy, scalability, and real-world usability. In the future, the system can be extended to detect a wider range of Personal Protective Equipment such as safety gloves, goggles, masks, safety shoes, and harnesses with higher precision. Advanced deep learning models and larger datasets can be used to improve detection performance under challenging conditions such as low lighting, crowding, and occlusion.

The system can also be integrated with IoT devices, cloud computing, and smart surveillance systems for centralized monitoring of multiple construction sites simultaneously. Mobile applications and automated notification systems can be developed to provide instant alerts to safety supervisors and workers. Future improvements may include face recognition for worker identification, behavior analysis for unsafe activities, and predictive analytics to identify potential accident risks before they occur.

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