International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0458
e ISSN: 2584-2854
Volume: 03
Issue: 09 September 2025
Page No: 2906 - 2909

Safe Sight: AI-Based Multi-Industry PPE Detection System Using YOLOv8

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Abstract

Workplace safety is a major concern across industries such as construction, mining, pharmaceuticals, food packaging, and healthcare, where compliance with Personal Protective Equipment (PPE) standards is essential to reducing occupational hazards. Traditional monitoring methods rely heavily on manual supervision, which is often error-prone, inefficient, and difficult to scale in dynamic environments. This paper presents Safe Sight, an AI-based multi-industry PPE detection system built on the YOLOv8 object detection framework. The model was trained on a diverse dataset covering six critical PPE classes: helmet, face mask, safety vest, gloves, goggles, and surgical gown. Experimental evaluation demonstrated strong performance in terms of mean Average Precision (mAP), precision, recall, and F1-score, validating the model's effectiveness for real-time applications. The system was deployed in a Python-based PyCharm application, enabling video and webcam-based detection with clear compliance indicators—green for PPE present and red for missing PPE. While the current prototype focuses on detection, the framework is scalable and can be extended with industry-specific datasets and IoT-based alerting and reporting systems to further strengthen workplace safety management.

Keywords: *PPE Detection, YOLOv8, Workplace Safety, Deep Learning, Real-Time Detection.*

1. Introduction

Ensuring workplace safety is a universal requirement across industries where employees are exposed to hazardous conditions. In sectors such as construction, mining, pharmaceuticals, food packaging, and healthcare, Personal Protective Equipment (PPE) is essential for protecting workers against in-juries and occupational hazards. However, compliance with PPE regulations is often difficult to enforce, particularly in environments with a large workforce or rapidly changing operational conditions. Traditional monitoring methods, which rely heavily on manual supervision, are time-consuming, error-prone, and lack scalability. As a result, many organizations are adopting automated solutions that leverage advances in computer vision and deep learning. Among these, the YOLO (You Only Look Once) family of object detection models has gained popularity for its balance between speed and accuracy (Jocher et al., 2023). Previous studies have successfully applied YOLO-based frameworks for PPE detection in construction sites and industrial environments (Mohona et al., 2024; Protik et al., 2023). Despite these advances, many existing systems are restricted to single-industry datasets, making it difficult to generalize across multiple domains where PPE requirements differ. For example, while construction workers require helmets and safety vests, hospital staff in operating theatres rely on masks, surgical gowns, and gloves. Addressing this gap, the present work proposes Safe Sight, a multi-industry PPE detection system based on YOLOv8. The main contributions of this study are summarized as follows:

- Development of a PPE detection framework trained on a multi-industry dataset, covering six critical PPE classes: helmet, face mask, safety vest, surgical gown, gloves, and goggles.
- Integration of the trained YOLOv8 model into a real-time application, tested with both video and webcam inputs on GPU-enabled hardware.
- Evaluation of system performance in terms of mAP, precision, and recall, confirming the

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model's effectiveness for practical deployment.
- Establishment of a scalable foundation, enabling future extensions such as IoT-based alerting, compliance reporting, and edge deployment for resource-constrained environments [1].

By combining deep learning with industry-specific safety requirements, this work highlights the feasibility of an AI-based system capable of improving workplace safety across diverse domains.

2. Methodology

The proposed system, Safe Sight, is designed to de-tact PPE compliance in real time using the YOLOv8 framework. The methodology consists of three key stages: dataset preparation, model training, and sys-term implementation.

2.1. Dataset Preparation

The dataset was carefully curated from reliable open-source sources and further supplemented with additional images representing diverse industry-specific use cases. PPE requirements significantly vary across different sectors: helmets and reflective safety vests are common in construction and mining; protective masks and surgical gowns are essential in pharmaceutical and healthcare industries, while gloves and safety goggles are widely used in food packaging and medical domains. To effectively cover this diversity, six essential classes were selected: helmet, face mask, safety vest, surgical gown, gloves, and goggles. All images were meticulously annotated with bounding boxes in Rob flow, which also provided advanced augmentation functions. Data augmentation techniques included horizontal flipping, brightness adjustment, scaling, and random cropping to considerably increase dataset size and further improve model robustness to variations in pose, background, and lighting conditions. Finally, the dataset was divided into 70% training, 20% validation, and 10% testing, ensuring balanced and fair representation of all selected classes [2].

2.2. Model Training

The YOLOv8-large (YOLOv8l) variant was selected for its trade-off between detection accuracy and re-al-time inference. Training was carried out on Google Collab with GPU acceleration. The model was trained for 50 epochs with the following hy-per parameters: batch size = 16, image resolution = 640×640, optimizer = stochastic gradient descent (SGD) with momentum = 0.937, and an initial learning rate of 0.01. During training, YOLOv8 automatically tracked evaluation metrics, including precision, recall, F1-score, and mean Average Precision (mAP@0.5). The trained model achieved an overall mAP@0.5 of 0.604, precision of 0.99, recall of 0.67, and an F1-score of 0.57. These results indicate that the model is highly reliable in detecting PPE items (few false positives), though some instances were missed, as reflected in recall and F1 values Shown in Figure 1.

Figure 1 Sample annotated images from the Rob flow dataset

2.3. Implementation

The trained model was deployed in a Python-based application developed in PyCharm with the following libraries:

- **Ultralytics YOLO:** for loading trained weights and running inference.
- **OpenCV:** for video capture, frame-by-frame processing, and handling webcam/video inputs.
- **CV Zone:** for drawing bounding boxes, over-lays, and color-coded indicators.

The implementation pipeline operates in real time. Each incoming frame is passed through the YOLOv8 model, which outputs bounding boxes, class labels, and confidence scores. These predictions are displayed on the video stream with compliance indicators:

- **Green:** PPE item present (compliance).
- **Red:** missing PPE item (violation).
- **Blue:** non-PPE objects.

Real-time testing on a GPU-enabled laptop achieved smooth frame rates (>25 FPS), demonstrating practical feasibility [3].

3. Results And Discussion

3.1. Results

The trained model was evaluated using the test set, and several performance curves were generated to assess detection quality. The F1-Confidence Curve reported a maximum F1-score of 0.57 at a confidence threshold of 0.589, showing a moderate balance between precision and recall. The Precision–Recall Curve yielded a mean Average Precision (mAP@0.5) of 0.604, reflecting good detection accuracy, although recall decreased in more complex scenarios. The Precision–Confidence Curve reached a peak precision of 0.99 at a confidence threshold of 1.0, confirming that highly confident predictions were almost always correct. The Recall–Confidence Curve peaked at 0.67, indicating that most PPE in-stances were detected, but some misses occurred under occlusion or low visibility (Figure 2).

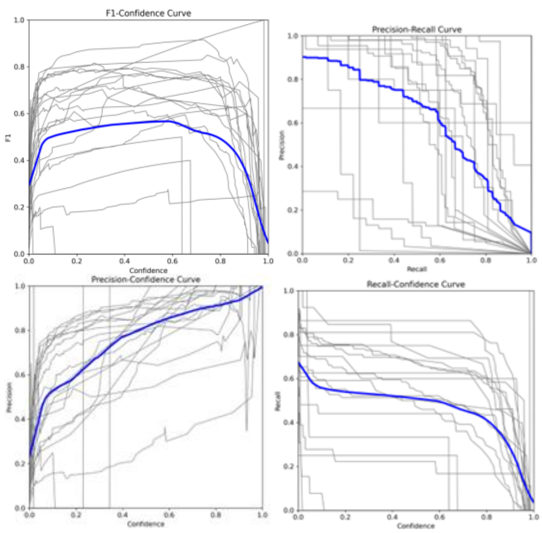

Figure 2 Model performance evaluation curves (F1-Confidence, Precision–Recall, Precision–Confidence, and Recall–Confidence).

In addition to quantitative analysis, the system was tested in PyCharm on a GPU-enabled laptop using both video files and live webcam input. The model processed frames in real time, maintaining smooth frame rates. Detection outputs included bounding boxes around PPE items with confidence values. A color-coded compliance scheme was implemented: green for PPE compliance, red for violations, and blue for unrelated objects (Figure 3).

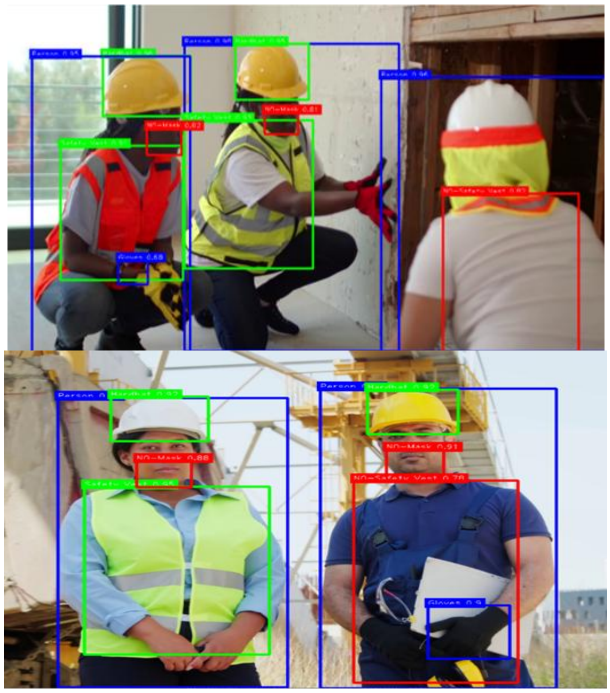

Figure 3 Example detection outputs showing PPE compliance (green) and violation (red).

Overall, the results show that the proposed system achieves high precision (0.99) and reasonable accuracy (mAP@0.5 = 0.604), with recall remaining moderate (0.67). This means the system reliably identifies PPE items with few false positives, though some instances are occasionally missed. The smooth real-time performance further confirms feasibility for industrial deployment. Future improvements could include expanding the dataset, fine-tuning hyperparameters, testing alternative backbones, and integrating IoT-based compliance reporting to strengthen practical workplace monitoring [4].

3.2. Discussion

The findings indicate that the Safe Sight system provides accurate and efficient detection of PPE across diverse industries. The high precision demonstrates that false detections are minimized, while the recall value shows that most PPE items are

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successfully identified. The visual feedback mechanism, with green and red bounding boxes, simplifies compliance interpretation, making it suitable for real-time workplace monitoring. Compared to manual inspections, the system provides continuous, unbiased, and scalable supervision. Some limitations were observed during testing. Missed detections occurred under poor lighting or partial occlusion, where PPE items were not clearly visible. Nevertheless, since the training dataset included images from multiple industrial domains, the model generalizes effectively across construction, mining, pharmaceutical, food packaging, and healthcare scenarios. Future improvements may focus on expanding dataset diversity, enhancing detection under low-light conditions, and incorporating automated alerting and reporting functions to support deployment in real workplaces [5].

Conclusion

This study effectively addressed the significant challenge of ensuring reliable Personal Protective Equipment (PPE) compliance across multiple industries where workplace safety is critical. Manual monitoring and traditional approaches are often inefficient and inadequate, frequently resulting in serious safety violations and preventable accidents. To effectively overcome these limitations, the proposed Safe Sight system employed a YOLOv8-based detection framework trained on six essential PPE classes: helmet, face mask, safety vest, surgical gown, gloves, and goggles. Real-time testing on both recorded video and live webcam in-puts clearly demonstrated that the system delivers smooth performance with accurate, clear, and color-coded compliance indicators. The results strongly highlight the system's overall effectiveness in automated PPE monitoring and further underscore its suitability for practical deployment in construction, mining, pharmaceuticals, food packaging, and healthcare environments.

Acknowledgement

The authors would like to express their sincere gratitude to their faculty mentors and the Department of Computer Science and Engineering, AMC Engineering College, for their constant guidance, encouragement, and support throughout this project. The authors also acknowledge the resources provided by Google Collab for model training, Rob flow for dataset preparation and augmentation, and the Ultralytics team for developing YOLOv8, which served as the foundation of this work. Finally, special thanks are extended to colleagues and peers for their valuable feedback during the implementation and testing phases.

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