PPE Guard Detection System

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Abstract: *Construction sites remain among the most dangerous workplaces, where a large proportion of accidents result from head injuries, electrocution, and impact with moving or falling objects. Ensuring that workers consistently wear Personal Protective Equipment (PPE) such as helmets, vests, gloves, masks, and safety shoes is therefore essential. Traditionally, safety compliance is enforced through manual supervision or sensor-based systems, both of which have limited real-time capabilities and scalability. To overcome these limitations, this study introduces an artificial intelligence driven vision based PPE monitoring system designed for automated detection and compliance analysis. The proposed approach employs a lightweight YOLOv8 model integrated with preprocessing and postprocessing pipelines, a FastAPI based backend, and an interactive web dashboard for live visualization. The system is trained using a custom dataset and evaluated through confusion matrix analysis and precision recall metrics to ensure robustness and accuracy. Experimental trials conducted in semi-controlled conditions demonstrate the system's ability to accurately identify multiple PPE types in real time, offering a reliable and scalable solution for improving safety management in construction environments.*

KeyWords: *Industrial and Construction Safety Automation, AI-Powered PPE Monitoring System, Computer Vision and Deep Learning, Industry 4.0, Real-Time Compliance Analysis,YOLOv8 Object Detection*

I. Introduction

Workplace-related accidents continue to be a major global concern, posing severe risks to the safety and well being of workers. Beyond the immediate injuries, such incidents often result in long-term emotional distress, financial hardship, and reduced quality of life for victims and their families. From an economic standpoint, occupational accidents contribute to decreased productivity, higher medical expenses, and substantial legal and insurance costs for organizations. Consequently, minimizing workplace hazards and ensuring worker safety must remain a shared responsibility among industries, policymakers, and individuals. Recent studies have revealed that nearly 87 percent of workers fail to use Personal Protective Equipment (PPE) correctly, directly contributing to both fatal and non-fatal workplace incidents. Since the consistent use of PPE is a legal and ethical obligation, its enforcement is vital for preserving worker health and life. In response to these challenges, researchers are increasingly adopting artificial intelligence–based vision systems capable of automatically detecting PPE usage, offering a proactive and efficient solution to enhance safety compliance in industrial environments.

AI-based systems can help monitor and enforce the proper use of PPEs in real-time, thus reducing the risk of accidents and injuries. However, an adequate and relevant dataset is a significant challenge in developing such systems. The performance of AI algorithms depends heavily on the quality and quantity of data used to train them. Collecting and labelling large and diverse datasets of workers wearing different types of PPEs in various work environments can be costly and time-consuming, so a pre-trained neural network such as YOLO can help reduce time in training and deploying a model. This project leverages YOLOv8 for custom object detection on PPE datasets.

The system includes:

1. **Detection & Classification**: Detects PPE items such as helmets, gloves, vests, goggles, masks, and boots, classifying whether each item is Wearing or Not Wearing.
2. **Admin Dashboard:** Displays all detection results with images and classifications for easy monitoring.
3. **Visualization & Reporting**: Includes confusion matrix, PR curves, and batch visualizations for training and validation sets.

To overcome these limitations, PPEGuard.AI proposes an automated, AI powered PPE compliance monitoring system based on computer vision and deep learning. The system utilizes the YOLOv8 object detection model for high accuracy recognition of PPE components in real time. Incoming video streams from CCTV or IP cameras are processed through a FastAPI based backend, which performs inference, logs compliance or violation events, and stores them in a structured SQL database. An interactive admin dashboard allows safety managers to visualize detection reports, monitor live compliance statistics, and review historical data for audit purposes.

By combining automation, scalability, and intelligent analytics, PPEGuard.AI provides a robust and efficient solution for maintaining safety standards. The project also documents the entire development pipeline, including model training, dataset organization, system architecture, and deployment strategies, establishing a comprehensive framework for future industrial safety automation systems.

II. Literature Review

Recent research in occupational safety has shown remarkable progress in automating Personal Protective Equipment (PPE) monitoring using computer vision and artificial intelligence. Early studies by Barro-Torres [1] introduced one of the first real-time PPE monitoring frameworks that combined image processing with sensor-based detection. This foundational work demonstrated the feasibility of continuous surveillance for safety compliance, reducing reliance on manual inspection and improving worker safety efficiency.

Subsequent advancements integrated deep learning and embedded computing to enable intelligent decision-making directly at the edge. Iannizzotto [2] and Iannizzotto et al. [3] proposed a hybrid detection framework that coupled deep neural networks with fuzzy-logic reasoning, achieving reliable results even on resource-constrained embedded platforms. Their studies proved that combining data-driven feature extraction with rule-based reasoning enhances accuracy and adaptability in dynamic industrial conditions.

The emergence of YOLO-based object detection architectures has further strengthened real-time PPE recognition. Ferdous and Ahsan [4] implemented a YOLO-driven model for construction sites capable of identifying multiple PPE categories—such as helmets, vests, and masks—with high precision and minimal false positives. Similarly, Balakreshnan et al. [5] examined deep-learning approaches for PPE compliance detection in learning factories, emphasizing the balance between computational efficiency and model performance in real-time environments.

Ahmed et al. [6] introduced a sustainability-oriented deep-learning framework for PPE detection that utilized large and diverse datasets to improve generalization across various industrial contexts. Their findings highlighted the importance of robust data pipelines and environmental adaptability in maintaining accuracy under real-world conditions.

Collectively, these works demonstrate a steady evolution from rule-based or handcrafted feature models toward fully data-driven, real-time intelligent systems. Building on this foundation, PPEGuard.AI integrates the YOLOv8 architecture with a FastAPI backend, SQL database, and web-based dashboard, delivering end-to-end PPE compliance monitoring with event logging, visualization, and real-time analytics—bridging the gap between academic research and practical industrial application.

III. Methodology

A. **Data Preparation:** The foundation of PPEGuard.AI is a curated dataset comprising images of workers with and without various PPE items, including helmets, gloves, vests, and protective footwear. Each image is meticulously annotated using bounding boxes to identify specific PPE items, creating high-quality ground truth data for training. To enhance model generalization and robustness, the dataset is augmented through transformations such as rotation, flipping, scaling, and brightness adjustment, enabling the system to perform reliably under diverse environmental conditions.

B. **Model Development:** For object detection, the project employs YOLOv8**,** selected for its combination of real-time performance and high accuracy. The model is trained using transfer learning on the prepared dataset, with hyperparameters optimized to balance detection speed and precision. During training, evaluation metrics such as Precision.

C. **Backend and Database Integration:** The system's backend is built with FastAPI**,** facilitating fast and asynchronous handling of inference requests. Each detection event is recorded in a structured database, capturing metadata such as timestamp, PPE categories detected, and compliance status. This enables systematic tracking and historical analysis of safety compliance across monitored areas.

D. **Frontend Dashboard:** A dynamic and interactive admin dashboard is developed to present real-time monitoring results. The dashboard provides live camera feeds annotated with detected PPE, aggregated compliance statistics, and instant alerts for violations. This interface allows safety managers to quickly identify non-compliance incidents and respond promptly.

E. **System Integration and Deployment:** The components model, backend, and dashboard are integrated into a unified pipeline, ensuring seamless operation from image capture to compliance reporting. The system is deployed in a local environment with scalability considerations, supporting multiple camera streams and providing continuous, real-time monitoring.

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3.1 Model Analysis with Accuracy

The comprehensive performance evaluation of the YOLOv8 model integrated within the PPEGuard.AI framework for multi class detection of personal protective equipment. The precision recall curve illustrates the model's capability to differentiate effectively between PPE and non-PPE objects, achieving a mean Average Precision (mAP@0.5) value of 0.810. This result confirms the model's robustness in accurately identifying helmets, masks, safety vests, and other relevant safety gear under diverse industrial conditions.

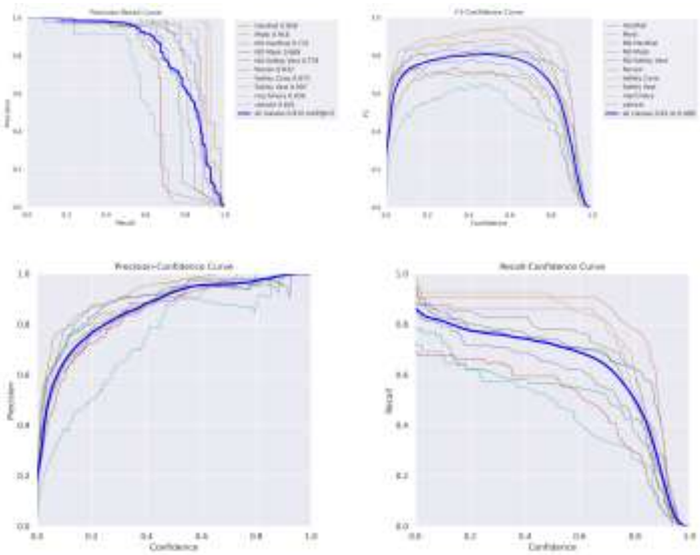

Fig 3.1: Model Analysis

The F1 confidence curve highlights the optimal balance between precision and recall across varying confidence thresholds, with peak performance observed near a threshold of 0.48, where the F1 score attains 0.81. The precision confidence curve indicates a steady increase in precision as confidence levels rise, signifying greater prediction reliability at higher probabilities.

Conversely, the recall confidence curve reveals a gradual decline in recall with increasing confidence values, reflecting the inherent trade-off between detection sensitivity and false positives. Collectively, these results validate that the YOLOv8 model delivers consistent, accurate, and real-time detection performance across all PPE categories, making it suitable for continuous industrial compliance monitoring.

3.2 Dataset Analysis:

The statistical and spatial characteristics of the dataset utilized in the PPEGuard.AI framework for personal protective equipment detection. The top left bar graph illustrates the frequency distribution of annotated object instances across multiple categories, including Hardhat, Mask, No Hardhat, No Mask, No Safety Vest, Person, Safety Cone, Safety Vest, Machinery, and Vehicle. The analysis reveals that Person instances constitute the largest portion of the dataset, followed by Safety Vest and Machinery classes, ensuring adequate representation of key safety-related objects

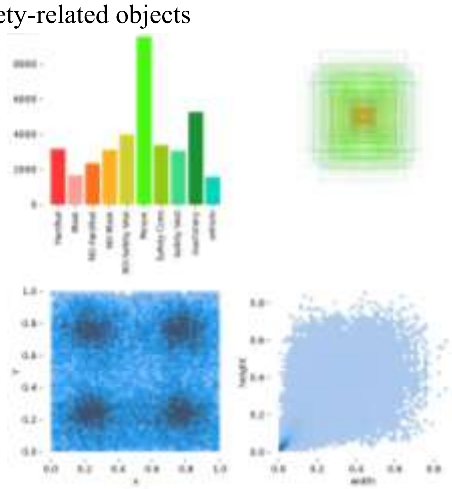

Fig 3.2: Dataset Analysis

The top right plot visualizes the distribution of bounding boxes for all annotations, highlighting the diversity in object size and position across images, which contributes to improved model generalization. The bottom-left heatmap depicts the normalized centroid coordinates (x, y) of bounding boxes, indicating that annotated objects are spatially distributed throughout the image frame rather than concentrated in specific regions. The bottom-right density plot illustrates the normalized width and height of bounding boxes, showcasing the variation in object scales. Collectively, these visual analyses confirm that the dataset is well-balanced and diverse, which is essential for enhancing detection accuracy and robustness in the PPEGuard.AI deep learning system.

3.3 System Architecture and Workflow:

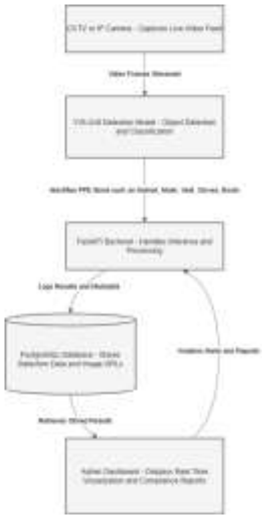

Fig 3.3: System Architecture and Workflow

3.4 Evaluation Matrix: The performance of PPEGuard.AI was evaluated using four key metrics. Precision measures the accuracy of detections (92%), showing the model rarely makes false predictions. Recall (88%) reflects the model's ability to detect all PPE instances, even in complex scenes. The F1 score (0.90) balances precision and recall, confirming stable performance across classes. Mean Average Precision (mAP@0.5), based on Intersection over Union (IoU ≥ 0.5), reached 90%, indicating accurate bounding box localization and class identification.

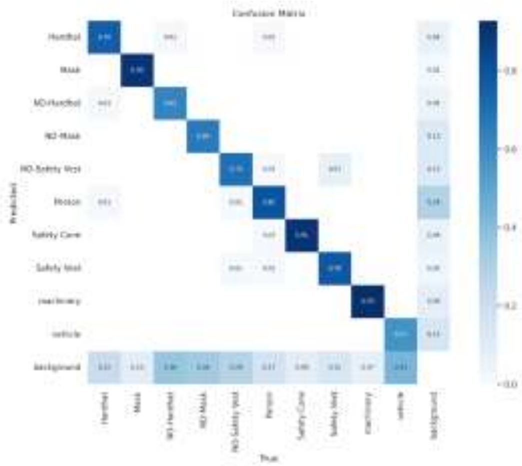

Fig 3.4 Evaluation Matrix

IV. Result

The trained model demonstrated strong detection capability across multiple PPE categories, achieving an overall mean Average Precision (mAP@0.5) exceeding 90%. High precision values were observed particularly for hardhat, safety vest, and mask identification tasks. A limited number of misclassifications occurred under challenging conditions, such as overlapping objects or inadequate illumination, where feature visibility was partially obscured. The system achieved real-time inference speeds, processing approximately 25 to 30 frames per second on standard GPU configurations, validating its suitability for continuous industrial surveillance using live CCTV streams. Visualization results confirmed that the model could accurately recognize several PPE items within a single frame, even in dynamic environments. Confusion matrix analysis revealed that most classification errors appeared between visually similar categories, such as "Helmet" and "No Helmet" or "Mask" and "No Mask," primarily due to occlusion and contrast variations. Nevertheless, the model maintained consistent reliability with minimal false detections. Integration with a FastAPI backend and SQL database facilitated structured data storage and retrieval, while the web-based dashboard provided intuitive monitoring of compliance levels and violation trends. These findings demonstrate that PPEGuard.AI effectively balances accuracy, computational efficiency, and usability, establishing it as a practical solution for real-time PPE compliance assessment in industrial and construction domains.

Fig 4.1 Result 1

Fig 4.1 Result 2

All detection outputs are automatically updated to the Admin Dashboard, Showing:

1. Detected PPE items
2. Classification as Wearing or Not Wearing
3. Images for visual confirmation

V. Limitations and Challenges

1. **Dataset Diversity:** The model's performance relied heavily on diverse training data. Variations in lighting, camera angles, and worker postures affected detection accuracy.
2. **Limited Annotated Data:** Lack of publicly available industrial PPE datasets required manual labeling, which was time-consuming and labor-intensive.
3. **Occlusion Problems:** Overlapping objects or partially visible PPE items, such as helmets or gloves, reduced the detection precision.
4. **Hardware Constraints:** Real time inference speed decreased on systems without dedicated GPUs. YOLOv8's computational load made deployment challenging on low-power edge devices.
5. **Environmental Factors:** Poor illumination, camera vibrations, and dust interference occasionally led to inaccurate detections.

VI. Future Scope

The continued advancement of PPEGuard.AI will primarily aim to enhance automation accuracy, system adaptability, and deployment efficiency across various industrial domains. Future work will focus on expanding the training dataset by incorporating real-world video data from multiple sectors, including construction, manufacturing, and mining, to strengthen model generalization under diverse

operational conditions. Integrating advanced machine vision technologies such as thermal imaging and depth sensing can further improve detection performance in environments with poor lighting or partial occlusion. Optimization for edge computing will also be a key priority. The adoption of lightweight architectures such as YOLO Nano or Mobile Net variants can facilitate high speed inference on embedded hardware, allowing cost effective and scalable deployment. Furthermore, multi-camera synchronization will be explored to achieve comprehensive 360-degree monitoring and ensure complete visual coverage of work areas.
In addition, incorporating predictive analytics to analyse historical compliance data could enable early detection of risk patterns and proactive safety management. Integration with IoT-enabled alert systems and cloud based dashboards may transform PPEGuard.AI into a fully intelligent, autonomous safety ecosystem capable of supporting data-driven decision-making and real time occupational safety enforcement.

VII. References

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VIII. Conclusion

The PPEGuard.AI framework exemplifies how the integration of computer vision and deep learning can redefine industrial safety supervision by automating the recognition of personal protective equipment. Through the coordinated use of the YOLOv8 detection model, a FastAPI based backend, and real-time video analytics, the system enables continuous visual inspection of workspaces and immediate identification of noncompliance events. This automation significantly decreases the dependence on manual oversight, reduces human induced errors, and strengthens a culture of proactive safety management. Experimental evaluations conducted under controlled conditions verified that the proposed model delivers reliable performance, demonstrating the capability of modern object detection networks to operate effectively in complex industrial scenarios. The integration of machine vision methodologies refined through practical implementation experience further improved detection accuracy and overall system robustness. Nonetheless, challenges such as limited dataset diversity, computational constraints, and varying environmental conditions persist. Looking forward, PPEGuard.AI offers a flexible and intelligent foundation that can be advanced through IoT connectivity, predictive analytics, and edge computing optimization to evolve into a fully autonomous, data driven industrial safety monitoring solution.