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Real – Time Personal Protective Equipment (PPE) Detection using yolov8 and computer Vision for Industrial Safety Compliances

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Abstract: In industries such as construction, manufacturing, and chemical processing, Personal Protective Equipment (PPE) plays a critical role in protecting workers from serious injuries. Even with strict safety rules in place, many workplaces struggle to ensure consistent PPE use, often due to negligence or lack of constant supervision. Relying on manual checks is time-consuming, error-prone, and impractical for large-scale monitoring. This study presents a real-time PPE detection system that combines computer vision with deep learning to address these challenges. The system uses the YOLOv8 object detection model to identify key safety items—helmets, safety vests, and face masks—directly from live video streams. A diverse and annotated dataset of industrial scenarios was used for training, enabling the model to reach a mean Average Precision (mAP) of 96%. The results show that the system can accurately and quickly detect PPE usage, offering a practical, scalable, and cost-effective alternative to manual oversight. By reducing reliance on human monitoring, this approach can improve compliance, enhance workplace safety, and help prevent avoidable accidents.

Keywords: PPE detection, YOLOv8, deep learning, computer vision, workplace safety, real-time monitoring.

I. INTRODUCTION

Worker safety is a critical concern in industries such as construction, manufacturing, and chemical processing, where employees are often exposed to hazardous environments. To reduce the risk of injuries and fatalities, the use of Personal Protective Equipment (PPE) — such as helmets, safety vests, and face masks — is a mandatory component of workplace safety regulations. PPE serves as the first line of defence against dangers like falling objects, chemical exposure, and collisions in busy work areas. Despite clear safety guidelines, ensuring consistent PPE usage remains a major challenge. Many incidents still occur because workers either neglect to wear protective gear or wear it incorrectly. Common causes include carelessness, discomfort, and the absence of constant monitoring. Traditional enforcement methods, such as in-person inspections and manual review of CCTV footage, are time-consuming, rely heavily on human attention, and often fail to provide immediate feedback — limiting their ability to prevent accidents in real time.In large or complex work

environments, these shortcomings can result in prolonged periods where safety violations go unnoticed, increasing the likelihood of workplace accidents. This has driven interest in automated solutions capable of continuous, accurate, and unbiased monitoring without the fatigue or inconsistency associated with manual checks. Recent advancements in artificial intelligence, especially in computer vision and deep learning, have made it possible to detect PPE usage automatically from live video streams. High-speed object detection models can now process frames in real time, classifying workers based on their compliance with safety requirements.

II. LITERATURE SURVEY

Ammad, S. Saad, and A. H. Qureshi et al [1] focusing on PPE use in construction projects. Their study showed that proper safety equipment is directly linked to increased productivity and lower accident rates. They argued that safety protocols should be integrated into day-to-day project operations, rather than being treated as separate or occasional checks. **Natha et al**. [2] proposed a deep learning-based system for detecting multiple types of PPE from visual data. They tested several detection architectures and concluded that fast, high-accuracy models are well-suited for on-site monitoring, as they can provide immediate compliance feedback.

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Ahsan et al. [3] applied convolutional neural networks (CNNs) to assess safety compliance in construction sites. Their results demonstrated that CNN-based object detection could identify PPE items such as helmets and vests across a variety of lighting and environmental conditions, maintaining reliable accuracy.
Wang et al. [4] compared multiple YOLO model variants — YOLOv3, YOLOv4, and YOLOv5 — for detecting different PPE categories. Their findings highlighted the trade-off between speed and accuracy, with YOLOv5x offering the highest detection accuracy (mAP 86.55%) and YOLOv5s providing the fastest inference times, making it more suitable for real-time scenarios.
Lee et al. [5] took a hybrid approach by combining an object detection model (YOLACT) with an object tracking algorithm (DeepSORT). This integration helped maintain tracking continuity and improved monitoring efficiency, achieving an mAP50 score of 66.4% in PPE detection tasks.

III. METHODOLOGY

1. Dataset Preparation
A well-structured and diverse dataset is essential for accurate PPE detection. For this project, images were collected from publicly available sources, including industrial safety datasets hosted on platforms such as GitHub. The dataset included multiple classes: hardhat, vest, mask as compliance categories, and no-hardhat, no-vest, no-mask as violation categories. Each image was manually annotated using standard labelling tools, with bounding boxes drawn around PPE items. The dataset was split into training, validation, and testing sets to ensure that model performance could be evaluated objectively. This division helped prevent bias and ensured that the model could generalize to new, unseen data.

2. Model Selection and Training
The detection model chosen for this study was YOLOv8 from Ultralytics, selected for its high detection speed, accuracy, and ability to run in real time. A pre-trained YOLOv8 model (trained on the COCO dataset) was used as the base, and transfer learning was applied to fine-tune the model on the PPE dataset.
Training Configuration:
Epochs: 100+
Batch Size: 16
Image Resolution: 640 × 640 pixels
Optimizer: SGD with momentum / Adam (tested for performance)
Learning Rate: Adaptive scheduling
Environment: Google Colab / Jupyter Notebook with GPU acceleration
The training process was executed using the Ultralytics YOLO command-line interface. Model weights were saved at checkpoints, and the best-performing version (based on validation mAP) was stored as ppe.pt for deployment.

3. Data Augmentation
To improve robustness and make the model adaptable to different real-world conditions, data augmentation techniques were applied, including:
Rotation and Translation – Simulating various worker positions.
Scaling – Adjusting object sizes to handle different distances from the camera.
Flipping (Horizontal/Vertical) – Increasing dataset variability.
Brightness/Contrast Adjustments – Handling lighting differences.
These augmentations allowed the model to handle scenarios such as shadows, glare, and partially obstructed PPE.

4. Performance Evaluation
The trained model was evaluated using standard object detection metrics:
Precision – Measures the proportion of correct detections.
Recall – Measures how many actual PPE instances were detected.
mAP@50 and mAP@50-95 – Mean Average Precision at different Intersection over Union (IoU) thresholds.
F1 Score – Harmonic mean of precision and recall, balancing accuracy and completeness.
Training and validation losses were monitored to prevent overfitting. The final model achieved high scores, including an mAP@50 of 96%, indicating strong performance across multiple environments.

5. Deployment and Testing
For real-time testing, the trained model was integrated into a Python application using OpenCV for live webcam streaming. Each frame from the camera was processed by YOLOv8, and detections were overlaid with bounding boxes and labels.

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The system was tested in various conditions, including indoor and outdoor industrial-like environments. Scenarios included full compliance, partial compliance, and complete non-compliance. The model maintained smooth performance on GPU setups (25–30 FPS) and acceptable speeds on CPU-only systems (12–15 FPS).

IV. RESULT

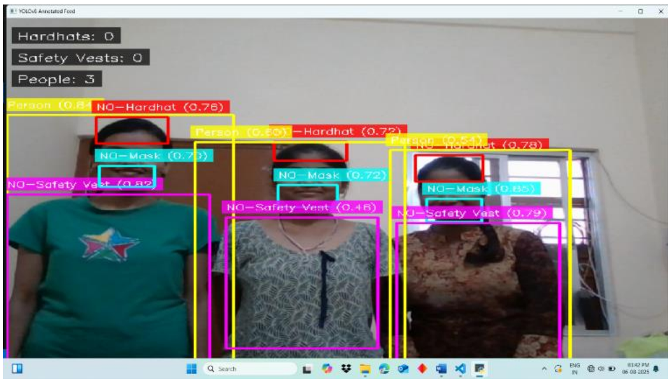

Fig. 1. People with no PPE

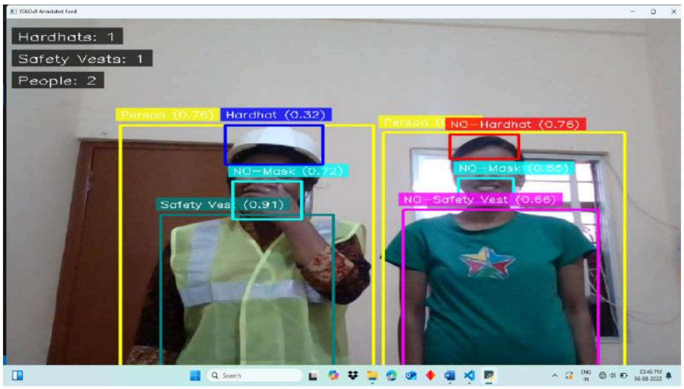

Fig. 2. Person 1 with hardhat and vest, person 2 with no PPE

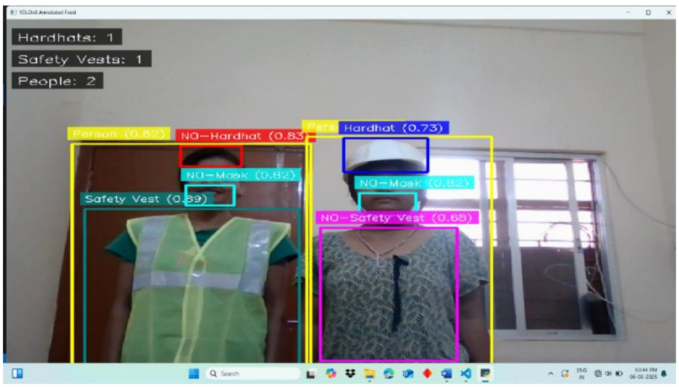

Fig. 3. Person 1 with safety vest and Person 2 hardhat.

V. CONCLUSION

This study presents an automated Personal Protective Equipment (PPE) detection system that leverages deep learning and computer vision to address the persistent challenge of workplace safety compliance. By integrating the YOLOv8 object detection model with real-time video processing, the proposed solution enables continuous monitoring of critical PPE items such as helmets, safety vests, and face masks. Testing across various environments demonstrated that the system delivers high detection accuracy (mAP@50 of 96%) while maintaining real-time performance on standard

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hardware. This confirms its potential as a scalable and cost-effective alternative to manual monitoring, which is often prone to errors, resource-intensive, and inconsistent in large-scale operations. The proposed system significantly reduces reliance on human supervision, provides immediate feedback in case of non-compliance, and is adaptable to a wide range of industrial scenarios. Its modular design also allows for easy integration with existing CCTV infrastructure or deployment in mobile setups for field use.

Future Enhancements

The proposed PPE detection system can be further improved by integrating advanced features that enhance its accuracy, scalability, and usability. One important upgrade would be to expand the detection capability to include additional safety gear such as gloves, safety goggles, boots, and hearing protection. Multi-camera integration could allow simultaneous monitoring of large or complex worksites, while cloud-based storage and remote access would enable safety officers to review incidents from any location. Real-time alert systems, such as SMS, email, or mobile app notifications, could be incorporated to immediately inform supervisors of violations. The system could also maintain a database of compliance records for trend analysis, automated reporting, and safety audits. In the future, combining PPE detection with worker tracking and behaviour analysis could provide a more comprehensive safety management tool, reducing risks and ensuring stricter adherence to workplace regulations.

REFERENCES

[1]. S. Ammad, W. S. Alaloul, S. Saad, and A. H. Qureshi, “Personal protective equipment (PPE) usage in construction projects: A scientometric approach,” Journal of Building Engineering, vol. 35, p. 102086, 2021. doi: 10.1016/j.jobe.2020.102086.

[2]. N. D. Natha, et al., “Deep Learning for site safety: Real-Time Detection of PPE,” in Proc. IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2020, pp. 1234–1242.

[3]. B. Ahsan, et al., “Construction safety factors assessment through Frequency Adjusted Importance Index,” International Journal of Construction Management, vol. 18, no. 5, pp. 321–330, 2018.

[4]. Q. Wang, et al., “The issue of workers’ safety by using deep learning neural networks,” Automation in Construction, vol. 130, p. 103860, 2022. doi: 10.1016/j.autcon.2021.103860.

[5]. Y.-R. Lee, et al., “Platform based on computer vision to monitor the proper use of PPE on construction sites,” Journal of Building Engineering, vol. 74, p. 106888, 2023. doi: 10.1016/j.jobe.2023.106888.

[6]. Occupational Safety and Health Administration (OSHA), Personal Protective Equipment, U.S. Department of Labor, 2022. [Online]. Available: https://www.osha.gov/personal-protective-equipment

[7]. M. Loibner, S. Hagauer, G. Schwantzer, A. Berghold, and K. Zatloukal, “Limiting factors for wearing personal protective equipment (PPE) in a healthcare environment evaluated in a randomized study,” PLoS ONE, vol. 14, no. 1, e0210775, 2019. doi: 10.1371/journal.pone.0210775.

[8]. X. Yang, Y. Yu, S. Shirowzhan, and H. Li, “Automated PPE-Tool pair check system for construction safety using smart IoT,” Journal of Building Engineering, vol. 32, p. 101721, 2020. doi: 10.1016/j.jobe.2020.101721.

[9]. J. Izudi, V. Ninsiima, and J. B. Alege, “Use of personal protective equipment among building construction workers in Kampala, Uganda,” Journal of Environmental and Public Health, vol. 2017, Article ID 7930589, 2017. doi: 10.1155/2017/7930589.

[10]. Y. Halabi, et al., “Causal factors and risk assessment of fall accidents in the US construction industry: A comprehensive data analysis (2000–2020),” Safety Science, vol. 146, p. 105537, 2022. doi: 10.1016/j.ssci.2021.105537.