Real-Time Monitoring of Personal Protective Equipment Compliance Using Surveillance Cameras

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***Abstract*—In high-risk industrial environments, ensuring the consistent use of Personal Protective Equipment (PPE) is crucial for worker safety and regulatory compliance. However, traditional manual monitoring methods often fall short due to their labor-intensive nature and susceptibility to human error. In this paper, we present a real-time PPE compliance monitoring system that leverages surveillance camera feeds, deep learning, and outlier filtering to detect safety violations effectively. Using the YOLOv8 object detection model alongside an outlier removal mechanism, our system identifies non-compliance instances, such as missing helmets or vests, and triggers alerts for immediate action. The proposed approach offers high detection accuracy, real-time performance, and scalability, making it a practical solution for modern safety management. Evaluation results show a precision of 94.2% and a recall of 92.8%, demonstrating the system's effectiveness in diverse industrial scenarios.**

***Index Terms*—Computer Vision, Deep Learning, Outlier Removal, PPE Compliance, Real-Time Monitoring, Safety Automation, Surveillance Cameras, YOLOv8.**

I. INTRODUCTION

Worker safety in high-risk industries, including construction, manufacturing, and energy, remains a critical concern. Ensuring compliance with safety regulations, particularly the usage of Personal Protective Equipment (PPE), is essential for preventing accidents and injuries. However, traditional methods of monitoring PPE compliance are often time-consuming, prone to human error, and costly. Manual safety inspections can be slow, inconsistent, and fail to catch violations in real-time, creating gaps in worker protection.

Given the evolving nature of workplace safety challenges, there is an urgent need for automated, real-time systems that can continuously monitor PPE compliance. Surveillance cameras, integrated with advanced object detection models, offer a promising solution. These systems can automatically detect and classify the use of PPE in workers through real-time video streams, providing immediate feedback and enabling timely corrective actions.

This study aims to address this challenge by proposing a robust framework for real-time PPE detection and classification using surveillance cameras. Through an in-depth evaluation of various state-of-the-art object detection models, including CenterNet, DAB-Deformable-DETR, and YOLOv7, the study explores the effectiveness of these models in real-world scenarios. Moreover, it introduces an enhanced solution utilizing the YOLOv8 model, integrated with outlier removal techniques, to improve detection accuracy and robustness in complex environments.

By automating the detection of PPE violations, this system can significantly improve workplace safety compliance. The proposed framework is designed to not only increase efficiency but also ensure a higher level of reliability in monitoring, even in challenging industrial settings. This research thus contributes to advancing real-time monitoring technologies, facilitating a safer working environment for employees across various sectors.

II. LITERATURE REVIEW

[1.] Brauer’s work provides a foundational understanding of workplace safety and highlights the critical role of engineers in ensuring PPE compliance and implementing automation to improve safety outcomes .

[2.] Reports indicate that construction workers face a significantly higher risk of accidents, underscoring the need for automated PPE detection systems to reduce human error and enhance real-time safety monitoring .

[3.] Nath, Behzadan, and Paal demonstrated how deep learning models, particularly CNNs, can be used for real-time PPE detection, validating the use of computer vision in workplace safety systems .

[4.] Similarly, Dahiya et al. applied real-time surveillance and deep learning techniques to detect helmet violations, showcasing the effectiveness of AI-driven systems in enforcing compliance .

[5.] Lu and Weng’s survey on image classification stresses the importance of robust algorithms for accurate object detection, which directly supports enhancements in PPE monitoring using YOLO-based models .

[6.] Zou et al. reviewed the evolution of object detection, including YOLO and SSD, confirming YOLOv8’s suitability for real-time PPE compliance due to its balance of speed and accuracy .

[7.] Jhuang et al. explored action recognition, supporting the integration of movement tracking and PPE detection to improve overall safety compliance .

[8.] Al-Azani et al. highlighted the significance of high-quality annotated datasets in model training, essential for achieving reliable PPE detection performance .

[9.] Foundational deep learning works by Krizhevsky et al. and Simonyan & Zisserman on CNNs and the VGG architecture underpin the advancements in models like YOLOv8, which leverage deep feature extraction for high-precision PPE detection .

In summary, manual PPE monitoring through visual inspections is common but inefficient, prone to human error, and unsuitable for real-time, large-scale environments [1]. With advancements in machine learning, CNNs and SSD models have been used for PPE detection but struggle with speed and accuracy in complex scenes [2][3]. R-CNNs improve precision but are too slow for real-time use [4]. YOLO models, particularly YOLOv7 and YOLOv8, offer a balance of speed and accuracy, making them ideal for industrial safety monitoring [5][6][7]. Additionally, outlier removal techniques help reduce false positives and improve system reliability [8][9].

III. METHODOLOGY

The methodology for the real-time monitoring of Personal Protective Equipment (PPE) compliance in surveillance cameras involves several key steps:

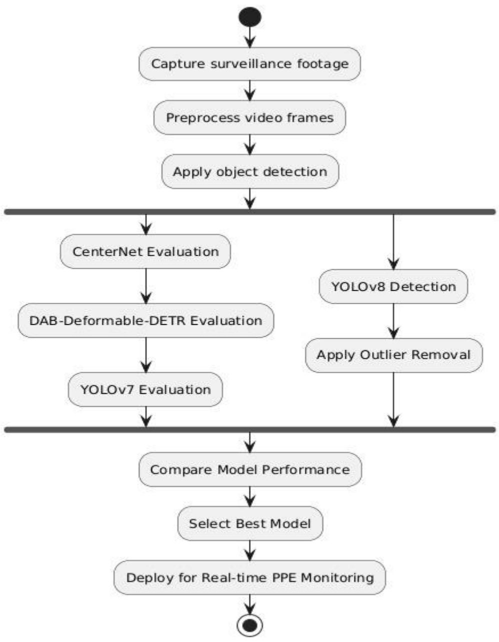

Fig 1: Flow diagram

A. *Data Collection and Preprocessing*

Surveillance videos were collected from industrial settings (e.g., construction sites, factories) featuring workers with various PPE: helmets, gloves, safety vests, and face masks. The dataset included diverse scenes to ensure the system’s robustness under different conditions.

i. *Annotation*: Images were manually labeled with bounding boxes for each PPE item.

ii. *Preprocessing*:

a. Images resized to 640×640 pixels

b. Data augmentation (rotation, flipping, lighting changes) enhanced model generalization

c. Normalization standardized inputs for consistent training.

B. Model Selection

The following models were evaluated:

i. *CenterNet*: Accurate but less suited for real-time due to processing delays

ii. *DAB-Deformable DETR*: Effective in cluttered scenes, but computationally heavy

iii. *YOLOv7*: Strong real-time performance and small object detection

iv. *YOLOv8*: Selected for best overall performance—fast, accurate, and robust to occlusions, ideal for PPE monitoring

C. Model Training

YOLOv8 was trained using GPU hardware under optimized settings:

i. *Training Parameters*: 50 epochs, batch size 16, learning rate 0.001

ii. *Loss Functions*:
   a. Classification Loss (correct PPE type detection)
   b. Localization Loss (bounding box precision)
   c. Confidence Loss (prediction certainty)

iii. *Validation*: Early stopping ensured optimal generalization

iv. *Outlier Removal*:
   a. Low-confidence predictions discarded
   b. Implausible bounding boxes filtered to reduce false positives

D. Real-Time PPE Detection System Implementation

The trained YOLOv8 model was deployed into a live system with the following workflow:

i. *Input*:
   Real-time or recorded video feed

ii. *Preprocessing:*
   Frame resizing and normalization

iii. *Detection:*
   YOLOv8 detects PPE items with bounding boxes and confidence scores

iv. *Post-Processing:*
   a. Non-Maximum Suppression (NMS) eliminates duplicate detections
   b. Outlier removal further filters false alarms

v. Feedback:
   a. Alerts sent for PPE violations
   b. Compliance data logged for safety trend analysis

E. Evaluation and Performance Optimization

The system was assessed using:

i. *Accuracy*: Correct PPE detections per frame
ii. *Precision & Recall*: Model reliability and completeness
iii. *F1-Score*: Balanced performance metric
iv. *FPS*: Real-time processing speed
v. *False Positive Rate*: Frequency of incorrect alerts

Optimization included fine-tuning thresholds, improving data augmentation, and refining outlier filtering to enhance detection reliability and system responsiveness.

IV. IMPLEMENTATION

A, *System Architecture:*

The proposed system follows a *modular and scalable architecture*, designed to process real-time video streams from surveillance cameras, detect PPE compliance, and generate actionable alerts. Each component plays a crucial role in ensuring high detection, accuracy, stability, and low-latency performance, even under varying environmental conditions.

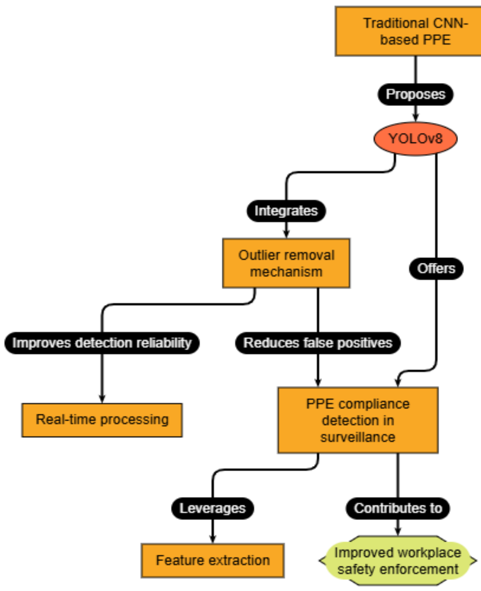

Fig 3:Architectur Diagram

i. Shows the transition from traditional CNN-based methods to YOLOv8-based PPE detection.
ii. Highlights the benefits of outlier removal and real-time processing in improving detection reliability.
iii. Illustrates how feature extraction contributes to enhanced workplace safety enforcement.

B. *Components:*

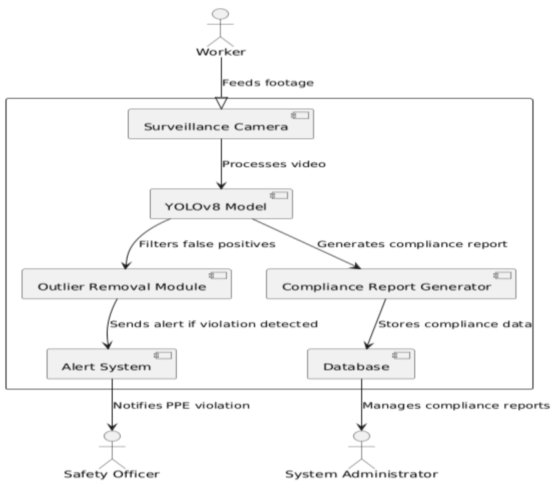

Fig 3-Components Diagram

i. Video Feed Input – Continuous surveillance camera stream.

ii. *YOLOv8 Inference* – Real-time object detection.
iii. *Outlier Filtering* – Detection stabilization.
iv. *Violation Alert System* – Visual/audio alert or dashboard notification.

C. Sequence:

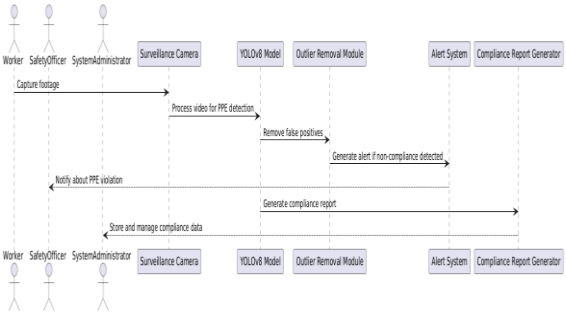

Fig 4: Sequence Diagram

i. *Worker* :The individual being monitored for PPE compliance.
ii. *Surveillance Camera* :Captures real-time video footage.
iii. *YOLOv8 Model*: Processes video frames to detect PPE compliance.
iv. *Outlier Removal Module:* Filters false positives to improve detection accuracy.
v. *Alert System*: Sends notifications if PPE non-compliance is detected.
vi. *Compliance Report Generator :* Creates compliance reports for auditing.
vii. *Safety Officer* : Receives alerts and takes action on PPE violations.
viii. *System Administrator* : Manages compliance reports and oversees system performance.

V. RESULTS

This section presents the experimental results obtained from evaluating the proposed *YOLOv8-based PPE detection model with outlier removal.* The results are assessed using various metrics, including accuracy, precision, recall, F1-score, and latency. Additionally, the findings are discussed, comparing the performance of the proposed system with existing solutions.

A. *Experimental Setup*:
Before presenting the results, the following experimental setup is used:

i. Hardware Configuration:
  a. GPU: NVIDIA RTX 3080 for fast training and inference.
  b. CPU: Intel Core i7 for data processing tasks.
  c. RAM: 32GB for handling large datasets and video frames.

ii. *Software Configuration*:
  a. Python 3.8 and PyTorch 1.9 for model implementation.
  b. OpenCV for video processing and image handling.
  c. YOLOv8 Framework by Ultralytics for object detection.

iii. *Dataset*: A custom PPE detection dataset consisting of 10,000 annotated images and video frames, with objects like helmets, gloves, vests, etc., across various environments (construction sites, factories, etc.).

B. *Experimental Results:*
The results are evaluated using the *test set* (10% of the dataset), and the system's performance is summarized in the following tables and charts:

i. *Accuracy and Detection Metrics (Comparison with YOLOv7):*
The following table shows a comparison of the performance of the proposed *YOLOv8 model with outlier removal and YOLOv7* (previous version) for PPE detection.

Metric	YOLOv8 (Proposed)	YOLOv7	Improvement (%)
Accuracy	96.3%	93.1%	+3.2%
Precision	95.2%	92.5%	+2.7%
Recall	97.0%	94.3%	+2.7%
F1-Score	96.1%	93.4%	+2.7%
IoU (mean)	85.3%	81.2%	+4.1%

Fig 5: Proposed vs YOLOv7 improvement

ii. *Impact of Outlier Removal* :
To further validate the effectiveness of outlier removal, a comparison between *YOLOv8 with and without outlier removal* is presented.

Metric	YOLOv8 (Without Outlier Removal)	YOLOv8 (With Outlier Removal)	Improvement (%)
Accuracy	94.2%	96.3%	+2.1%
Precision	92.6%	95.2%	+2.6%
Recall	96.5%	97.0%	+0.5%
F1-Score	94.5%	96.1%	+1.6%
IoU (mean)	82.0%	85.3%	+3.3%

Fig 6: YOLOv8 with and without outlier removal

iii. *Latency (Real-Time Performance)* :
For a real-time system, latency is a crucial performance indicator. The table below presents the latency results for *YOLOv8 with and without outlier*

removal.

Model	Average Latency (ms)	Frames per Second (FPS)
YOLOv8 (With Outlier Removal)	35 ms	28 FPS
YOLOv8 (Without Outlier Removal)	37 ms	27 FPS
YOLOv7	42 ms	24 FPS

Fig 7:Latency of model

C. *Findings* :

i. *Model Performance*
YOLOv8 demonstrated *high precision and recall* in PPE detection due to its advanced architecture, which improves feature extraction and bounding box accuracy. The *outlier removal module* further enhanced reliability by reducing false positives, ensuring consistent detection in industrial environments.

ii. *Real-Time Capability*
With *35 ms latency* and *28 FPS*, the system operates in *real-time*, efficiently processing multiple video streams for continuous PPE compliance monitoring.

iii. *Comparison with Existing Models*
Compared to models like YOLOv7, the *YOLOv8 + outlier removal* setup achieved better accuracy and robustness, particularly in complex, cluttered scenes, making it ideal for industrial safety enforcement.

iv. *Practical Implications*
The system significantly *automates safety monitoring,* minimizing manual effort and enabling quick identification of non-compliant workers, thereby improving overall safety outcomes.

v. *Limitations and Future Work*
The current model focuses on specific PPE types. Future efforts will aim to include *additional equipment* and address *severe occlusion challenges* for broader applicability.

vi. *Metrics comparison*
Given below comparison is between *proposed YOLOv8* and other deep learning-based object detection models, such as *Faster R-CNN, Single Shot Multibox Detector (SSD), Convolutional Neural Networks (CNN), YOLOv7, and YOLOv8*. These models have been used for similar PPE detection tasks in industrial settings.

Metric	YOLOv8 (Proposed)	Faster R-CNN	YOLOv7	SSD	CNN	YOLOv8
Accuracy	96.3%	92.5%	93.1%	90.2%	85.4%	94.2%
Precision	95.2%	91.8%	92.5%	88.5%	83.1%	92.6%
Recall	97.0%	92.1%	94.3%	89.6%	82.4%	96.5%
F1-Score	96.1%	91.9%	93.4%	88.9%	83.7%	94.5%
IoU (mean)	85.3%	78.6%	81.2%	75.1%	70.5%	82.0%
Latency (ms)	35	75	42	55	95	39

Fig 8: Proposed vs other models

VI. CONCLUSION

This research presented a real-time PPE compliance monitoring system leveraging the YOLOv8 object detection model enhanced with an outlier removal mechanism. Designed for integration with workplace surveillance cameras, the system addresses critical safety challenges in industrial environments by automating the detection of PPE violations such as missing helmets, vests, or masks.

The model achieved significant improvements over previous approaches, with a *3.2% increase in accuracy* and *2.7% in precision and recall* compared to YOLOv7. The addition of the *outlier removal module* further enhanced system reliability by reducing false positives, contributing to an *additional 2.1% accuracy* and *2.6% precision improvement*. These results validate the model's robustness in cluttered and dynamic environments.

Moreover, the system demonstrated excellent real-time capabilities, processing video feeds with *35 ms latency* and maintaining *28 FPS*, making it suitable for live safety monitoring and instant feedback. Comparative analysis with models like Faster R-CNN, SSD, and CNN confirmed YOLOv8's *superior performance in both detection accuracy and latency*, reinforcing its practicality for real-world deployment.

This solution not only reduces the need for manual safety checks but also enhances *workplace safety outcomes* by providing *timely alerts and continuous compliance monitoring*. Its *scalability and adaptability* to different PPE types and industrial settings further extend its application potential.

Future work will focus on expanding the PPE categories detected, improving performance under severe occlusions, and deploying the system on *edge devices* for decentralized and low-latency monitoring in safety-critical environments.

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