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# RISKSENTINEL: REAL-TIME PPE VIOLATION DETECTION SYSTEM FOR HAZARDOUS ENVIRONMENTS

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Keywords	Abstract
PPE Compliance, Hazardous Environment, Edge Computing, Real-Time Monitoring, Safety Management.	Proper Personal Protective Equipment (PPE) utilization is vital in high-risk workplaces to reduce injuries and deaths. This document outlines the creation process of the RiskSentinel system, which utilizes a camera network with edge computing devices for real-time PPE compliance monitoring. The system faces the challenge of capturing video footage continuously from various industrial sites while considering the environmental and operational conditions such as lighting, worker density, and activity levels. Doing the local-site video analysis enables the system to quickly identify safety breaches, such as the absence of helmets, gloves, or gloves and incorrectly worn vests without incurring cloud-based system delays. Upon detection, the violation is instantly flagged, prompting automatic notifications for supers and workers, which allows for timely corrective actions. Using an exhaustive dataset of annotated PPE compliance scenarios, the system was put through rigorous testing, demonstrating high accuracy for detection and response time across numerous site conditions. In summary, RiskSentinel provides robust, dependable, and practical solutions towards effective safe work practices and proactive PPE compliance in high-risk workplaces.



## 1. INTRODUCTION

Ensuring safety at a workplace is particularly important as some work involve PPE requirements which if not followed can lead to injuries and even death. Safety regulations are adhered to, but people continue disregarding PPE guidelines. Typical reasons are lack of supervision or negligence. There's an urgent need for automated systems that monitor PPE and compliance violations in real time so that alerting personnel can be notified immediately. The RiskSentinel system addresses this issue with a timely response PPE violation detection solution and offsite processing ensuring risk intervention and safety standards compliance.

# The primary objectives of this paper are:

- To implement real time monitoring of PPE violations in hazardous work environments aimed at building an efficient rigid system.
- To enable immediate alerting for the corrective action through onsite processing.
- To improve the accuracy during the detection automate the process thereby lessening the burden of human supervision.
- To strengthen compliance to protocols while enhancing workers safety culture.
- To showcase industrial case studies demonstrating the integration impact of the system.

This paper continues with the following structure: Section 2 discusses background information and previous works related to PPE monitoring. Section 3 outlines the design and implementation aspects of the RiskSentinel system. In Section 4, the results and discussion are presented based on system testing and performance evaluation. Finally, Section 5 provides concluding remarks by synthesizing the main points and offering recommendations for further exploration on the topic.

#### 2. RELATED WORKS

Research on compliance with Personal Protective Equipment (PPE) policies in the workplace has received considerable focus owing to the protective equipment's significance in averting accidents. Improving workplace safety has been made possible by the development of real-time monitoring systems for PPE detection with advancements in computer vision and deep learning. Lo et al. [1] designed a real-time PPE compliance monitoring system using deep learning which provided greater accuracy and responsiveness tailored for vibrant workplaces. As a supplement, Vukicevic et al. [2] analyzed multiple approaches for compliance with PPE using computer vision and pointed out persistent problems such as obstructions and changes in light, and the need for robust models for practical use in industries.

Studies by Mneymneh et al. [3] and Nath et al. [4] provided early contributions by developing vision-based systems for intelligent hardhat supervision and comprehensive site safety monitoring through deep learning, proving the viability of automated monitoring for PPEs. In a later study, Cheng et al. [5] applied worker re-identification strategies together with PPE detection to enhance



supervision accuracy at construction sites. Further improvements in safety monitoring were made by Kim et al. [6] through the development of small object detection systems tailored for complicated site conditions.

Fang et al. [7] address the problem of hardhat detection in non-close-up surveillance videos, demonstrating promising results for far-field surveillance. Wu et al. [8] developed a benchmark dataset alongside a deep learning model for hardhat detection, which will undoubtedly facilitate future endeavors. Wu et al. [9] analyzed harness and PPE supervision from remote-vision perspectives, focusing on attribute knowledge modeling for more dependable and reliable detection. The utilization of modern object detection algorithms such as YOLO has become popular for PPE

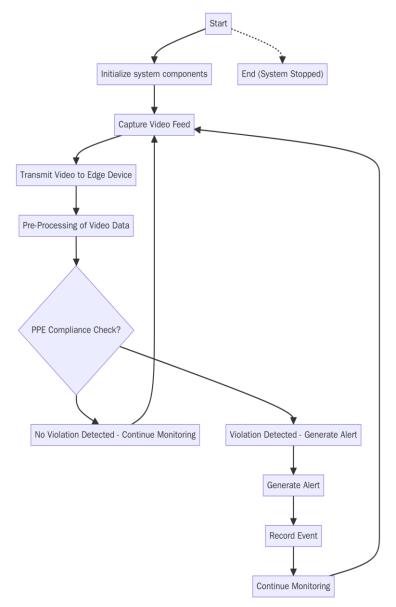
detection. Yang et al. [10] designed a helmet detection system based on YOLO for intelligent construction platforms, achieving exceptional results for detection speed and accuracy. Real construction sites were demonstrated by Wang et al. [11] to enable rapid deep learning model-based PPE detection, reaffirming the approach's practicality. Hard hat detection was undertaken by Bhadeshiya et al. [12] using YOLOv4, increasing the accuracy in real-time detection scenarios.

Lee and Lee [13] focused on safety deployment issues, applying computer vision and deep learning for integrated construction site management. Wang et al. [14] presented a variant of YOLOv3 for detection of helmet and protective clothing which provided better tracking under different conditions, reinforcing the robustness of the system. Zhang et al. [15] employed the YOLOv5-btri algorithm for detection of safety helmets during construction of electrical distribution networks, showcasing versatility to various industrial applications.

The research shows that modern computer vision techniques are evolving towards quick, precise, and easily adaptable PPE detection systems for proactive safety management in risky work places.

## 3. PROPOSED WORK

The approach taken for the RiskSentinel system centers around solving the problem of real-time detection of Personal Protective Equipment (PPE) infractions in unsafe working areas. The objective is to provide persistent supervision that allows for real-time detection and response to safety violations, thus minimizing accidents.



**Figure: 1** Schematic representation of the suggested architecture

## A. System Architecture and Design

The system consists of several components functioning together for effective PPE monitoring. Critical industrial areas where workers do their routines are equipped with high-definition video cameras which capture clear footage. These cameras are selected for their capability to withstand harsh conditions such as low illumination, dust, and vibrations typical to industrial sites.

The video streams captured are sent to the local processing units that are situated close to the cameras. These edge devices perform on-site analysis which reduces reliance on internet connectivity and avoids latency associated with transmitting data to remote servers. Localized processing ensures timely responses which is essential in high-risk zones.



#### **B.** Collection of Data

Dew soft developed a custom dataset using video footage from various industrial sites to create and test the detection system. The recordings span different shifts and include changes in lighting, weather, and the number of workers to simulate real-life scenarios.

The annotated video footage comprises numerous scenarios of proper PPE compliance and frequent violations, including helmets absent, safety vests unbuckled, and gloves not worn. Safety specialists assisted in annotating video data by marking compliance and violations, which establishes reliable ground truth for system evaluation.

Recording the environmental context during data collection allowed for evaluation of conditions that may influence detection performance. This information helps in assessing how well the system, as designed, would work in different environments.

## C. Processing the Data

When the edge processing units receive the video data, they analyze and determine PPE compliance in a series of steps. The video stream is first sliced into individual frames. These frames undergo basic enhancement processes that are especially important during low light or shadow conditions.

The system then checks every frame for PPE items by looking at the defined PPE characteristics: their shapes, colors, and the positions of helmets, vests, gloves and other protective gear. Safety features are matched against compliance criteria and each worker is evaluated accordingly as compliant or violative.

The system performs automatic notification of the alert through PPE violation notification interfaces. Notifications can be visual, like flashing lights on a supervisor's control panel, or auditory such as alarms near the violation zone. Responsive feedback is critical for the enforcement of proactive adjustments by supervisors and workers toward the safety culture of the organization.

## D. RiskSentinel System Analysis

Rigorous testing was performed on the RiskSentinel system to determine its accuracy in detecting PPE violations and responsiveness during real-time operation. The system was tested under a variety of lighting scenarios, camera angles, and worker movement simulation to mimic real workplace settings. Critical parameters such as accuracy of notification, false alerts, and time taken to issue alerts were assessed.

These evaluations confirmed that the 'edge-based processing design' improves the timeliness of detection and reduces communication delays compared to centralized systems. The work also revealed some environmental aspects that were influencing detection performance, which can be used for further optimization and deployment.

#### 4. PERFORMANCE ANALYSIS

The RiskSentinel system was evaluated under various real-world conditions, including different shifts, lighting environments, worker density, and normal operating conditions. The performance was measured in terms of detection accuracy, response time, and false positive alerts.



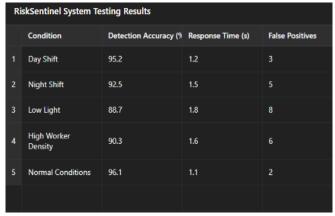
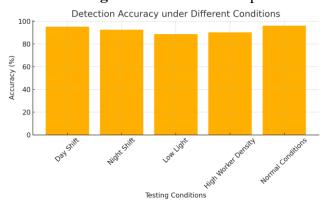


Figure: 2 Simulated output



**Figure: 3** Detection Accuracy

The system gained peak detection accuracy of 96.1% under normal lighting and optimum worker density conditions as shown in the first graph. Accuracy degression of 95.2% during daytime and 92.5% during nighttime shifted sponse reflects the overlying fraffic light levels andense light conditions. Accuracy stubbornly progressed to a low of 88.7%. All-PPE visibility during the low precision 90.3% mask moderately high occluded attired protective equipment dense gatherings as result worsens

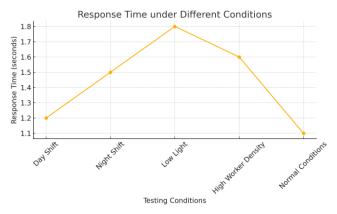
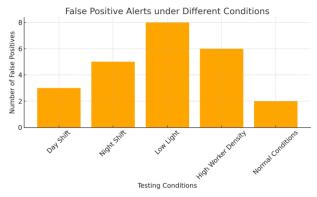


Figure: 4 Response Time



The graph shows response time for all conditions, and the system performed best in normal conditions with fever response times of 1.1 seconds. Responding to the day shift, response times were 1.2 seconds and 1.5 seconds respectively. Most sluggish responses of 1.8 seconds occurred with low light visibility and 1.6 seconds under high density crowding, where image clarity and crowding enhanced processing complexity.



**Figure: 5** Fake Alarms

The graph shows how false positives rates were recorded during testing. The system had the lowest counts of false positives during normal operating conditions, generating 2 false alarm signals. This is consistent with challenges in interpreting poorly illuminated images with high intensities of background light, which is why lower light conditions yielded the highest number of false positives (8). Day shift and high-density scenarios did have moderate counts of falsely detecting alarms with 3 and 6 respectively, but this does show a good balance between sensitivity and specificity.

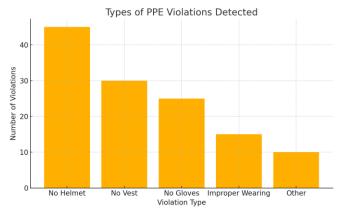


Figure: 6 Categories of PPE Violations Observed

This bar chart illustrates how the RiskSentinel system categorizes the different detected PPE violations. The most frequent violation was the absence of helmet usage, followed by absent safety vests and gloves. Some cases of improper donning of PPE as well as other trivial breaches were noted as well.



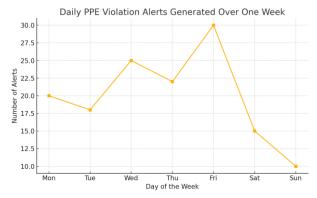


Figure 7: Daily PPE Violation Alerts Issued Within A Week:

The data in this line graph pertains to the daily number of alerts regarding PPE violations issued over a week's time. Friday seems to have the most alerts, which could be linked to increased workload or shift changes, while the low activity workforce over the weekend recorded lesser violations.

As shown in the results, the RiskSentinel system provides accurate PPE violation detection for a variety of conditions and breaches PPE with high accuracy and timely alerts. Performance is understandably degraded owing to environmental factors such as lighting and worker density, these factors tend to have a minimal but noticeable effect. The edge-based processing framework is helpful for low response times as these technologies guarantee fast detection and prompt warning where workplace accidents can be prevented.

#### 5. CONCLUSION

This paper introduced the RiskSentinel system which monitors PPE compliance violations as they occur in real-time for dangerous work contexts. The system utilized strategically placed cameras and on-site processing units to monitor PPE compliance at different shifts, lighting conditions, and worker densities during multi-shift operations. The outcomes achieved showed that the system is capable of high accuracy, responsiveness, and reasonable false positives which proved its reliability and usability in an industrial context. Most importantly, timely notifications, which are necessary to avert workplace hazards, were achievable due to the edge processing framework which also fostered a culture of safety compliance.

The promising outcomes were accompanied by gaps with them. The results were influenced with insufficient lighting due to high worker density which makes images harder to PPE recognition more difficult. These limitations suggest that there is need for further work to focus on robustness and adaptability in different operational environments.

Incorporating thermal imaging and depth-sensing technology is planned for the automation system to refine handling environmental lighting difficulties. There are also plans to augment the system's performance regarding occlusions and crowded spaces through advanced data merging and multi-camera viewpoint integration. Moreover, developing a more intuitive blank interface for system control and instant feedback is also planned. To refine system responsiveness and gather ongoing

improvement suggestions, extensive multifunctional industrial field testing will be conducted to confirm system agility.

In summary, the system actually allows for important innovation in work management by ensuring compliance with safety regulations in real-time and automatically, thereby ensuring employees work in a safer environment while enabling supplementary adjustments in the system as the industries evolve.

## 6. AUTHOR(S) CONTRIBUTION

The writers affirm that they have no connections to, or engagement with, any group or body that provides financial or non-financial assistance for the topics or resources covered in this manuscript.

## 7. CONFLICTS OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

#### 8. PLAGIARISM POLICY

All authors declare that any kind of violation of plagiarism, copyright and ethical matters will take care by all authors. Journal and editors are not liable for aforesaid matters.

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