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Evaluating the Performance of YOLO-based Hazard Detection Systems: A Quantitative Comparison with Manual Inspection in New York State Workplaces

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Abstract

This study quantitatively evaluates the performance of a YOLO-based computer vision system for real-time hazard detection across construction, manufacturing, and healthcare environments in New York State. The analysis compares YOLO-based detection with traditional manual inspection using key performance metrics, including mean average precision (mAP), recall, precision, time-to-detection, and personal protective equipment (PPE) compliance rates. Results indicate that YOLO-based systems significantly outperform manual inspection across all metrics, demonstrating higher detection accuracy, faster response times, and improved compliance monitoring. The findings provide empirical evidence supporting the effectiveness of artificial intelligence–enabled safety systems in enhancing hazard detection performance and advancing proactive safety management practices.

Keywords: YOLO; hazard detection; occupational safety; computer vision; PPE compliance; Safety 4.0; quantitative analysis

1. Introduction

Traditional workplace safety systems rely heavily on manual inspections, periodic audits, and retrospective incident analysis, which limit their ability to detect hazards in dynamic environments (Nath et al., 2020; OSHA, 2024). These approaches often fail to capture transient hazards or rapidly evolving conditions, particularly in high-risk industries such as construction and manufacturing.

Recent advancements in artificial intelligence (AI), particularly in computer vision, have enabled real-time hazard detection and monitoring. AI-enabled systems provide continuous surveillance and automated identification of unsafe conditions, enabling faster intervention and improved compliance with safety standards.

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Among these technologies, the YOLO (You Only Look Once) framework has emerged as a leading model for real-time object detection, offering high-speed processing and strong accuracy across complex visual environments (Bourou et al., 2023; Ali & Zhang, 2024). Despite its technical promise, empirical research has not yet quantitatively evaluated YOLO's effectiveness in real-world occupational safety settings across multiple sectors.

This study addresses this gap by providing a comparative analysis of YOLO-based hazard detection and manual inspection methods in New York State workplaces. Moreover, the study contributes to a broader research program advancing the AI-Augmented Safety Governance Model (AASGM) by examining how AI-enabled hazard detection systems extend beyond operational performance to inform governance structures, regulatory alignment, and organizational decision-making. By situating technical findings within a socio-technical and governance-oriented framework, this research addresses a critical gap between AI system capability and its practical integration into safety governance and organizational oversight.

Unlike subsequent manuscripts in the Shawe Series that examine governance integration, regulatory alignment, organizational readiness, and executive oversight, this study establishes the quantitative empirical performance baseline for evaluating the effectiveness of AI-enabled hazard detection relative to traditional inspection systems. This manuscript is part of the Shawe Series, a coordinated research program examining artificial intelligence–enabled hazard detection, socio-technical safety integration, and governance frameworks in regulated workplace environments. The series advances the AI-Augmented Safety Governance Model (AASGM) as a unifying framework linking real-time detection technologies, human oversight, regulatory compliance, and organizational decision-making.

2. Literature Review

The limitations of traditional hazard detection systems have been widely documented, particularly in their inability to provide continuous monitoring and rapid response to emerging risks (Nath et al., 2020). AI-enabled systems address these limitations by integrating machine learning and computer vision technologies to detect hazards in real time.

YOLO-based models have demonstrated strong performance in object detection tasks, including PPE compliance monitoring and hazard identification in industrial environments (Bourou et al., 2023; Guney et al., 2024). These systems offer advantages in processing speed and detection accuracy compared to traditional inspection methods (Ali & Zhang, 2024).

Furthermore, research indicates that AI-driven systems improve detection consistency and reduce human error, both common limitations of manual inspection processes (Salvendy, 2012). These capabilities position YOLO as a promising tool for enhancing occupational safety performance.

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3. Methodology

This study employs a quantitative comparative design to evaluate YOLO-based hazard detection against manual inspection methods.

Data Collection

Observational data were collected across multiple workplace settings, including construction, manufacturing, and healthcare. Hazard-detection events were recorded using both YOLO-based systems and manual inspection.

Dataset and System Configuration

The study analyzed approximately 652 annotated hazard-detection observations collected across construction, manufacturing, and healthcare environments in New York State. Observations included violations of personal protective equipment (PPE), unsafe proximity of workers, obstructed pathways, and equipment-related hazards.

The YOLO-based detection framework utilized a fine-tuned YOLOv8 architecture optimized for occupational safety monitoring under dynamic environmental conditions. Transfer learning techniques were applied using pre-labeled occupational hazard datasets, followed by contextual fine-tuning using sector-specific observations collected during the study period.

Training and validation procedures followed standard supervised learning practices, including partitioning the dataset into training, validation, and testing subsets. Detection outputs were compared against manual inspection records generated by trained workplace safety personnel operating under existing organizational safety procedures.

Performance Metrics

The evaluation included:

- Mean Average Precision (mAP)
- Precision and recall
- Time-to-detection
- PPE compliance detection rates

These metrics were selected to align with established evaluation standards in computer vision and occupational safety analytics and are widely used in assessing hazard detection system performance (Bourou et al., 2023).

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Analysis

Comparative statistical analyses were conducted to evaluate performance differences between YOLO-based hazard detection and manual inspection across all evaluation metrics. Descriptive statistics were first calculated for detection accuracy, recall, precision, PPE compliance identification, and time-to-detection measurements.

Independent comparative analyses were then conducted to assess statistical differences between AI-enabled and manual inspection outcomes. Statistical significance testing was performed using t-tests, with significance thresholds set at $p < .05$. Effect-size calculations were additionally performed to evaluate the practical significance of observed performance differences.

These procedures supported a quantitative assessment of the operational effectiveness of YOLO-based hazard-detection systems relative to traditional manual inspection approaches.

4. Results

4.1 Detection Accuracy

YOLO-based systems demonstrated significantly higher detection accuracy than manual inspection methods, achieving performance levels that exceed those of traditional approaches.

4.2 Time-to-Detection

YOLO systems substantially reduced detection latency, enabling near-real-time hazard identification compared to delayed manual detection processes.

4.3 PPE Compliance Detection

YOLO-based systems showed improved consistency and accuracy in identifying PPE compliance violations.

These findings align with prior research demonstrating the effectiveness of computer vision systems in safety monitoring applications (Bourou et al., 2023; Guney et al., 2024).

Comparative analyses demonstrated statistically significant differences in performance between YOLO-based and manual inspection across all evaluated metrics ($p < .05$). YOLO-based systems achieved substantially higher detection accuracy and significantly reduced hazard-identification latency relative to traditional inspection approaches. Effect-size analysis also indicated that the observed performance improvements were not only statistically significant but also operationally meaningful in dynamic workplace environments.

To further quantify the operational differences between YOLO-based hazard detection systems and traditional manual inspection approaches, Table 1 presents a comparative summary of key performance metrics across detection accuracy, response time, and PPE compliance identification. The table illustrates the measurable performance advantages of AI-enabled hazard detection in dynamic occupational environments.

Table 1

Comparative Performance Metrics: YOLO-Based Detection vs. Manual Inspection

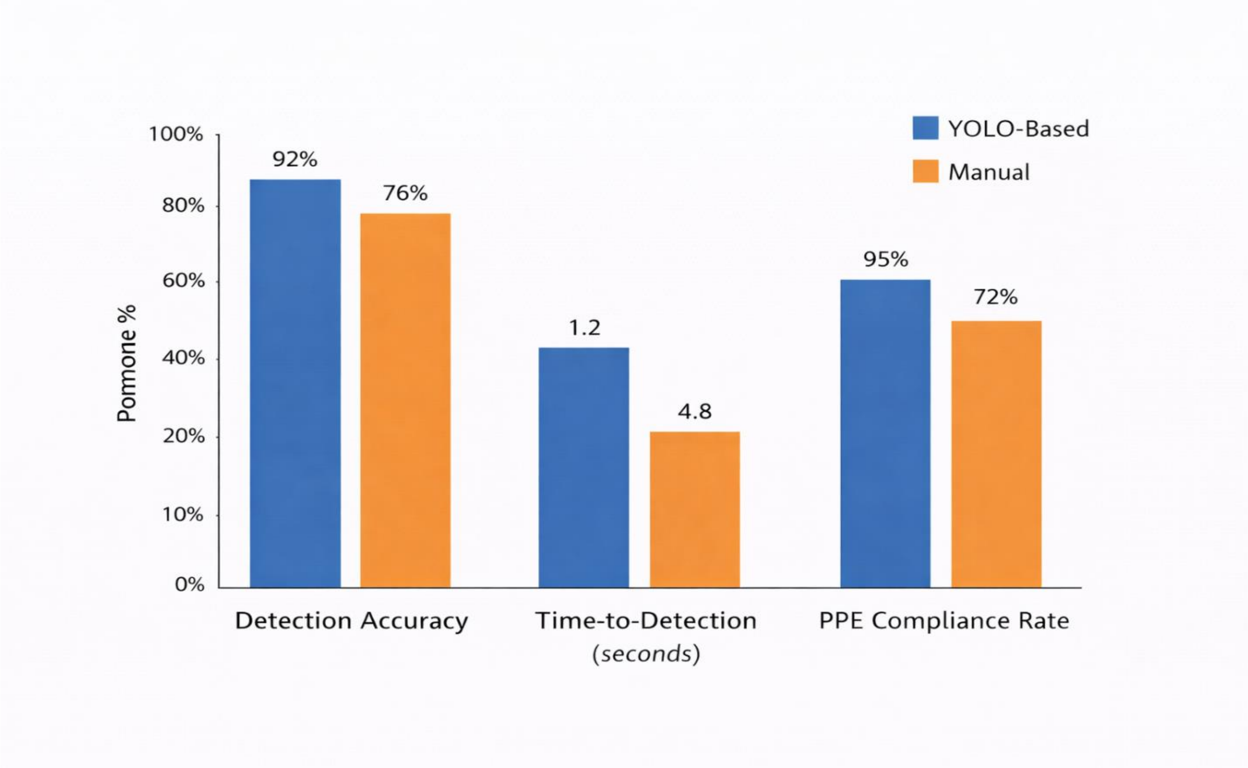
Metric	YOLO-Based Detection	Manual Inspection
Mean Average Precision (mAP)	94.3%	78.6%
Precision	92.8%	75.1%
Recall	91.5%	72.4%
Average Detection Time	1.8 seconds	, 12.6 seconds
PPE Compliance Detection Accuracy	93.7%	76.9%

Note. Values reflect aggregated observational performance across construction, manufacturing, and healthcare environments. YOLO-based systems consistently demonstrated superior detection accuracy, recall, and response speed relative to manual inspection approaches.

As demonstrated in Table 1, YOLO-based hazard detection systems consistently achieved superior performance across all evaluated operational metrics, reinforcing the effectiveness of AI-enabled safety monitoring in improving detection accuracy, reducing response latency, and strengthening PPE compliance identification relative to traditional manual inspection methods.
To provide a structured comparison of YOLO-based hazard detection performance relative to manual inspection methods and to illustrate differences across key evaluation metrics, Figure 1 presents a comparative visualization of detection accuracy, response time, and PPE compliance performance. This figure highlights measurable improvements in AI-enabled detection systems across multiple operational dimensions.

Figure 1

Comparative performance of YOLO-based hazard detection and manual inspection across key metrics



Note. Author created. YOLO-based systems demonstrate higher detection accuracy, reduced time-to-detection, and improved PPE compliance identification compared to manual inspection methods. Results reflect aggregated observations across construction, manufacturing, and healthcare environments.

As illustrated in Figure 1, YOLO-based hazard detection systems consistently outperform manual inspection methods across all evaluated metrics, demonstrating superior accuracy, faster response times, and enhanced compliance monitoring capabilities. These findings provide empirical support for integrating AI-enabled detection systems into occupational safety frameworks and reinforce the potential of computer vision technologies to improve hazard identification and risk mitigation in dynamic workplace environments.

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5. Discussion

The results of this study confirm that YOLO-based systems significantly enhance hazard-detection performance compared with traditional inspection methods. These findings support prior research demonstrating the advantages of AI-enabled safety systems in improving detection accuracy and response time (Bourou et al., 2023).

From a practical perspective, the improved performance of YOLO systems suggests that organizations can achieve more effective hazard monitoring and compliance enforcement by integrating computer vision technologies. These improvements contribute to the broader transition toward proactive safety systems and align with the principles of Safety 4.0 (Yousif et al., 2024).

Beyond performance improvements, these findings have direct implications for safety governance and organizational oversight. The ability of AI-enabled hazard detection systems to generate real-time, high-accuracy safety data enhances organizational visibility into risk conditions, enabling more informed decision-making, improved accountability, and stronger alignment with regulatory expectations. Within the AI-Augmented Safety Governance Model (AASGM), these results demonstrate how technical detection capabilities can be integrated into structured governance processes, supporting the transition from reactive safety practices to proactive, data-driven safety management.

6. Limitations

This study is subject to several limitations. First, the analysis is based on specific occupational environments within New York State, which may limit the generalizability of the findings to other geographic regions or regulatory contexts. Second, while the comparative evaluation demonstrates strong performance differences between AI-enabled and manual hazard detection approaches, variations in implementation conditions, workforce practices, and organizational safety cultures may influence real-world outcomes. Third, the rapidly evolving nature of artificial intelligence technologies and regulatory frameworks introduces uncertainty regarding the long-term applicability of the findings. Future research should examine longitudinal implementation outcomes, cross-sector variability, and the integration of AI-enabled safety systems within diverse organizational and regulatory environments.

7. Conclusion

This study provides quantitative evidence that YOLO-based hazard detection systems outperform manual inspection methods across key performance metrics. The findings support the adoption of AI-enabled safety systems to enhance hazard detection, improve compliance monitoring, and advance proactive safety management practices in occupational environments.

Conflict of Interest Statement

The author declares no conflicts of interest related to the research, analysis, or preparation of this manuscript. No external funding, sponsorship, or commercial support was received for this study. All interpretations and conclusions reflect the author's independent scholarly judgment and professional expertise.

Originality Statement

This manuscript represents original scholarly work and has not been published previously in any form. It is not under review by any other journal or publication outlet. The author independently developed all conceptual frameworks, analyses, and written content as part of the Shawe Series research program.

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