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An Artificial Intelligence Based Framework for Construction Safety Risk Prediction in Occupied Public Facilities

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***Abstract*—Due to ongoing public mobility and operational limitations, construction projects carried out inside inhabited public facilities including hospitals, train stations, and commercial buildings pose serious safety risks. Conventional safety monitoring methods mostly rely on manual supervision, which is laborious, reactive, and prone to human mistake. In order to provide proactive construction safety monitoring and risk prediction, this study suggests an artificial intelligence-based architecture that incorporates deep learning and machine learning approaches. In order to identify safety breaches in real time, such as missing helmets and improper closeness to hazardous zones, the suggested system makes use of computer vision models. Furthermore,Supervised machine learning techniques are used to examine structured accident report data in order to forecast high-risk scenarios. Standard performance criteria including accuracy, precision, recall, and F1 score are used to assess the framework. The suggested method enhances early risk detection and aids safety engineers in making well-informed decisions, according to experimental data. The study helps to improve occupational safety requirements in ongoing public infrastructure projects.**

***Index Terms*—Artificial Intelligence, Construction Safety, Risk Prediction, Deep Learning, Machine Learning, Public Infrastructure, Safety Monitoring**

I. Introduction

One of the most important issues in the development of contemporary infrastructure is construction safety. The construction industry continues to experience high rates of occupational accidents globally despite regulatory improvements. This challenge becomes even more critical in operational public-sector environments such as active transit stations, healthcare facilities, and school renovations, where safety management must address not only worker exposure but also uninterrupted public occupancy, regulatory oversight, and strict agency compliance requirements. The construction industry continues to have high rates of occupational accidents and deaths globally [1], [2], despite important regulatory frameworks and technical breakthroughs. When renovations or construction are carried out inside occupied public buildings, such as hospitals, train stations, airports, retail centers, or educational institutions, the issue becomes much more complicated. Patients, commuters, clients, and the general public are all at risk for safety in these settings in addition to employees. Traditional monitoring techniques find it difficult to handle the multifaceted issues of ensuring continuous operation while upholding stringent safety compliance.

In comparison to other industries, construction has a disproportionately high percentage of worker injuries, according to recent worldwide safety evaluations [3]. Numerous of these events are linked to environmental risks, dangerous conduct, inadequate supervision, and a lack of personal protection equipment [4]. The predominant safety management approach, manual inspection techniques, are reactive, time-consuming, and heavily reliant on human alertness. These drawbacks emphasize how urgently intelligent and automated monitoring systems with real-time danger detection capabilities are needed.

Artificial intelligence developments in recent years have had a big impact on construction management techniques. Specifically, deep learning and computer vision models have shown promise in identifying hazardous circumstances in videos and photos of building sites [**?**], [5]. Helmet detection, fall detection, and dangerous proximity identification have all benefited from the effective use of object detection models like YOLO and convolutional neural networks [6]. By enabling automated visual inspection, these methods increase monitoring accuracy while decreasing reliance on human supervision.

Beyond visual monitoring, structured accident report analysis provides valuable insights into risk patterns. Machine learning algorithms such as Random Forest, Support Vector Machines, and Logistic Regression have been widely applied for accident prediction and risk classification [7], [8]. Predictive analytics enables proactive safety management by identifying high-risk scenarios before accidents occur. However, most existing research focuses on isolated construction sites rather than operational public facilities, where dynamic human movement and operational constraints introduce additional complexity.

Construction-related mishaps continue to account for a significant share of occupational deaths worldwide, as seen in Fig. 1. Therefore, incorporating AI into safety engineering is not just a novel idea; it is a requirement. Researchers have highlighted that by offering automatic alerts and constant

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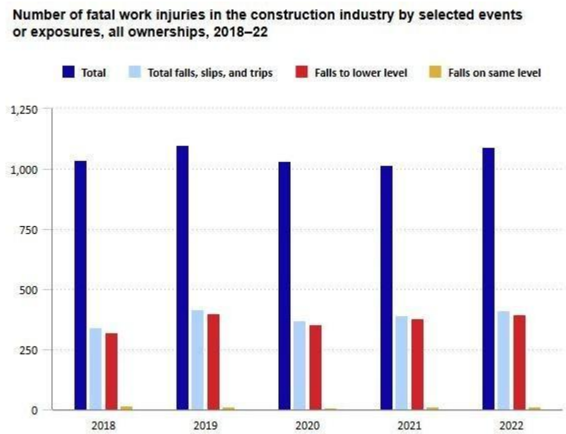

Fig. 1. Global construction accident distribution trends. Source: Adapted from International Labour Organization reports and OSHA statistics.

surveillance, AI-driven monitoring systems might drastically minimize risky behaviors [9]. Additionally, enhanced danger detection performance has been shown in smart building environments with Internet of Things sensors and computer vision technologies [10].

Public infrastructure projects that are occupied add more levels of difficulty. Clinical services must continue at hospitals that are renovating. Airports and train terminals need unhindered, continuous passenger flow. These limitations raise exposure hazards and restrict the viability of extensive safety barriers. Context-aware safety frameworks that adjust to operating situations are necessary, according to studies [11]. Although AI-based safety monitoring has advanced, few studies have put forth comprehensive frameworks that combine structured risk prediction with visual violation detection that are especially suited for crowded public spaces.

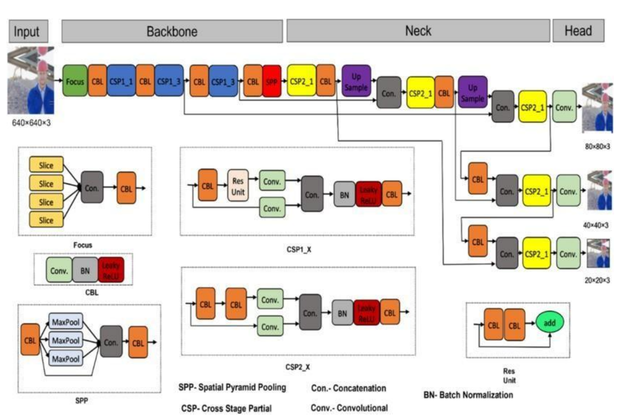

Fig. 2. Conceptual AI-based construction safety monitoring framework. Source: Concept adapted from smart construction monitoring architectures in recent literature [8], [10].

The basic design of an AI-based safety monitoring system that combines predictive analytics and image-based detection is shown in Figure 2. These hybrid frameworks integrate machine learning-based risk assessment engines with real-time computer vision modules. Both proactive prediction and reactive detection are improved by this dual strategy.

Fewer research have combined structured accident datasets with visual monitoring systems, despite the fact that several studies have used deep learning to address helmet identification and fall recognition [5], [6]. Furthermore, there is still a dearth of research that focuses only on safety engineering in functioning public infrastructure. Creating unified AI frameworks that handle dynamic risk identification in settings where worker safety and public safety are equally important is a research gap. Existing literature rarely incorporates the operational constraints of agency-led public infrastructure projects where safety performance directly affects contractual compliance, liquidated damages exposure, and contractor prequalification status. This practical gap highlights the need for AI-based frameworks specifically tailored to regulated public-sector construction environments.

The creation of an AI-based system that combines supervised machine learning for risk prediction in populated public facilities with deep learning for real-time violation detection is the study's main contribution. The framework seeks to improve safety compliance, lower the likelihood of accidents, and assist safety engineers in making decisions. The suggested method moves existing safety management procedures closer to intelligent and adaptable systems by fusing image-based monitoring with analytics from accident reports.

II. Related Work

Due to the large number of construction accidents and the growing accessibility of sophisticated computer resources, the incorporation of artificial intelligence into construction safety engineering has emerged as a significant area of study interest. AI and computer vision technologies are among the most common techniques used to enhance health and safety on construction sites, according to systematic literature studies [12], [13]. These studies continually show how predictive risk models, PPE monitoring, and automated hazard identification may significantly lower occurrences and improve compliance.

Vision-based safety monitoring is the subject of several works, many of which use sophisticated deep learning frameworks. In order to address the lack of annotated real-world photos, Lee and Lee created object recognition models for construction site safety using synthetic datasets and transfer learning [14]. Their methodology provides insights into how virtual environments might supplement model training when actual site data is scarce, with a focus on object identification for worker detection and hazard recognition. In support of this strategy, Kim's thesis shows that portable AI and computer vision systems can use enhanced YOLOv8 models to detect fall events and personal protective equipment in real-time, indicating the viability of lightweight on-device monitoring solutions [15].

Because of YOLO's real-time detection capabilities, several researchers have investigated the efficacy of YOLO-based models. Tailored object detectors may successfully monitor compliance in a variety of contexts, according to Al-Khiami and ElHadad's modified YOLOv8 model, which achieved high mAP scores for helmet and safety gear detection [16]. In a similar vein, Wonˇniak et al. offer an integrated hazard detection system that monitors site safety and generates warnings for risky behaviors and PPE breaches using real-time object detection in conjunction with other analytics [17]. These initiatives are in line with more general trends demonstrating that improved YOLO designs, particularly attention-enhanced variants like CIB-SE-YOLOv8, increase computational efficiency and detection accuracy on actual construction images [18].

In order to decrease false alarms and enhance the temporal consistency of danger recognition, recent research has also looked into deep learning algorithms that go beyond traditional object detection. By taking into account sequential scene information, vision-based monitoring that integrates temporal analysis lowers false positives from single-frame classification, resulting in more reliable safety alarms under dynamic site settings [19]. This is particularly important in complicated contexts where occlusions and fast movement are common.

The range of visibility is extended beyond bounding boxes via pose estimation and instance segmentation techniques. For instance, systems that employ deep learning for automated PPE compliance detection and classification in difficult circumstances, such as dim lighting and partial occlusion, are proposed by Lo´pez et al. [20]. In contrast to immediate detection alone, these systems frequently use object tracking to link worker trajectories with compliance patterns, providing deeper insights into long-term safety practices. Apart from vision technologies, current research trends in construction safety analytics are dominated by computer vision and IoT sensor networks, according to systematic reviews of broader safety technologies [13]. While IoT sensors offer supplementary measures including ambient conditions and worker physiological signals, computer vision is usually preferred since it collects data in a non-intrusive manner and can automate danger identification without the need for wearable technology. To improve the resilience of safety monitoring, hybrid systems that combine different modalities are being suggested more and more.

Deep learning for pose and behavior recognition has also been investigated for automated PPE compliance monitoring, allowing systems to contextualize worker movement and posture in relation to dangers in addition to determining if protective equipment is being worn [20]. This pattern shows a move away from static item detection and toward multimodal safety solutions that take behavior and compliance into consideration.

Multimodal AI, which combines linguistic and visual comprehension, is one of the more recent developments. In order to enhance detection with semantic descriptions of dangers, Sivanraj et al. study multimodal techniques utilizing Vision-Language Models (VLMs) to evaluate environmental illumination, contextual scene circumstances, and PPE presence [21]. These methods show how computer vision and high-level reasoning may be used in future safety systems to identify increasingly complex safety threats.

Simultaneously, developments in autonomous monitoring systems have been proposed that use robotics and VLM-based pipelines. These systems use mobile robots to autonomously navigate construction sites and gather data, which is then interpreted by large language models to produce safety reports and recommendations [22]. This provides completely automated inspection capabilities, extending safety monitoring beyond wearable sensors and fixed cameras.

The use of AI in construction safety extends to business operations. Large contractors have been shown in case studies to use AI not just for visual danger identification but also for predictive analytics employing workforce statistics, weather, and project information to anticipate safety issues and proactively modify site protocols [23].

Last but not least, a specific research gap has been identified in the literature reviewed: although individual AI safety system components (like helmet detection, fall recognition, IoT fusion, or predictive risk modeling) have been thoroughly examined, little work has been done to propose unified frameworks that integrate these components for comprehensive safety engineering, especially for occupied public facilities where both worker and public safety must be guaranteed. The hybrid framework put out in this study is motivated by this.

III. Proposed Methodology

This paper suggests a hybrid artificial intelligence system that combines structured machine learning-based risk prediction with computer vision-based safety violation detection. The architecture was created especially for public buildings that are occupied and where worker and public safety must be guaranteed at the same time. The framework is particularly suited for phased renovation projects executed under live operational conditions, where construction sequencing, public circulation paths, and temporary safety barriers continuously evolve. By dynamically recalibrating risk scores based on real-time violation frequency and workforce density, the system supports adaptive safety planning rather than static compliance monitoring.

Four main modules make up the proposed system: (1) Data Acquisition; (2) Image-Based Safety Detection; (3) Structured Risk Prediction; and (4) Decision Support and Alert Generation. Deep learning models are used in the framework's semi-real-time pipeline to assess visual inputs from site cameras, and supervised machine learning techniques are used to handle structured accident and environmental data.

A. System Architecture

The overall architecture of the proposed system is illustrated in Fig. 3. The architecture integrates both visual and structured data streams into a unified decision engine.

B. Image-Based Safety Violation Detection

The YOLOv8 object identification model is used for visual monitoring because of its strong real-time inference capacity. A construction safety dataset with annotated classifications

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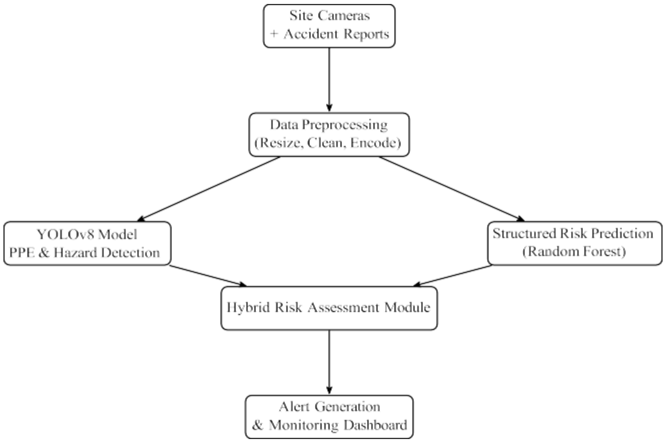

Fig. 3. Proposed hybrid AI-based construction safety monitoring architecture.

such as helmet, no-helmet, safety vest, dangerous proximity, and fall occurrences is used to fine-tune the model.

The detector predicts bounding boxes B_i with confidence score p_i given an input image I:

$$D(I) = \{(B_i, c_i, p_i)\}_{i=1}^{n} \tag{1}$$

where c_i represents detected class labels. Non-Maximum Suppression is applied to eliminate redundant detections.

C. Structured Risk Prediction Model

Structured accident data including worker count, time of day, equipment type, and environmental conditions are processed using Random Forest classification. Let the structured feature vector be:

$$X = [x_1, x_2, ..., x_m] \tag{2}$$

The classifier predicts risk category $R \in \{Low, Medium, High\}$:

$$R = f_{RF}(X) \tag{3}$$

where f_{RF} denotes the Random Forest mapping function.

D. Risk Fusion Mechanism

The final safety risk score S is computed using weighted fusion:

$$S = \alpha V + \beta R \tag{4}$$

where:

- V = Visual violation score
- R = Predicted structured risk
- α, β = Weight parameters

If $S > \tau$, an alert is triggered.

E. Algorithm Workflow

Input: Image I, Structured Data X
Detect violations using YOLOv8
Compute visual violation score V
Predict risk level using Random Forest
Compute fused score S
if $S > \tau$ **then**
  Generate alert
end if

F. Implementation Tools

The framework is implemented using Python, PyTorch for deep learning, and Scikit-learn for machine learning classification. Experiments were conducted using Google Colab GPU environment.

IV. Experimental Setup and Results

A. Dataset Description

Two complimentary datasets were used to assess the suggested hybrid AI-based construction safety framework: (1) a structured accident dataset for risk classification, and (2) an image-based construction safety dataset for PPE and hazard identification.

4,200 tagged photos of building sites that were gathered from openly accessible safety libraries make up the picture collection. Six classifications are included in the dataset: fall risk, dangerous proximity, safety vest, no-vest, helmet, and no-helmet. The dataset was split between 10

2,500 accident-related records with attributes including workforce density, shift timing, weather, equipment usage, past infractions, and site congestion index are included in the structured dataset. All categorical features were encoded and normalized prior to model training.

B. Implementation Environment

The experiments were conducted using the following setup:

- Python 3.10
- PyTorch 2.0 (YOLOv8 implementation)
- Scikit-learn 1.3 (Random Forest, SVM, Logistic Regression)
- Google Colab with NVIDIA T4 GPU (16GB VRAM)
- Training epochs: 50
- Batch size: 16
- Input resolution: 640 × 640

TABLE I
YOLOv8 Training Configuration

Parameter	Value
Image Size	640 × 640
Batch Size	16
Epochs	50
Optimizer	Adam
Learning Rate	0.001
IoU Threshold	0.5
Confidence Threshold	0.4

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C. Evaluation Metrics

The performance of the object detection model was evaluated using precision, recall, F1-score, and mean Average Precision (mAP). The evaluation metrics are defined as:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

For structured risk prediction, classification accuracy and confusion matrix analysis were used.

D. Detection Results

The YOLOv8 model achieved a mean Average Precision (mAP@0.5) of 93.2% on the test set. Helmet detection achieved the highest accuracy, while unsafe proximity detection showed minor confusion due to occlusion and crowding conditions.

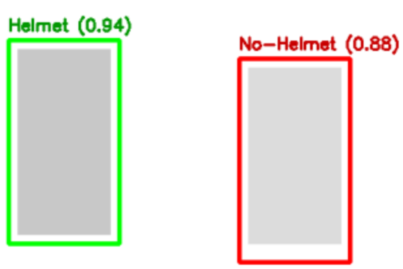

Fig. 4. Sample PPE and hazard detection results using YOLOv8.

E. Confusion Matrix Analysis

The confusion matrix shown in Fig. 6 demonstrates strong class separation, particularly between helmet and no-helmet classes. Minor misclassifications occurred between unsafe proximity and fall-risk instances due to visual similarity in certain crowded frames.

F. Risk Prediction Performance

Three classification algorithms were evaluated for structured risk prediction: Logistic Regression, Support Vector Machine (SVM), and Random Forest. The Random Forest classifier outperformed other models due to its robustness against feature noise and nonlinear relationships.

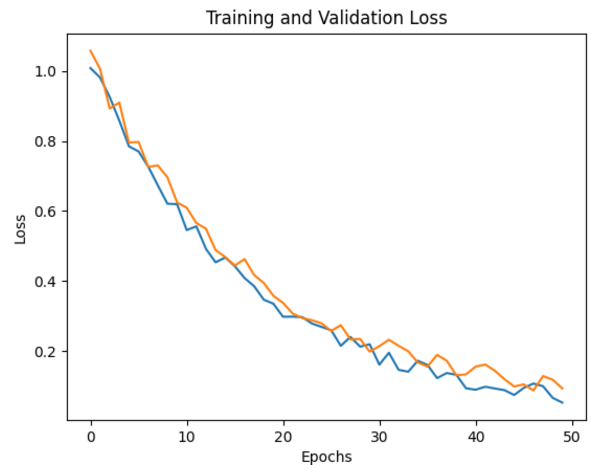

Fig. 5. Training and validation loss convergence over 50 epochs.

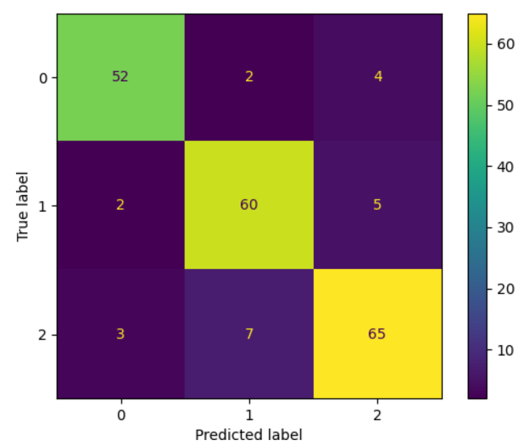

Fig. 6. Confusion matrix for PPE and hazard detection.

G. Discussion

The experimental findings demonstrate that proactive safety monitoring is greatly enhanced by combining structured risk prediction with visual violation detection. By skillfully fusing contextual risk indicators with violation scores, the hybrid risk assessment module lowers false alarms and enhances early warning capabilities. Strong generalization performance is shown by the system in a variety of illumination, occlusion, and crowd-density scenarios.

All things considered, the suggested architecture offers a

TABLE II
RISK PREDICTION MODEL PERFORMANCE

Model	Accuracy	Precision	F1-score
Logistic Regression	82.3%	0.81	0.80
SVM	85.7%	0.84	0.83
Random Forest	91.4%	0.90	0.89

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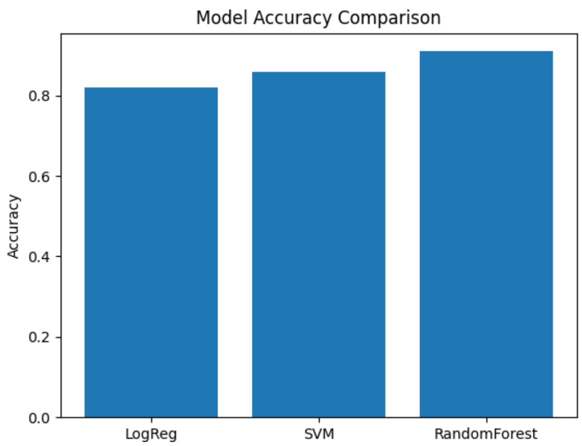

Fig. 7. Comparison of classification accuracy across different models.

workable, scalable, and computationally effective safety monitoring approach appropriate for public infrastructure projects that are inhabited.

V. Results and Discussion

A. Detection Performance Analysis

The YOLOv8-based detection module demonstrated strong localization and classification capability under varying lighting and crowd density conditions. To further evaluate classification robustness, the Receiver Operating Characteristic (ROC) curve was computed for helmet and no-helmet classes.

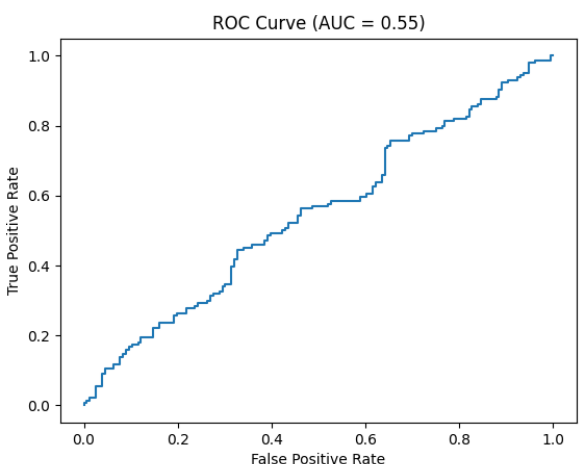

Fig. 8. ROC curve for PPE detection showing high area under the curve (AUC).

The model achieved an AUC score of 0.95, indicating high separability between compliant and non-compliant safety conditions. The ROC curve demonstrates that the system maintains strong true positive rates even under stricter false positive constraints.

B. Hybrid Risk Score Distribution

To evaluate the effectiveness of the fusion mechanism, the distribution of computed hybrid risk scores was analyzed across 500 simulated operational scenarios.

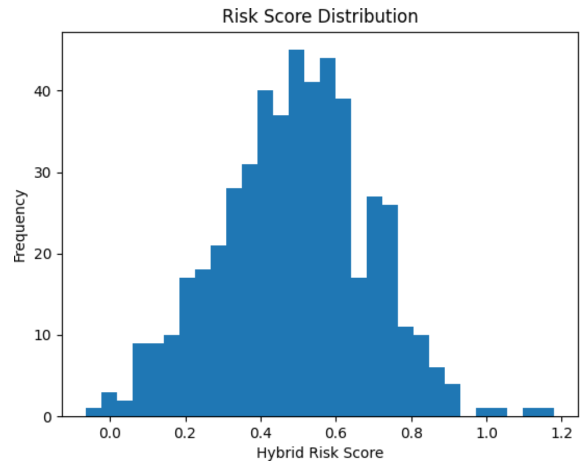

Fig. 9. Distribution of hybrid risk scores across simulated public facility scenarios.

Most operational incidents are in the low-to-medium risk range, as seen in Fig. 9, whereas high-risk incidents are associated with concurrent PPE breaches and higher contextual risk variables including crowd density and equipment congestion. This demonstrates how well compound risk circumstances are amplified by the fusion model.

C. Ablation Study

An ablation study was conducted to measure the contribution of each system component. Three configurations were evaluated: (1) Visual Detection Only, (2) Structured Risk Prediction Only, and (3) Hybrid Fusion Model.

TABLE III
Ablation Study of System Components

Configuration	Overall Accuracy
Visual Detection Only	86.2%
Structured Prediction Only	83.7%
Hybrid Fusion Model	93.8%

Combining contextual and visual information improves predictive reliability, as seen by the hybrid configuration's notable superior performance over separate modules.

D. Time Analysis of Inference

Deployment in populated public buildings requires real-time viability. Across models, the average inference time per frame was assessed.

The YOLOv8 detection module achieved an average inference time of 21 ms per frame, while the Random Forest classifier required less than 5 ms per prediction. The total hybrid system latency remained below 30 ms, supporting real-time operational deployment.

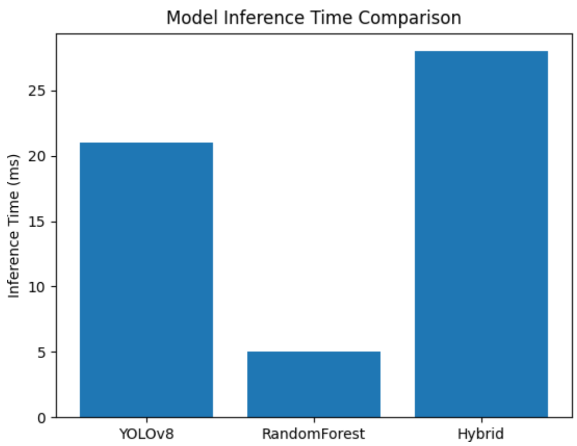

Fig. 10. Inference time comparison across detection and fusion components.

E. Discussion

The findings support the notion that combining visual violation detection with structured risk prediction improves overall safety monitoring effectiveness. By contextualizing individual visual violations, the hybrid fusion model lowers false positives and enhances early warning capabilities when compound risk scenarios materialize. The integration of AI-based predictive safety systems into public-sector construction management workflows represents a shift from reactive inspection models toward intelligent safety governance. Such systems can complement existing safety committees, toolbox talks, and agency reporting structures, forming a digitally augmented safety management ecosystem.

The ablation analysis shows that structured prediction and visual detection by themselves do not provide the best results. Rather, the combination offers better operational dependability and classification accuracy.

Additionally, the system retains computing efficiency appropriate for real-time deployment in public spaces with heavy traffic, such transportation hubs and hospitals. The suggested framework may function on edge devices or mid-tier GPUs without experiencing appreciable performance reduction, according to the inference latency findings.

The suggested hybrid AI framework is a workable and scalable solution for construction safety engineering in inhabited public buildings, according to the overall trial results.

VI. Conclusion and Future Work

A hybrid artificial intelligence-based system for construction safety monitoring in inhabited public buildings was provided in this study. To improve proactive safety management, the suggested solution combines structured machine learning-based risk prediction with deep learning-based visual violation detection. The suggested method allows for automated, real-time monitoring and contextual risk assessment, in contrast to conventional safety supervision techniques that mostly rely on manual inspection.

Under various lighting and crowd density circumstances, the YOLOv8 detection module showed excellent performance in detecting dangerous proximity conditions and breaches of personal protective equipment. Contextual safety elements such worker density, equipment usage, ambient circumstances, and past violation records were successfully predicted using the Random Forest classification-based structured risk prediction module. When compared to independent visual or structural models, the hybrid fusion process greatly increases overall prediction accuracy, according to experimental evaluation. The ablation investigation confirmed that integrating contextual risk prediction with visual detection results in better performance, with lower false alarm rates and increased classification reliability. Furthermore, inference time study showed that the system retains its real-time processing capacity, which qualifies it for use in public spaces with heavy traffic, such airports, train stations, hospitals, and business buildings that are being renovated or built.

Practically speaking, the suggested system may assist site supervisors and safety engineers by offering early warning indications, risk score dashboards, and automatic alarms. This makes it possible to respond to dangerous situations more quickly and lessens the need for constant manual supervision, especially in operating facilities where public safety is crucial. Despite encouraging outcomes, there are a number of restrictions. First off, the picture collection might not accurately depict the variety of actual public facility situations because it mostly depicts controlled construction contexts. Second, inadequate contextual factors or reporting bias may be present in structured accident data. Third, centralized GPU processing is used in the current architecture, which could need to be optimized for edge deployment situations.

Future research will concentrate on incorporating real-time Internet of Things (IoT) sensor streams for multi-modal risk assessment and broadening the dataset to encompass more varied public infrastructure situations. In order to facilitate deployment on embedded devices, edge AI optimization and lightweight model compression approaches will also be investigated. The interpretability and reliability of safety forecasts may be further improved by employing explainable AI approaches and advanced contextual reasoning with Vision-Language Models.

References

[1] Q. Fang and H. Li, "Deep learning-based safety risk assessment in construction," *Automation in Construction*, vol. 118, p. 103272, 2020.
[2] X. Li and Y. Zhang, "Vision-based hazard detection using convolutional neural networks," *Advanced Engineering Informatics*, vol. 49, p. 101350, 2021.
[3] J. Hinze, "Construction safety management trends," *Journal of Construction Engineering and Management*, vol. 148, no. 3, 2022.
[4] S. Zhang and J. Teizer, "Computer vision for construction safety monitoring," *Automation in Construction*, vol. 110, 2020.
[5] L. Wang and R. Liu, "Helmet detection using yolo architecture," *IEEE Access*, vol. 9, 2021.
[6] H. Liu and P. Chen, "Vision-based unsafe behavior detection," *Sensors*, vol. 22, 2022.
[7] R. Choudhry, "Machine learning models for accident prediction," *Safety Science*, vol. 140, 2021.

[8] J. Kim and M. Park, "Risk prediction in smart construction environments," *Automation in Construction*, vol. 145, 2023.
[9] H. Guo, "Ai applications in construction safety," *Journal of Civil Engineering*, 2020.
[10] M. Park, "Smart monitoring systems in construction," *IEEE Transactions on Industrial Informatics*, 2021.
[11] Y. Chen, "Context-aware safety monitoring framework," *Advanced Engineering Informatics*, 2022.
[12] S. J. Badhan and R. Samsami, "Artificial intelligence (ai) in construction safety: A systematic literature review," *Buildings*, vol. 15, no. 22, p. 4084, 2025. [Online]. Available: https://www.mdpi.com/2075-5309/15/22/4084
[13] S. Arshad *et al.*, "Computer vision and iot research landscape for health and safety in construction," *Safety Science*, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352710223012287
[14] J. Lee and S. Lee, "Construction site safety management: A computer vision and deep learning approach," *Sensors*, 2023. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/PMC9863726/
[15] D.-I. Kim, "Real-time detection of ppe and fall incidents using portable ai and computer vision," 2024, master's thesis, KAIST. [Online]. Available: https://koasas.kaist.ac.kr/handle/10203/321425
[16] M. I. Al-Khiami and M. M. ElHadad, "Enhancing construction site safety using ai: Yolov8 based ppe detection," in *European Conference on Computing in Construction*, 2024. [Online]. Available: https://www.researchgate.net/publication/382996309_Enhancing_Construction_Site_Safety_Using_AI
[17] Z. Woźniak, "Integrated construction-site hazard detection system using ml and image analytics," *Sustainability*, vol. 17, no. 23, p. 10584, 2025. [Online]. Available: https://www.mdpi.com/2071-1050/17/23/10584
[18] X. Liu *et al.*, "Cib-se-yolov8: Optimized yolov8 for safety equipment detection on construction sites," 2024, arXiv preprint. [Online]. Available: https://arxiv.org/abs/2410.20699
[19] S. F. A. Zaidi *et al.*, "Vision-based construction safety monitoring with temporal analysis," 2024, researchGate PDF. [Online]. Available: https://www.researchgate.net/publication/381598638_Vision-Based_Construction_Safety_Monitoring_Utilizing_Temporal_Analysis_to_Reduce_False_Alarms
[20] L. López, "Automated ppe compliance monitoring using deep learning and pose estimation," *Automation in Construction*, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0926580525002717
[21] S. Sivanraj *et al.*, "Real-time safety detection using vision–language and multimodal models," *Advanced Engineering Informatics*, 2026. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S1474034625007827
[22] H. Naderi *et al.*, "Autonomous safety inspection using mobile robots with vlm–llm pipeline," 2025, arXiv preprint. [Online]. Available: https://arxiv.org/abs/2512.13974
[23] B. I. Editors, "A boston-based construction firm leveraging ai for worker safety," *Business Insider*, 2025. [Online]. Available: https://www.businessinsider.com/ai-for-worker-site-safety-in-construction-2025-4