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## Emerging Trends and Advances in Machine Learning for Construction Safety Compliance: A Systematic Review of Evolution and Future Directions

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### ABSTRACT

This systematic review examines the evolution and emerging trends of machine learning (ML) technologies in construction safety compliance from 2010 to 2025. Using the PRISMA framework, an initial search obtained 7,229 results from ScienceDirect and IEEE Xplore; however, 37 studies were finally selected to synthesise the progression from traditional computer vision approaches (e.g., HOG, SVM) to advanced deep learning, multimodal, and zero-shot paradigms. Findings demonstrate substantial improvements in real-time PPE detection, compliance accuracy, and data efficiency through the use of weakly supervised and Edge-AI systems. However, limitations persist in environmental robustness, dataset generalizability, and integration with predictive analytics or Building Information Modelling (BIM). The review concludes that while machine learning has advanced construction safety compliance from traditional vision-based systems to deep and multimodal architectures, most existing models remain task-specific and lack holistic, adaptive intelligence. Persistent challenges include environmental sensitivity, limited hazard scope, data imbalance, and poor generalization across real-world conditions. Future research should integrate multimodal fusion, edge-AI optimization, predictive analytics, and privacy-preserving frameworks, while emerging paradigms such as Vision-Language Models and Generative AI hold promise for building intelligent, explainable, and human-centric safety compliance systems.

**Keywords:** Computer Vision, Construction Safety Compliance, Machine Learning, Personal Protective Equipment Detection, Risk Prediction.

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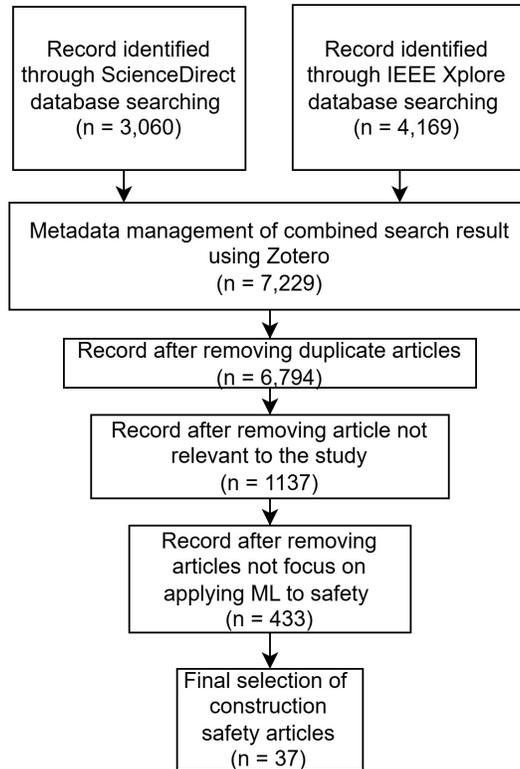
### 1. INTRODUCTION

Safety remains a cornerstone of organizational sustainability, essential to employee well-being, operational continuity, and long-term competitiveness, and although safety culture is increasingly embedded in regulatory frameworks across industries, efforts to shape it are often impeded by





This systematic approach enhanced thematic coherence, minimized reviewer bias, and improved the interpretability of the findings. The entire workflow is visually depicted in the PRISMA diagram (Figure 1).



**Fig 1:** PRISMA Diagram For The Entire Workflow

## 2. LITERATURE REVIEW

In this section, articles identified as highly relevant were reviewed manually to assess their methodological rigour, theoretical grounding, and contribution to the application of machine learning in construction safety.

### 3.1 Overview of PPE Compliance Monitoring Methods and Challenges

Over the decades, safety management has evolved from prescriptive, rule-based systems to dynamic, culture-driven paradigms that emphasise proactive risk identification and continuous improvement (Nævestad et al., 2021; Huang et al., 2016). The critical importance of safety is underscored by its influence not only on accident reduction but also on broader organisational outcomes such as job satisfaction, employee engagement, and firm survival (Huang et al., 2016; Carretero-Gómez et al., 2023). Colombo et al. (2019), through a historical and systemic analysis grounded in a socio-technical theoretical framework, explored the transformation of Health, Safety, and Environment (HSE) roles in Italy, tracing their evolution from technicians to professionals and





### 3.3 Technology-driven Compliance Monitoring

Building on the conceptual and institutional evolutions in safety management, recent advances in computational intelligence, particularly machine learning (ML) are catalysing a paradigm shift in how safety compliance is monitored, predicted, and enforced. Machine learning focuses on designing and developing algorithms and statistical models that enable computer systems to automatically analyse data, learn from experience, and improve their performance on specific tasks without explicit programming, by building predictive models through computational methods (Jordan & Mitchell, 2015; Mahesh, 2020; Pugliese, et al., 2021; Zhou, 2021).

ML offers significant potential to overcome the limitations of traditional safety approaches by enabling real-time data analysis, uncovering hidden patterns in large and complex datasets, and supporting proactive decision-making in high-risk environments (Pham et al., 2025; Junjia et al., 2025). By integrating sensor data, video surveillance, employee feedback, and historical incident reports, ML models have been increasingly employed to predict near-misses, identify non-compliant behaviours, and personalise safety interventions (Cocca et al., 2016; Awolusi et al., 2018; Park et al., 2024). This data-driven approach complements and extends the socio-technical and culture-based frameworks discussed by Colombo et al. (2019), suggesting a convergence between human-centred and algorithmically enhanced safety strategies. In recent times, advances in ML have catalysed a paradigm shift in safety compliance monitoring. For instance, ML-driven systems offer predictive analytics and real-time feedback, enabling organisations to move beyond reactive compliance checks toward proactive risk mitigation (Li et al., 2017; Ayhan & Tokdemir, 2019; Aithal et al., 2025). Also, studies have demonstrated the efficacy of deep learning architectures for real-time PPE detection (Nath et al., 2020; Fariza et al., 2024), IoT-enabled enforcement systems (Aithal et al., 2025), and interpretable ML models for risk analysis (Abdulrashid et al., 2025).

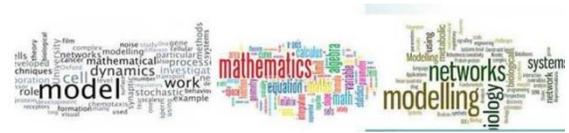
These approaches address key limitations of traditional methods by automating compliance verification, enhancing accuracy, and providing actionable insights for resource allocation (Sadiq et al., 2019; Karatopak & Sen, 2023). Despite these advances, significant uncertainties remain. Many ML solutions are constrained by domain-specific datasets, limited generalizability, and challenges in adapting to unstructured or dynamic environments (Li et al., 2017; Mneymneh Bahaa et al., 2019). Furthermore, existing systematic reviews have highlighted the promise of AI and data mining in compliance management but have also noted a lack of unified frameworks and insufficient attention to real-time, multi-component safety contexts (Sadiq et al., 2019).

#### 3.3.1 Few-Shot & Attribute Recognition

This group, represented by Wang and El-Gohary (2024), focuses on detecting rare safety hazards (e.g., fall risks) under data scarcity by combining few-shot object detection with attribute recognition. The methodology leverages deep learning to identify granular objects (e.g., unstable ladders) and their safety-critical attributes, achieving high precision (88.2% detection, 94.8% attribute recognition). However, it is limited to static images and cannot handle dynamic site conditions or complex attribute interactions. The key research gap lies in extending these techniques to video streams and real-time hazard forecasting (Wang & El-Gohary, 2024).







Similarly, Karnati and S. R. (2024) reported significant improvements in model accuracy and generalization when GAN-generated medical images were used to correct dataset imbalance in diagnostic imaging, underscoring the broader applicability of generative augmentation across domains. Leveraging on these insights in construction safety, diffusion and GAN-based models can simulate complex, high-risk site conditions, enabling safer, data-rich, and ethically responsible training of ML systems for compliance monitoring and hazard prediction (Jackson & Valles, 2024; Karnati & S. R., 2024). Ultimately, these emerging technologies promise to usher in a new era of intelligent, explainable, and predictive safety compliance systems, which can combine computational power with contextual reasoning. By integrating multimodal understanding, generative synthesis, and ethical AI principles, future safety management frameworks can transition from reactive detection to proactive, adaptive, and human-centric safety governance, fundamentally redefining how safety is perceived, monitored, and enforced in the construction industry

## 4. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

### 4.1 Conclusion

Machine learning (ML) has profoundly reshaped the landscape of construction safety compliance, marking a progressive shift from traditional computer vision techniques such as HOG-based and SVM classifiers to sophisticated deep learning and emerging paradigms, including YOLO variants, context-aware frameworks, and zero-shot learning. Earlier studies primarily focused on isolated personal protective equipment (PPE) detection (e.g., hardhats) under constrained environmental conditions (Mnemyneh et al., 2017), whereas contemporary research increasingly integrates multimodal data sources such as UAV imagery, LiDAR, and depth sensing to contextualize both hazards and worker behavior (Chern et al., 2023; Wang & El-Gohary, 2024).

Notable advancements include real-time inference capabilities (up to 37.8 frame per second (FPS) in YOLOv5), enhanced compliance verification accuracy (94.8%), and weakly supervised learning that mitigates the dependence on extensive manual annotation (Yang et al., 2024). Despite these achievements, the evolution of ML in construction safety remains fragmented. Most existing systems are task-specific and reactive, lacking the holistic intelligence necessary for dynamic risk prediction and behavioral analysis across diverse environments. Consequently, while ML-driven frameworks have achieved remarkable precision and computational efficiency, they continue to fall short in achieving generalizable, adaptive, and context-aware safety intelligence.

### 4.2 Limitations

The reviewed literature demonstrates considerable technical progress but also reveals enduring limitations that hinder scalability and real-world applicability. A significant portion of visual detection models, particularly YOLO and SSD variants, exhibit sensitivity to environmental disturbances, with performance deterioration exceeding 60% under low illumination, occlusion, fog, or rain (Mahmud et al., 2023; Wen et al., 2024). The application scope remains narrow, as approximately 80% of research concentrates on detecting helmets and safety vests, neglecting other crucial PPE (e.g., harnesses, gloves) and non-PPE hazards such as unsafe postures and falling objects (Zhou et al., 2024). Computational trade-offs also persist: lightweight models (e.g., YOLOv8n) prioritize speed at the expense of accuracy, while high-performance architectures (e.g., EM-YOLOv7) often lack validation in real-world field conditions (Savaram et al., 2025; Blessie et al., 2024).









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