Integrating AI Image Recognition and LINE BOT To Develop Dynamic Construction Safety Information Management

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Abstract –

Construction projects are characterized by highly dynamic environments and concurrent multi-project execution, where safety risks continuously evolve during construction activities. Conventional construction safety management still relies on manual inspections and static reporting mechanisms, limiting real-time information integration and timely decision-making.

Although recent studies have introduced artificial intelligence (AI)–based image recognition and information and communication technologies (ICT) into construction safety management, most existing approaches focus on individual technologies or isolated project scenarios, lacking integrated and interactive system architectures.

To address these limitations, this study proposes a dynamic construction safety information management system that integrates AI-based image perception, multi-object tracking, and chatbot-enabled communication within a unified framework. The proposed system employs a fine-tuned YOLOv9 model for safety-related object detection and StrongSORT for multi-object tracking to support temporal reasoning and suppress false alarms caused by transient misdetections. A LINE Bot is incorporated as the primary interaction interface to enable proactive hazard notification and real-time safety information delivery.

A prototype system was implemented and validated through Phase I functional evaluation using open-source construction site videos. The results indicate high recall for worker and head detection (0.90 and 0.93), while lower performance is observed for safety equipment (0.70 for helmets and 0.64 for safety vests). The proposed system demonstrates technical feasibility and potential for supporting real-time and proactive construction safety management in multi-project environments.

Keywords –

AI Image Recognition; Multi-object tracking; Chatbot; LINE BOT; Dynamic safety management

1 Introduction

Construction projects are characterized by highly dynamic working environments and the concurrent execution of multiple projects, where safety risks continuously evolve throughout construction processes [1,2]. As construction activities progress, safety risks continuously evolve, placing high demands on the real-time collection and dissemination of safety-related information. This dynamic nature places high demands on the real-time collection and dissemination of safety-related information. However, current construction safety management practices largely rely on manual inspections and static reporting mechanisms, which provide limited support for timely information integration and real-time feedback [2,3]. As a result, these approaches are often insufficient to effectively support safety-related decision-making by frontline personnel.

In recent years, artificial intelligence (AI)–based image recognition and information and communication technologies (ICT) have been increasingly applied in construction safety management to enhance hazard detection and monitoring capabilities [1,4,5,6]. These approaches have demonstrated promising results in identifying safety-related objects and unsafe behaviors under controlled conditions. However, most existing studies primarily focus on individual techniques, such as object detection or action recognition, without considering the integration of multiple components required for real-world applications [5]. In addition, many studies are limited to single-project or experimental scenarios, lacking support for multi-project environments and real-time interactive communication mechanisms between system outputs and field personnel .

To address these limitations, this study integrates chatbot technology with AI-based image recognition to develop a dynamic construction safety information management system for multi-project environments. The proposed system is deployed on the LINE mobile communication platform to enable proactive alert delivery and real-time interaction, thereby enhancing the efficiency of construction safety management and reducing the risk of occupational accidents.

2 Literature Review

2.1 AI-Based Object Detection for Construction Safety

Deep learning–based object detection has been widely applied in construction safety management for identifying safety-related objects such as helmets, safety vests, and hazardous zones [1,4,5]. Compared with two-stage detection models, one-stage algorithms (e.g., the YOLO family) offer superior real-time performance, making them suitable for on-site safety monitoring applications [4].

Previous studies have demonstrated the effectiveness of object detection models in recognizing safety equipment and unsafe conditions in construction environments [4,5]. However, these approaches are typically limited to frame-level detection tasks and do not consider temporal consistency or object behavior across consecutive frames. As a result, they may suffer from instability and false detections in complex and dynamic construction environments [5].

However, existing studies have reported that general-purpose pretrained models are susceptible to performance degradation in complex construction environments due to occlusion, varying illumination conditions, and background clutter. As a result, the use of construction site–specific datasets and model fine-tuning has been recognized as a critical approach for improving detection robustness and stability in practical applications.As summarized in Table 1, existing object detection approaches demonstrate varying trade-offs between detection accuracy and real-time performance, motivating the adoption of one-stage detectors with site-specific fine-tuning in this study.

Table 1. Object Detection Methods for Construction Safety

Method	Environment	Target Objects	Real-Time	Limitations
Faster R-CNN [1]	Outdoor	Safety-related objects	Medium	Limited real-time performance
YOLOv5 [11]	Outdoor	Helmet	High	Single object focus
YOLOv8 [4]	Indoor/	PPE	Medium	Limited generalization
YOLOv9 + StrongSORT (This study)	**Outdoor**	**Workers + Helmet + Reflective vests**	**High**	**Phase I validation**

2.2 Multi-Object Tracking for Dynamic Safety Monitoring

To address the limitations of frame-based detection, multi-object tracking (MOT) techniques have been introduced to capture temporal continuity and analyze dynamic behaviors of construction workers [7,8,9,10]. Most existing methods adopt a tracking-by-detection framework, which associates detected objects across frames using motion models and appearance features.

Recent approaches such as DeepSORT and StrongSORT have improved tracking robustness by incorporating deep re-identification models and advanced data association strategies [7,8]. These methods have shown improved performance in handling occlusions and identity switches. However, current studies primarily focus on tracking accuracy and algorithmic performance, with limited integration into practical safety management systems or decision-making processes in real construction environments [8,10].

Compared with traditional tracking methods, recent algorithms such as StrongSORT have demonstrated improved robustness in reducing identity switches and false alarms under occlusion and crowded conditions. These characteristics make such approaches more suitable for application in construction sites with high worker density and frequent dynamic changes. Table 2 summarizes representative multi-object tracking methods used in dynamic construction safety monitoring, highlighting their tracking frameworks, association strategies, and applicability to complex and crowded construction environments.

Table 2. Multi-Object Tracking Methods

Method	MOT Type	Occlusion Robustness	ID Stability
SORT [7]	Motion-based	Low	Low
DeepSORT [8]	Appearance-based	Medium	Medium
StrongSORT [9]	Enhanced embedding	High	High
This study	**YOLOv9 +StrongSORT**	**High**	**High**

2.3 ICT and Chatbot-Based Safety Management Systems

Information and communication technologies (ICT), including mobile computing and cloud-based systems, have been increasingly adopted to support construction safety management by enabling data collection, communication, and information sharing [3]. More recently, chatbot technologies have been introduced to facilitate user interaction and improve accessibility to safety-related information [11].

Despite these advancements, most existing systems are primarily designed for information retrieval or administrative support, with limited capability for integrating real-time perception data from AI models. Furthermore, they often lack mechanisms for proactive safety alerting and real-time interaction based on dynamic site conditions, particularly in multi-project environments [3].

2.4 Research Summary

Based on the reviewed literature, existing studies largely investigate object detection, multi-object tracking, and ICT applications independently. There remains a lack of integrated construction safety management systems that combine real-time visual perception, robust multi-object tracking, and chatbot-based interaction within a unified operational framework.

3 System Architecture and Methodology

3.1 System Architecture

This study develops a dynamic construction safety information management system, the overall architecture of which is illustrated in Figure 1. The system consists of three main modules: (1) an AI-based safety image perception module, (2) a LINE BOT interaction module, and (3) a dynamic construction safety information management module.

By integrating real-time visual perception, multi-object tracking, and safety task reasoning, the proposed system is capable of automatically identifying safety-related abnormal events on construction sites. In addition, the system leverages an instant messaging platform to proactively deliver safety alerts and enable interactive safety information exchange, thereby supporting dynamic safety management across multiple construction projects.

3.2 Construction Safety AI Image Perception Module

3.2.1 Construction Site Camera Capture Module

To support real-time video input from multiple sources, a multi-threaded image acquisition mechanism is designed to process video streams from multiple cameras concurrently. This design effectively mitigates image I/O blocking issues and ensures that the system maintains real-time performance and scalability in multi-camera monitoring environments.

The camera capture module is responsible for image acquisition and stream control. A multi-threaded architecture is adopted, in which an independent image capture process is assigned to each video source. This design decouples image acquisition from subsequent processing stages, effectively isolating time-consuming image reading operations and preventing delays in the main processing pipeline. As a result, asynchronous processing capability is achieved.

The overall workflow of image acquisition and frame management is illustrated in Figure 2. Through the proposed multi-threaded camera capture mechanism, the system can efficiently and stably process video streams from multiple cameras simultaneously.

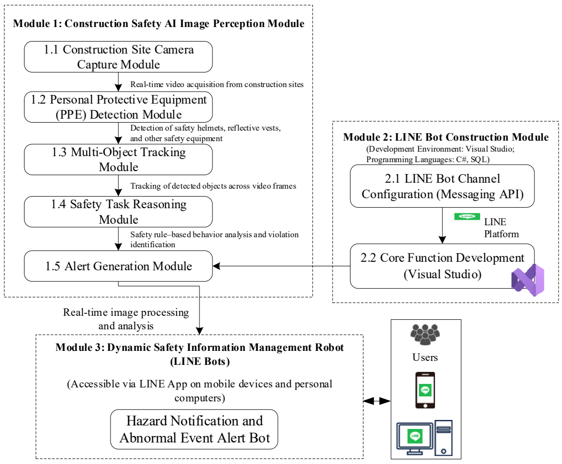

Figure 1. System architecture of the proposed dynamic construction safety information management system.

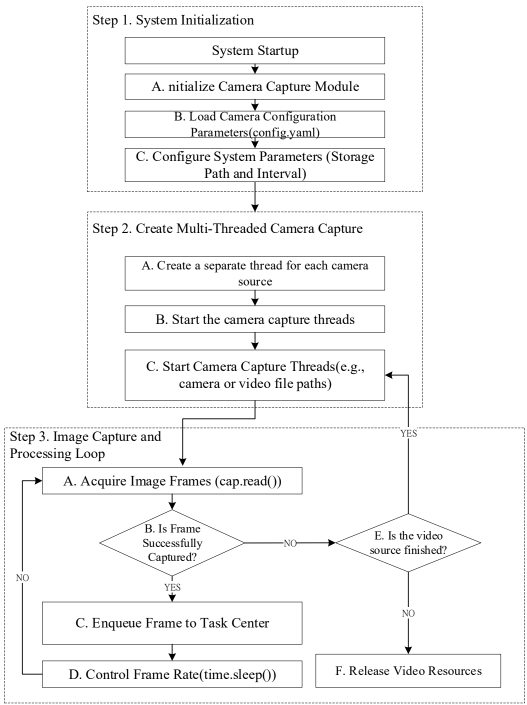

Figure 2. Workflow of the multi-threaded image acquisition and frame management module.

3.2.2 Personal Protective Equipment (PPE) Detection Module

This study adopts YOLOv9 as the core object detection model to identify safety-related objects in construction environments, including workers, safety helmets, and reflective vests. By constructing a construction site–specific training dataset and applying model fine-tuning, the proposed approach effectively improves detection accuracy and robustness under complex site conditions. During the inference stage, ONNX Runtime is employed to meet the real-time requirements of construction site monitoring.

The training dataset for personal protective equipment (PPE) detection is based on the SH17 dataset [13], which covers 17 categories of construction safety–related objects, such as workers, safety helmets, safety vests, safety masks, and safety shoes, as illustrated in Figure 3. Among these categories, this study focuses specifically on three types: workers, safety helmets, and safety vests.

Once objects are detected, the model outputs the bounding box coordinates (i.e., [x1,y1,x2,y2] representing the top-left and bottom-right corners), the corresponding class labels, and confidence scores. These detection results serve as essential inputs to the subsequent multi-object tracking module. In system implementation, the trained YOLOv9 model is converted to the ONNX format and executed using ONNX Runtime to maximize inference efficiency and support real-time monitoring. Detected object information is encapsulated in a standardized format, e.g., [x1, y1, x2, y2, confidence, class_id] , and then passed to the multi-object tracker.

3.2.3 Multi-Object Tracking Module

To address the transient misdetections that may arise from single-frame object detection, this study incorporates the StrongSORT multi-object tracking algorithm to establish cross-frame object identification and trajectory association. StrongSORT integrates a Kalman filter, deep appearance-based re-identification models, and multi-stage data association strategies, effectively reducing identity switches and false alarms in occluded and crowded scenarios. As a result, stable temporal object information can be maintained across video frames. The overall tracking workflow is illustrated in Figure 4.

Multi-object tracking plays a critical role in false alarm suppression, which can be attributed to several key mechanisms. First, temporal consistency verification is enforced, as erroneous bounding boxes or incorrect class predictions generated in individual frames typically lack temporal persistence. StrongSORT requires objects to be stably tracked and consistently classified over multiple consecutive frames before they are confirmed as valid tracked entities.

Second, trajectory filtering is applied to eliminate short-lived "ghost" detections that appear only briefly and fail to form stable trajectories. Such detections are treated as noise and automatically filtered out to prevent unnecessary alert triggering. This mechanism is controlled through temporal threshold parameters in the task evaluation module, whereby only violations that persist over a defined duration are considered valid events.

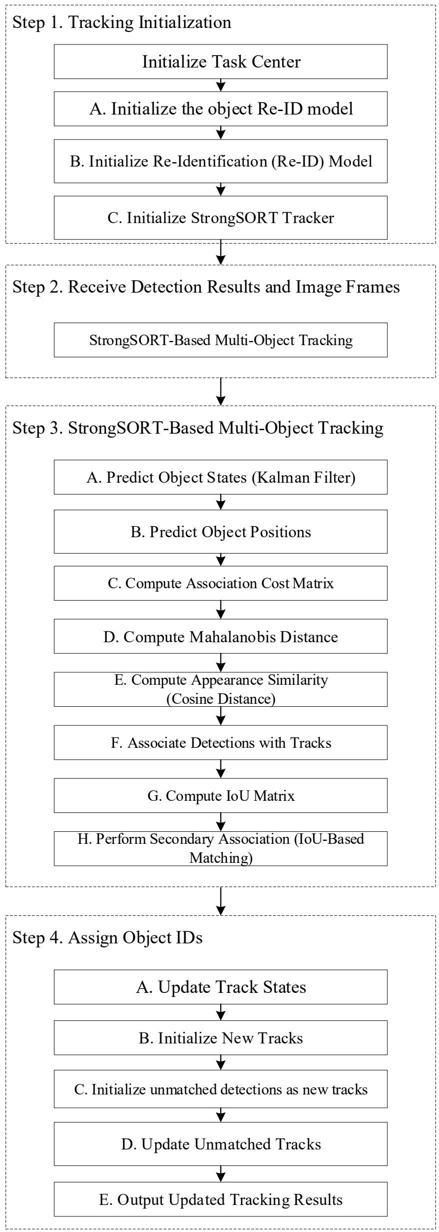

Figure 3. Workflow of the StrongSORT-based multi-object tracking and ID assignment process.

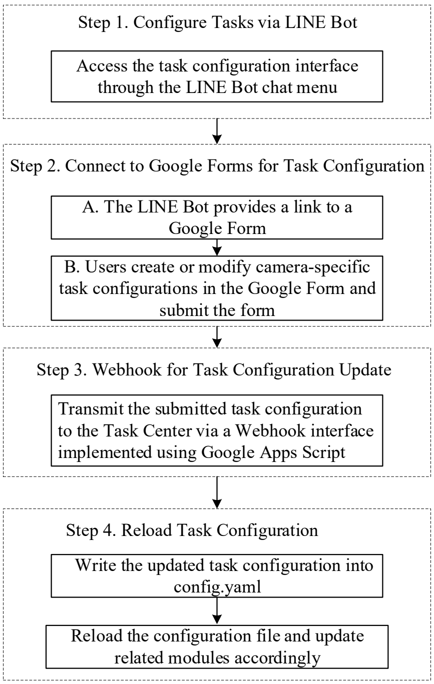

Figure 4. Workflow of task configuration and dynamic update via LINE BOT and Google Forms.

Third, behavioral pattern analysis is enabled by stable tracking trajectories, which serve as the foundation for higher-level safety reasoning. For example, determining whether a worker remains within a hazardous zone for an extended period, rather than merely passing through, or identifying sustained non-compliance with personal protective equipment requirements, relies on long-term tracking information rather than single-frame detections. Consequently, multi-object tracking not only contributes to false alarm suppression but also provides essential temporal context for subsequent safety behavior analysis and event reasoning.

In the proposed system, the multi-object tracking module is configured within the task management framework, with tracking parameters and re-identification models specified through external configuration files. This design enables accurate and robust tracking performance and supplies reliable object motion and state information for downstream safety task reasoning.

3.2.4 Safety Task Reasoning Module

The task reasoning module receives object information with associated tracking IDs from the multi-object tracking module and performs temporal analysis of construction activities based on predefined construction safety rules. The input information includes tracking IDs, spatial locations, and temporal features derived from object trajectories.

By integrating temporal persistence and spatial position reasoning mechanisms, the system is able to distinguish between transient misdetections and sustained safety violations. Only behaviors that persist over a defined duration and satisfy spatial safety constraints are identified as valid violation events and subsequently used as the basis for alert triggering.

The task reasoning logic is collaboratively executed by the task evaluation component and the task management mechanism, enabling consistent and rule-based safety decision-making.

3.2.5 Alert Generation Module

When a safety abnormal event is confirmed by the system, the alert generation module automatically stores the corresponding visual evidence and obtains image access links through cloud services. Subsequently, alert notifications are proactively delivered to designated construction managers or safety officers via the LINE BOT interface.

Each alert message includes essential information such as the violation type, occurrence time, associated tracking ID, and violation duration, along with an annotated image captured at the moment the alert is triggered. This visualized alert content enhances situational awareness and supports timely response to safety incidents on construction sites.

Through this design, safety events are processed in a closed-loop manner, seamlessly linking perception, reasoning, and notification. As a result, the proposed system improves the timeliness and responsiveness of construction safety management.

3.3 LINE BOT–Based Interaction Module

The LINE BOT developed in this study adopts a rule-based interaction mechanism to assist construction participants in quickly accessing safety-related information. This interaction design emphasizes predictable and consistent responses, which are particularly important for safety-critical applications in construction environments.

The development of the LINE BOT module comprises two main components: (1) configuration of the LINE BOT communication channel using the Messaging API, and (2) implementation of core interaction and query functions to support safety information delivery and user requests. The rule-based structure enables guided user interaction while limiting ambiguity in system responses. This module builds upon prior research conducted by the authors' research group [14], extending earlier chatbot-based construction management applications toward proactive and real-time construction safety information management.

3.4 Dynamic Safety Information Management Robot

To enhance safety awareness prior to on-site construction activities, the proposed system synchronously delivers visual information to both construction managers and participants when abnormal conditions are detected. This design establishes a dynamic construction safety information management process with real-time feedback and interactive capabilities. The overall workflow of this process is illustrated in Figure 5.

By integrating real-time perception, risk identification, and information feedback, the proposed mechanism supports a dynamic safety management cycle that enables timely monitoring and informed decision-making in multi-project construction environments.

4 Prototype Implementation and Functional Validation

4.1 Experimental Design and Phase I Validation

To validate the feasibility of the proposed dynamic construction safety information management system, a prototype system was implemented and evaluated through a Phase I functional validation. This phase focused on verifying the correctness and stability of the core system logic, including AI-based object detection, multi-object tracking, safety task reasoning, and alert triggering mechanisms.

Open-source construction site videos were adopted as the primary evaluation data to provide a controlled testing environment while covering diverse construction scenarios. This design allows systematic verification of the end-to-end system workflow without introducing additional uncertainties associated with on-site deployment.

The prototype system was implemented using a modular architecture to support flexible configuration and future scalability. The AI-based perception module was deployed on a GPU-enabled workstation to support real-time video processing. A fine-tuned YOLOv9 model was used for safety-related object detection, and StrongSORT was integrated to maintain temporal consistency of detected objects across video frames. To improve inference efficiency, the trained detection model was converted to the ONNX format and executed using ONNX Runtime.

During Phase I validation, system parameters related to tracking duration and violation thresholds were iteratively adjusted to evaluate their effects on alert triggering behavior. The evaluation emphasized functional correctness, robustness against transient detection errors, and the ability to suppress false alarms caused by short-term misdetections.

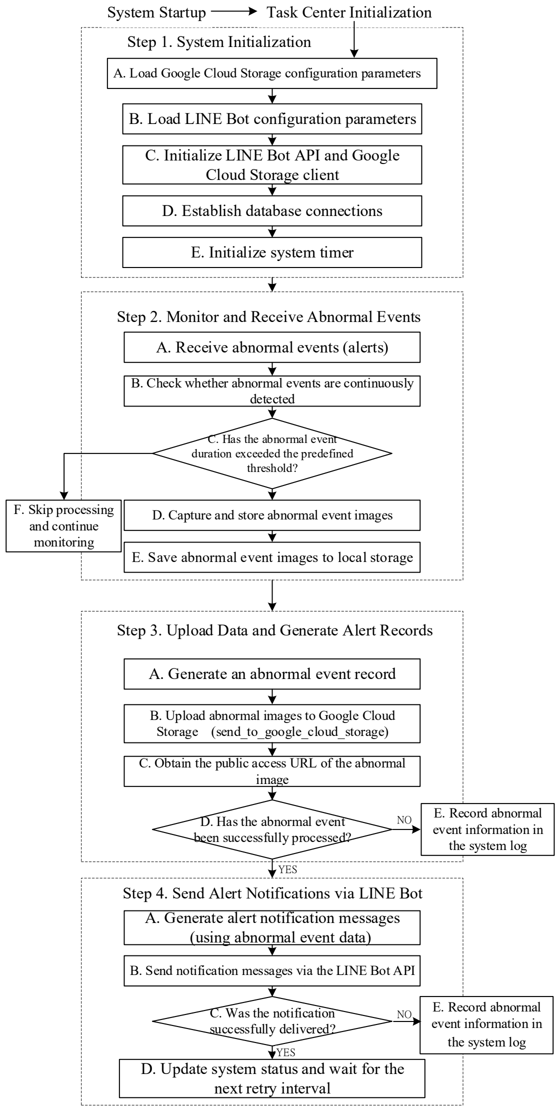

Figure 5. Workflow of abnormal event handling, cloud storage, and alert notification via LINE BOT.

Figure 6 presents example results of the proposed system during Phase I functional validation using open-source construction site videos, illustrating the integration of AI-based object detection, multi-object tracking, and safety task reasoning.

To evaluate the performance of the AI-based safety perception module, quantitative metrics including precision and recall were computed for representative safety-related categories based on Phase I validation results. The evaluation outcomes are summarized in Table 3.

Figure 6. Example results of Phase I functional validation using open-source construction site videos.

Table 3. Performance evaluation of YOLOv9 for safety-related objects

Category	Precision	Recall
Worker	0.90	0.89
Head	0.93	0.90
Helmet	0.70	0.64
Reflective vest	0.64	0.58

The results indicate that the model achieves recall rates of 0.90 and 0.93 for worker and head detection, respectively, demonstrating strong capability in identifying human presence in dynamic construction environments. In contrast, the detection performance for safety equipment is relatively lower, with recall values of 0.70 for helmets and 0.64 for safety vests, which may be attributed to factors such as smaller object size, occlusion, and variability in visual appearance under complex site conditions.

The comparatively lower performance for helmet and safety vest detection can be attributed to several factors. First, these objects often appear at smaller scales within the image, making them more difficult to detect accurately. Second, occlusion frequently occurs in construction environments, where safety equipment may be partially covered by other objects or body parts. Third, variations in lighting conditions, background complexity, and color similarity between safety equipment and surrounding environments can further reduce detection robustness.

It is noted that the current results are based on Phase I validation using open-source video datasets. In future work, Phase II will involve deployment in real construction sites, where additional domain-specific data will be collected to further fine-tune the model and improve detection performance, particularly for safety equipment recognition under complex and real-world conditions.

4.2 Hazard Notification and Alert Delivery via LINE BOT

Based on the validated perception and safety task reasoning results obtained in Phase I, the hazard notification and alert delivery mechanism was further examined through integration with the LINE BOT platform. When safety violations persisted beyond predefined temporal thresholds, the system automatically generated alert events containing violation type, occurrence time, tracking ID, and annotated image evidence.

The alert notification module uploaded abnormal event images to cloud storage and generated public access links, which were subsequently embedded in alert messages. These messages were proactively delivered to designated safety managers via the LINE BOT interface, enabling rapid situational awareness and timely response.

The successful delivery of alert messages and visual evidence confirms the functional integrity of the end-to-end workflow, from real-time video analysis to interactive safety communication. Figure 7 presents an example of the alert notification results delivered through the LINE BOT interface.

Figure 7. Example of hazard alert notification delivered via the LINE BOT interface.

5 Conclusion

This study presented a dynamic construction safety information management system that integrates AI-based image recognition, multi-object tracking, and chatbot-enabled communication within an operational framework. The proposed system aims to support proactive and real-time construction safety management by combining automated visual perception with interactive safety information delivery.

A prototype system was implemented and validated through Phase I functional validation using open-source construction site videos. The results demonstrate that the integration of fine-tuned YOLOv9 object detection and StrongSORT multi-object tracking can effectively support stable temporal reasoning of safety-related behaviors and reduce false alarms caused by transient detection errors. The functional validation confirms the feasibility of the proposed end-to-end workflow, from real-time video analysis to safety task reasoning.

In addition, the integration of a LINE BOT as the primary communication interface enables hazard alerts and visual evidence to be proactively delivered to safety managers, bridging the gap between automated safety monitoring and practical decision-making. The results indicate that the proposed system is technically feasible and suitable for supporting dynamic construction safety information management.

Future work will extend the current Phase I validation to on-site deployment and long-term field evaluation. Further improvements will focus on enhancing detection performance for small and occluded safety equipment, expanding dataset diversity, and evaluating system scalability and robustness under real construction conditions.

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References

[1] W. Fang, L. Ding, H. Luo, and P. E. D. Love. Computer vision applications in construction safety assurance. *Automation in Construction*, 110, Article 103013, 2020.

[2] Z. Zhou, J. Irizarry, and Q. Li. Applying advanced technology to improve safety management in construction. *Journal of Construction Engineering and Management*, 13:606-622, 2012.

[3] Y. Chen, and J. M. Kamara. A framework for using mobile computing for information management on construction sites. *Automation in Construction*, 20(7):776-788, 2011.

[4] P. P. Malokar, A. R S, R. R, and D. B. G. Vision Based PPE Detection Using Deep Learning. In *Proceedings of 2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare(64220)*, pages 1–3, Vellore, India, 2025.

[5] S. Han, S. Lee, and F. Peña-Mora. Vision-Based Detection of Unsafe Actions of a Construction Worker: Case Study of Ladder Climbing. *Journal of Computing in Civil Engineering*, 27(6):635-644, 2013.

[6] J. Choa, and G. Lee. Chatbot System for Construction Daily Report Information Management. In *Proceedings of 36th International Symposium on Automation and Robotics in Construction (ISARC 2019)*, pages 429–437, Banff, Canada, 2019.

[7] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft. Simple online and realtime tracking. In *Proceedings of 2016 IEEE International Conference on Image Processing (ICIP)*, pages 3464–3468, AZ, USA, 2016.

[8] N. Wojke, A. Bewley, and D. Paulus. Simple online and realtime tracking with a deep association metric. In *Proceedings of the IEEE International Conference on Image Processing (ICIP)*, pages 3645–3649, Beijing, China, 2017.

[9] Y. Du, Z. Zhao, Y. Song, Y. Zhao, F. Su, T. Gong, and H. Meng. StrongSORT: Make DeepSORT great again. *IEEE Transactions on Multimedia*, 25:8725-8737, 2023.

[10] Y. Zhang, P. Sun, Y. Jiang, D. Yu, F. Weng, Z. Yuan, P. Luo, W. Liu, and X. Wang. ByteTrack: Multi-object tracking by associating every detection box. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 1–21, Tel Aviv, Israel, 2022.

[11] C. Jadhav, and N. Ansari. Real-time safety helmet detection using deep learning. In *Proceedings of 2024 5th International Conference for Emerging Technology (INCET)*, pages 1–5, Belgaum, India, 2024.

[12] H. M. Ahmad, and A. Rahimi. SH17: A dataset for human safety and personal protective equipment detection in manufacturing industry. *Journal of Safety Science and Resilience*, 6(2):175-185, 2024.

[13] Y. J. Cheng, M. T. Cao, S. H. Wang, N. M. Nguyen, S. S. Chen, W. C. Wang. Integrating LINE BOT and Building Information Model to develop construction information management system, *Journal of Civil Engineering and Management*, 31(5):482-501, 2025.