Enhancing Construction Safety Monitoring Through Yolo-Based PPE Detection Systems

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ABSTRACT

Non-compliance with the use of personal protective equipment (PPE) remains a persistent safety issue during construction project implementation, contributing to a high incidence of site accidents. While prior studies have extensively highlighted the importance of PPE use, enforcement, and monitoring practices on construction sites, these practices continue to rely heavily on manual supervision, which is inconsistent, labour-intensive, and prone to oversight. A critical gap, therefore, exists in the continuous, objective monitoring of individual workers' PPE compliance, particularly in complex, dynamic site environments. This study proposes an artificial intelligence–based PPE monitoring system using the You Only Look Once (YOLO) object detection algorithm to automatically identify the use of safety helmets, safety footwear, and reflective vests on construction sites in Malaysia. The research focuses on evaluating the detection model's performance in terms of accuracy and its ability to provide timely information to personnel responsible for safety supervision. Model performance was assessed through detection accuracy and system responsiveness during controlled testing. The findings indicate that the proposed model can identify PPE non-compliance with a satisfactory level of accuracy, demonstrating its potential as a supplementary tool for site safety monitoring. Although the system does not replace human supervision, it provides a foundation for automated safety inspection and supports proactive safety management. The study contributes to ongoing research on digital safety monitoring and highlights the role of computer vision in strengthening construction site safety practices.

Keywords: Personal Protective Equipment (PPE), Construction Safety Management, Artificial Intelligence (AI), Real-Time Monitoring, Built Environment, Digital Construction

INTRODUCTION

In the construction sector, a significant number of personnel and equipment are constantly moving, placing an enormous burden on safety professionals trying to make safety-related decisions in an ever-changing, fragmented, and risky work environment. The construction of infrastructure within Malaysia is one of the most important drivers of the Malaysian economy. The noteworthy fact is that using Personal Protective Equipment (PPE) regulations remains a major problem. Non-compliance with the PPE Regulation remains one of the key reasons for many avoidable site fatalities. Human behaviour and the culture of an organization play a significant role in determining traditional safety outcomes (Mohammadi et al., 2018), so a move towards the use of real-time data and digitalized surveillance will provide the best route to successfully improving site safety (Guo et al., 2017).

Currently, safety management practices face a latency gap, as they rely on manual processes, opinions, and observations, which can be subject to human error, delays in reporting, and decision-making (Winge et al., 2019; Zhou et al., 2015). Although computer vision and artificial intelligence (AI) technologies have the potential to enhance construction performance and safety, their use in PPE monitoring in the Malaysian construction industry remains limited due to organizational trust and technical implementation challenges (Lee and Lee, 2023; Badhan and Samsami, 2025). Hence, this study is conducted to determine the role of an AI-based monitoring system that can replace manual monitoring, enabling timely interventions to minimize accidents.

Problems Statement

Currently, the PPE monitoring method relies on a reactive, human-reliant approach. The approach involves using the checklists and supervisor assessment, which lead to inconsistent and costly validation (Fang et al., 2015). Since traditional inspections provide a static snapshot of PPE compliance, non-compliance is only visible after accidents and injuries have been reported. Hence, manual interventions create an oversight gap that requires urgent action to avoid workplace accidents, where risks can vary from moment to moment.

Access to real-time information is constrained, as all data are logged in manual reports or saved in digital formats, especially Excel files (Zhou et al., 2015). Dependence on non-digital, disaggregated reporting formats is ineffective for providing an accurate hazard analysis that can quickly identify repetitive unsafe behaviours and high-risk zones (Guo et al., 2017). These limitations also highlight a lack of integration with technologies, and the industry continues to operate with a delayed decision-making cycle, where reporting and communication cannot be done, and violations and incidents cannot be addressed instantly.

REVIEW OF THE CURRENT APPROACH

On most construction sites, Personal Protective Equipment (PPE) inspection procedures are still mainly manual and rely on paper-based documentation, as shown in Figure 1. Traditional record-keeping methods, such as spreadsheets and logbooks to track equipment status and inspection results, continue to be used on construction projects worldwide (Winge et al., 2025). The traditional manual method leads to inconsistencies across construction sites, as different supervisors may use different inspection methods and standards. Research by Chen et al. in 2024 indicated that a typical challenge to unified safety monitoring in construction is variation in administrative procedures across sites. In the "Manual PPE Inspection" stage, there may be an error in which the site supervisor misses violations, preventing continuous monitoring.

The manual method lacks automated verification, systematic data storage, and real-time monitoring as compared to digital or AI-based safety systems. PPE usage can be continuously monitored, compliance data can be centrally documented, and violations can be immediately notified by digital systems that use computer vision and artificial intelligence (Fang et al., 2020). In contrast, manual inspections are reactive and periodic, which can lead to exposure of safety issues because dangerous activities may be missed between inspections.

If there is any violation of PPE requirements, the supervisor will report it to the management team manually via WhatsApp, messages, email, or verbal reporting, especially during the stage starting from "Record Manually". The corrective action is taking longer due to fragmented information resulting from decentralized communication channels. According to the 2015 study by Zhou et al., one of the main factors contributing to inefficiencies in construction safety management systems is poor communication skills. Furthermore, it is seldom conducted systematically to track the lifespan of PPE, such as the expiration dates or conditions of helmets or harnesses. Without a structured, centralized digital system, the supervisor has to rely on manual reminders or periodic reviews of outdated documents, leaving procedures vulnerable to oversight. Besides, the absence of a central database makes record-keeping more difficult. Reports from the past inspections are often scattered across various folders, devices, and physical files. According to research, traceability, audit readiness, and long-term safety monitoring are the main issues for construction organizations that rely on decentralized, manual record-keeping (Mohammadi et al., 2018).

According to Pandithawatta et al., (2024), decentralized, paper-based safety documentation affects managerial decision-making and organizational learning. These limits indicate that automation is more than an optional enhancement; it is necessary to meet current construction safety standards.

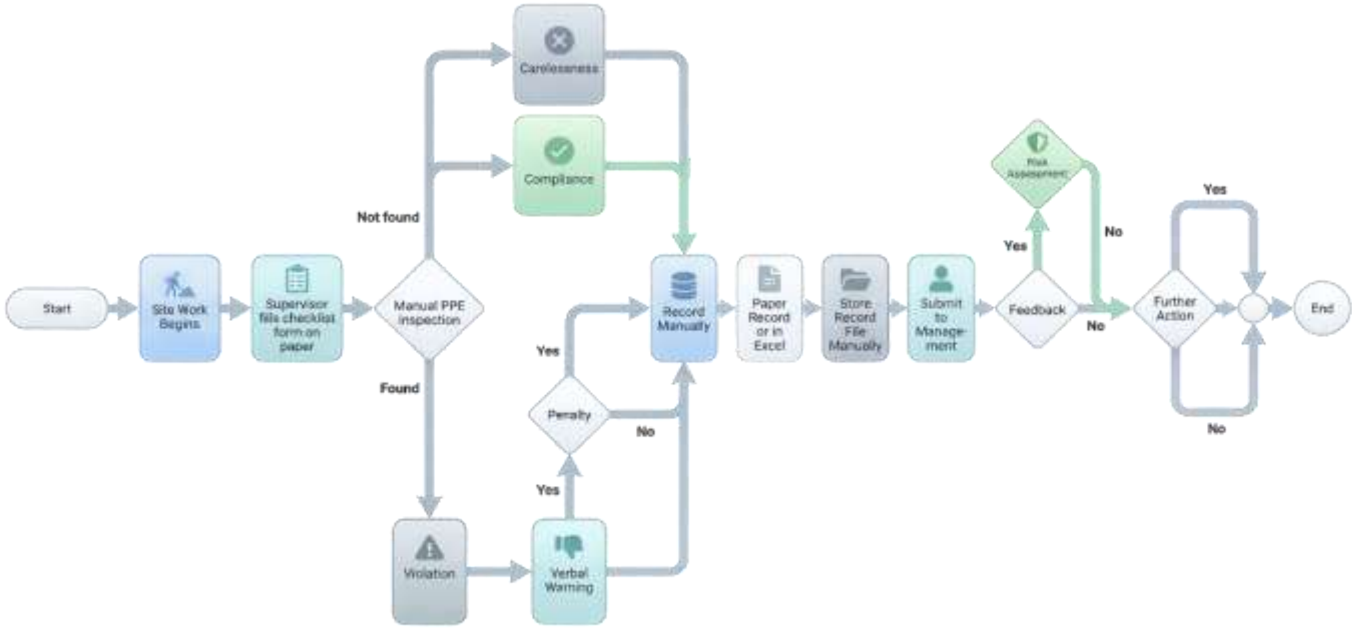

Fig. 1. Flowchart of Current Process in PPE Inspection

Weaknesses, Inefficiencies and Decision-Making Gaps in the Current Approach

Several inefficiencies in the manual PPE inspection process directly affect data accuracy and safety performance. Due to the manual PPE inspection system's reliance on human input, mistakes such as missing records, inconsistent evaluations, and insufficient data are more likely. Managers may use erroneous or outdated information when dealing with PPE violations, which directly affects the decisions (Al-Bayati et al., 2023).

Next, the weakness in the current approach is the lack of real-time PPE compliance data. Risky actions may go undetected for longer periods because manual inspections are conducted at specific times. Based on the research, the absence of real-time safety data will slow an organization's ability to respond effectively to potential risks (Lee & Lee, 2023).

Further, poor communication skills are a consequence of the existing strategy. PPE violations are usually reported manually via WhatsApp messaging, emails, and orally. These methods are likely to be disregarded, pushed aside, or not captured, which could lead to unnecessary action and increased risk exposure. The study found that poor communication skills are correlated with risky workplace practices and PPE violations (Mohammadi et al., 2018).

Finally, the manual approach does not support risk forecast evaluation or structured safety trend analysis. Without a centralized database, management cannot identify high-risk personnel, dangerous locations, or frequent breaches. The organizations can only react after problems occur because the risks cannot be avoided in advance, which would prolong the construction process. According to research, conventional methods lack the analytical capacity to support proactive decision-making (Badhan et al., 2025).

Importance of System Development

To achieve the research objective of strengthening PPE compliance, decision-making accuracy, and response duration on construction sites, a digital or AI-based PPE inspection system must be created. Continuous monitoring, trustworthy data storage, and immediate alerts, all necessary for proactive safety management, are not possible with manual systems. As shown by recent research, AI-enabled, knowledge-driven safety platforms effectively enhance hazard detection and in-time reporting, while reinforcing the accuracy of safety data, features that are impossible to achieve with manual systems (Badhan et al., 2025).

Moreover, system development enables centralized, organized safety data collection, facilitating evidence-based decision-making from a managerial perspective. This aligns with research emphasizing the importance of structured decision models, such as ANP–VIKOR, for optimizing PPE lifecycle planning (Jin et al., 2024). To guarantee efficient PPE inspection and replacement, integrating real-time information exchange and robotic reminders into safety management will be an essential core function for which digital tools are well-suited. This supports the research objective of enhancing decision-making and compliance levels.

It is generally believed that technological innovation in PPE management has been demonstrated by evidence, as data-driven safety analysis boosts on-site learning and risk mitigation (Sonali et al., 2024). The establishment of a digital PPE inspection system is not only practical and advantageous but also essential to address these operational and regulatory requirements, ensuring proactive safety management, shorter response times, and higher compliance across all construction sites. Workers' exposure time to hazards is reduced by automated warnings and real-time notifications that ensure rapid response to PPE violations.

Technological Solution And Available Tools

Proposed Approach

The methodology for this study introduces an Artificial Intelligence (AI)- based PPE monitoring system to support safety management practices in the construction field, as shown in Figure 2. This proposed system integrated the You Only Look Once (YOLO) algorithm with a on-site camera, enabling the AI to be trained and to identify PPE compliance in real time, especially for safety helmets, vests, and boots. It is one of the object detection models that shows superior accuracy and speed compared to other older models (Wang et al., 2023). The customization, which involves PPE-compliant and non-compliant images and videos from construction sites or similar virtual environments, is required for AI model training. YOLO was chosen because it automates the site's visual surveillance, enabling ongoing safety monitoring rather than relying on manual inspections by safety officers.

The system automatically records the frame and violation logs, particularly when the worker is operating without helmet and vest compliance in a risky area, using image or video feeds. All these recorded violations will be saved and stored in a structured database. In this proposed system, Natural Language Processing (NLP) is used to generate violation and hazard reports from captured images. It enables the automated conversion of unprocessed data into structured information that can be read and understood by a computer (Antony, A., & Xavier, A. S., 2025). With the extension of NLP, documentation and reporting accuracy and efficiency are enhanced in this system, as records are sorted and processed automatically, simplifying repetitive paperwork and reducing administrative burden by eliminating manual typing and writing for quicker follow-up action (Cunha Reis, 2025).

According to the Occupational Safety and Health Association (OSHA), all organizations have to inform OSHA within 8 hours of a worker's death at work or within 24 hours of a worker's inpatient hospitalization, amputation and blind. This statement highlighted the importance of reporting and, at the same time, reflects the reliability and advantages of the system in generating reports more quickly and reducing on-site safety hazards. To overcome these issues, the proposed system applies Kernel Density Estimation (KDE) to convert violation data into a “Heatmap” form automatically. KDE helps identify high-risk areas on site, enabling effective analytics by continuously highlighting workers' unsafe behaviours across different locations. Hence, it allows management to stop treating violations as common incidents and to take this issue seriously through targeted training that emphasizes critical decision-making rather than general training.

Last and foremost, to enhance communication between management, the real-time alert and server function is essential as the connector within the organization. A Telegram bot is used as a platform for a more responsive monitoring system, where violations are detected by AI and the site supervisor is instantly notified via mobile phone. Telegram bots provide an effective solution for robotic information sharing, offering greater flexibility and compatibility with other platforms (Adrian et al., 2025). Using a telegram bot, it can reach the site supervisor on site straightaway, without the delay of information sharing via verbal communication and email. The server will store all violation logs, data, and reports to ensure accessibility by all management levels for further action and planning more quickly.

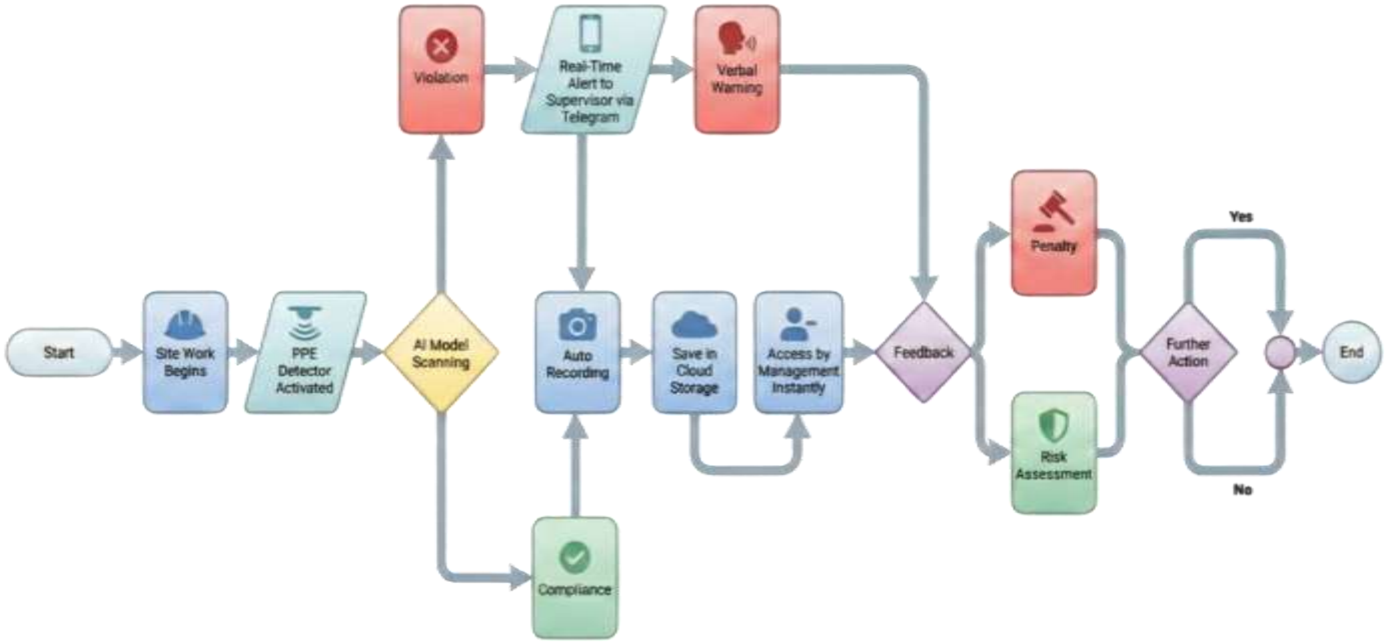

Fig. 2. Flowchart of New Process in PPE Inspection

Comparative Table

The comparative table highlights how each component addresses a specific bottleneck in traditional safety management. While YOLO delivers high-accuracy detection for real-time monitoring, NLP automates OSHA compliance reporting, and KDE contributes spatial intelligence to identify risky zones. Also, the telegram bot plays a crucial role in this system, as it bridges the gap between digital detection and physical response to hazards by offering instant mobile alerts. Although the initial cost of integrating these technologies is higher, they may demonstrate their value and reduce the risk of accidents on construction sites in the long run.

Component	Strengths	Weakness
YOLO	● High precision for helmets, vests, and boots ● Quick real-time detection	● Attenuate real detections ● Less stable in a busy or overlapping workforce
NLP Reporting	● Assures timely OSHA reporting compliance ● Minimises administrative effort ● Automatically provides structured reports.	● Relying on the quality of the dataset ● Perhaps misinterpreting uncommon situations
KDE Analysis	● Finding hotspots for PPE violations ● Support for predictive planning	● Needs a basic analytical setup and appropriate detection data

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Telegram Bot	• Instant alerts • Digital evidence trail creation	• Requires initial configuration • Relies on the internet

Personal Protection Equipment (PPE) Detection Model

The accuracy of the PPE detection model is measured using performance evaluation metrics such as Precision, Recall, F1-score and mAP@50 (Qin et al., 2025). In the system, the model is trained on 11,407 datasets using Robflow (92% train, 4% valid, and 3% test), created by Conal Oliver (Oliver, 2025). As shown in Figure 3, the evaluation using a confusion matrix across eight classes includes compliant and non-compliant PPE. The findings indicate effective performance in extraction compliance, especially helmet, no-gloves, and vest, which achieve true positive counts of 225, 227, and 205, respectively. However, false positives are detected due to background interference and small-object detection. Gloves and no-gloves are found in the higher counts, with 48 and 39 false positives under background interference; on the other hand, reciprocal misclassification between shoes and no-shoes is indicated in 10 and 8 cases due to limitations in small-object detection. The overall model performance has been demonstrated in Figure 4. The model's precision improved to approximately 0.92, indicating the system is highly reliable and that nearly 9 out of 10 alerts delivered to the supervisor are true violations, minimizing alert fatigue from false alarms. The recall shows a clear trend toward a 0.85 high-accuracy rate in identifying actual non-compliance with PPE, reducing the blind spots observed in manual monitoring. Both metrics yield an F1-score of 0.88, indicating a balanced rate of detection. The mAP@50 above 0.90 also indicates that the model can properly detect PPE across all classes and faster, demonstrating its reliability and suitability for application on construction sites to ensure safety standards. Compared with Alibek Barlybayev's (2024) proposed models across different YOLOv8 sizes, the model achieved average performance with 0.92 precision, 0.83 recall, and 0.90 mAP@50. It shows that our model achieves better performance and simultaneously reaches a higher F1-score, improving detection sensitivity. Hence, the system can balance minimizing false positives with capturing true non-compliance in practical environments. However, the performance in detecting PPE items may differ from that in this study, as it is also affected by real-world site conditions such as occlusion, lighting, and crowd density. To successfully apply this tool in construction safety, it still requires further training, improvement and validation.

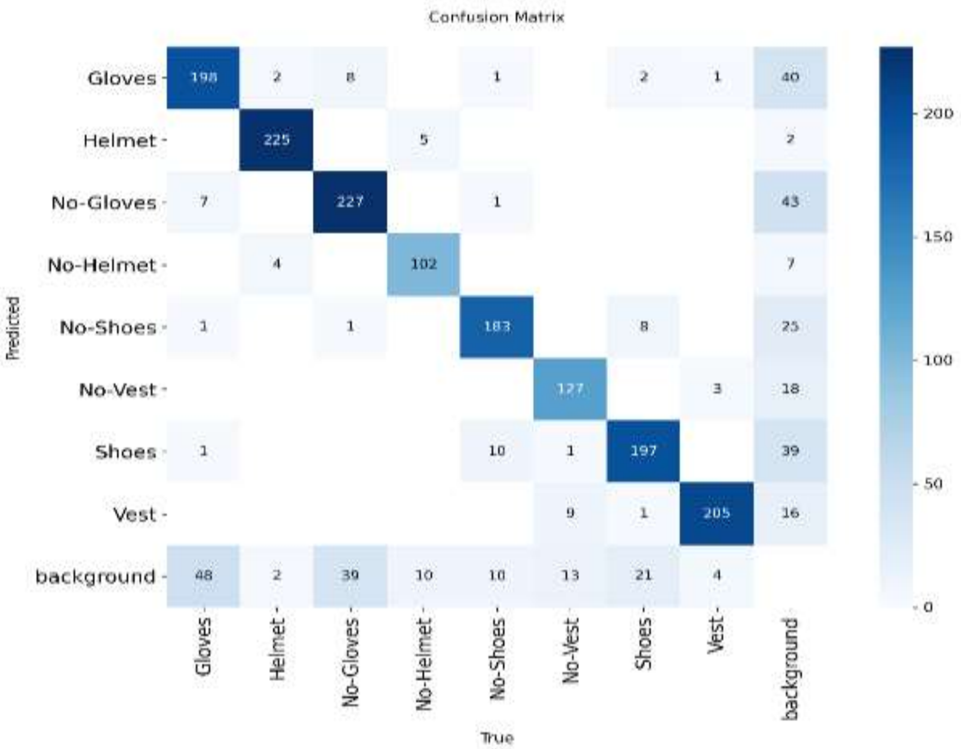

Fig. 3. Confusion Metrix of PPE Detection Model

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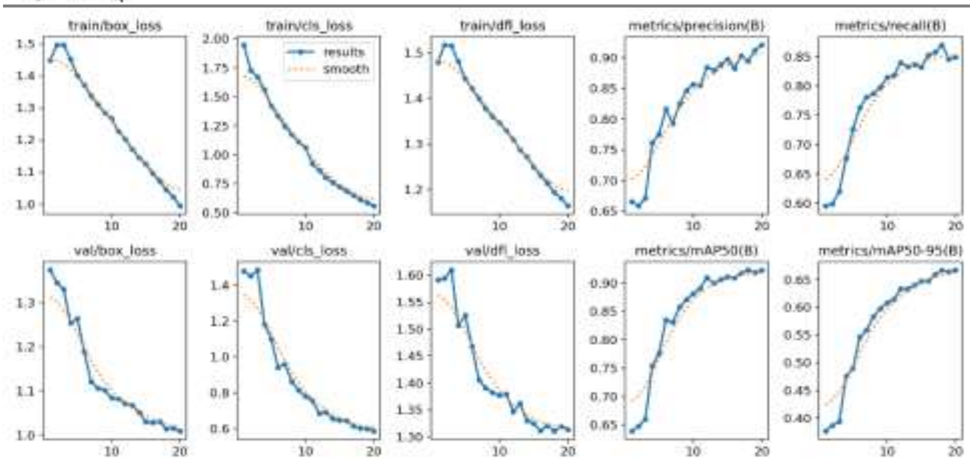

Fig. 4. Performance Evaluation of PPE Detection Model

Natural Language Processing (NLP) Report Generating and Cloud Server Storage

The capabilities of on-site safety management can be greatly enhanced by integrating cloud server storage and NLP-driven report generators, as shown in Figures 5 and 6. This function allows site supervisors to rapidly identify emerging risks, such as frequent violations, peak violation periods, and high-risk zones, without manual analysis. The server ensures that every member of the management staff can access the log and report anytime, anywhere. When combined, these characteristics turn dispersed detection data into actionable insights that enable proactive decision-making, efficient resource allocation, and a quantifiable decrease in safety blind spots around the construction site.

Fig. 5. PPE Violation Logs in Table Form

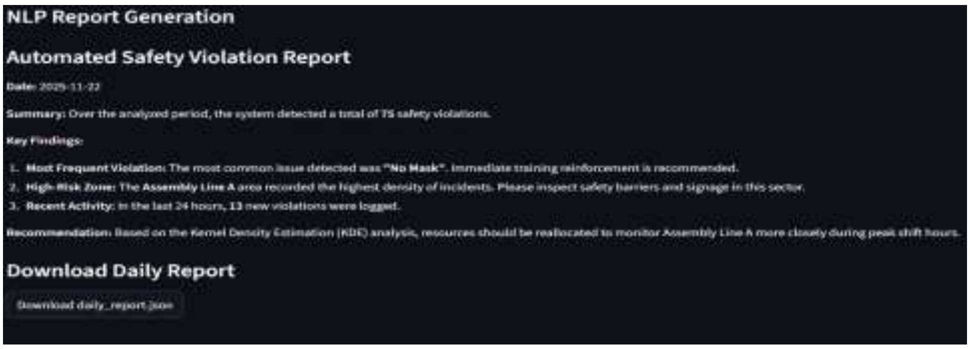

Fig. 6. Summary Report Generation by NLP

Kernel Density Estimation (KDE) Heatmap

The KDE heatmap delivers a high-resolution view of the site's hotspot of safety violations, as shown in Figure 7. The map identifies operational hotspots that need immediate attention by revealing hidden spatial patterns

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by turning distributed detection points into continuous risk zones. This lets the safety team effectively manage resources, schedule inspections, and strategically reduce risks before they become accidents.

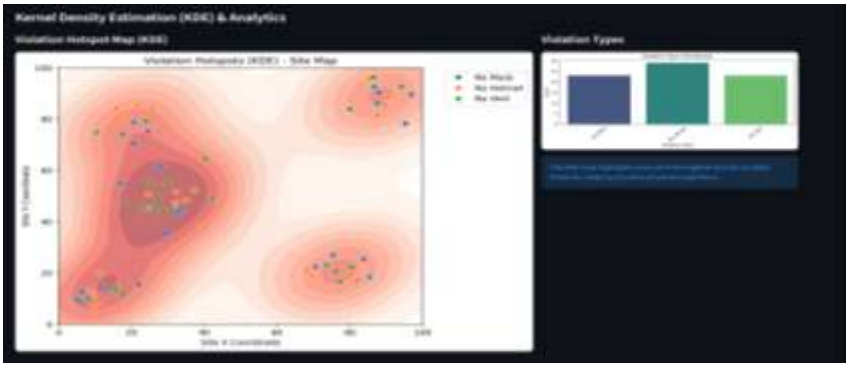

Fig. 7. Heatmap based on the Construction Site

Telegram Bot Real-Time Alert

The site supervisor will receive real-time safety intelligence via the robotic Telegram alert system, ensuring that no significant violations go unreported. The bot promotes rapid situational awareness and faster decision-making by consolidating all detected PPE violations into a single, brief notification, minimizing response times and enhancing on-site safety governance, as shown in Figures 8 and 9. It will be an amazing function for site supervisors, as the fast communication channel transforms raw data into useful information without any action from the supervisor.

Fig. 8. Creating a New Telegram Bot

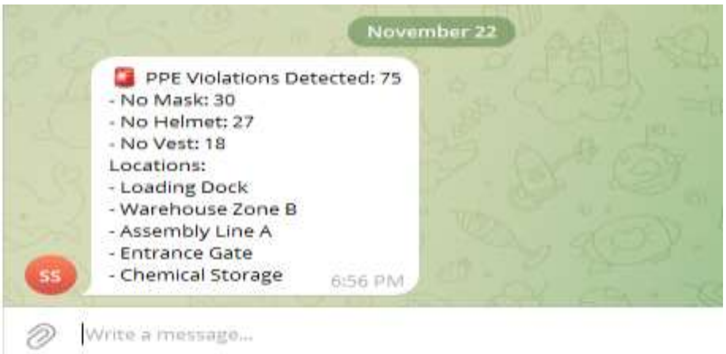

Fig. 9. Automatic Alert via Telegram Bot

Proposed System

Comparison Between Current Process vs New Process

The existing PPE inspection process on construction sites relies heavily on manual supervision, with site supervisors conducting visual checks and recording compliance using paper-based checklists or simple spreadsheets. This approach is inherently limited by human attention, time constraints, and subjective judgment, resulting in inconsistent inspection coverage and delayed identification of unsafe behaviour. Documentation is often completed after inspections, increasing the risk of incomplete or inaccurate records and limiting their value for timely risk assessment. Furthermore, the absence of a real-time notification mechanism means that corrective actions are typically taken only after non-compliance has already occurred, reducing the preventive effectiveness of the inspection process. Management access to safety records is also delayed, as reports must be compiled and submitted manually, restricting their ability to respond promptly to emerging safety risks. Consequently, risk assessments are retrospective in nature, and safety-related decisions are largely influenced by individual supervisor experience rather than consistent, data-driven evidence.

In contrast, the proposed process introduces an automated, system-driven approach that fundamentally alters how PPE compliance is monitored and managed. PPE inspections are conducted using an AI-based detection model that scans workers when the PPE detector is activated, enabling continuous, objective monitoring. Compliance data are automatically recorded and stored on a central server, eliminating manual documentation and reducing administrative workload. Real-time alerts are instantly transmitted to supervisors via Telegram, allowing immediate on-site intervention when non-compliance is detected. This real-time data flow enables management to access inspection records instantly, supporting proactive risk assessment rather than delayed post-incident analysis. Decision-making is no longer reliant solely on personal judgement, as supervisors are supported by real-time, system-generated evidence that enables faster, more consistent responses. Overall, the new process significantly improves efficiency, data reliability, and the timeliness of safety interventions, strengthening PPE compliance and construction site safety management.

Aspect	Current Process	New Process
Inspection Method	Manual PPE inspection by supervisor using paper checklist.	Automated AI model scanning after PPE detector activation.
Documentation Method	Manual recording in paper or Excel.	Auto-generated logs using NLP and stored in server storage.
Notification System	No real-time notification and verbal warnings only after manual detection.	Instant alerts sent to supervisors via Telegram.
Access by Management	Records submitted manually cause delayed review.	Management accesses reports instantly from the server.
Risk Assessment	Conducted after manual report submission.	Conducted with real-time data.
Overall Efficiency	Slow, prone to error and high administrative workload.	Faster, automated and consistent data flow.
Decision-Making Assessment	Decisions are made based on the supervisor's personal judgment and experience after manual detection.	Real-time detection enables faster decisions by providing instant alerts to supervisors for continuous monitoring and immediate response on-site.

Benefit of the Proposed System

The implementation of the proposed system introduced numerous benefits, such as improved safety compliance, operational efficiency, scalability and adaptability, and enhanced data management, automation, and communication between workers in the current PPE inspection workflow. These benefits enhance workplace safety and compliance by utilizing artificial intelligence (AI), natural language processing (NLP) and cloud-based systems to improve secure data flow.

The proposed system uses real-time monitoring and alerts during the site inspection process. Real-time monitoring helps supervisors receive immediate notice of violations during on-site inspections. This system features alerts generated by an AI model that sends a violation notice to the Telegram platform when violations are detected on-site. As a result, the system not only saves time but also reduces the manual recording errors, thus preventing accidents at construction sites (Gholizadeh et al., 2020; Fang et al., 2019). Hence, this feature prevents delays and also makes the PPE assessment more accurate and flexible.

Moreover, the system uses Natural Language Processing (NLP), leveraging automated technology to manage PPE knowledge stored in the safety and security system on the server, thereby improving on-site safety protocols and management strategies. This feature can automatically generate an NLP-driven violation report and store the report data on the server for further review. Its function allows supervisors to review the violation report without having to use manual records. Modern digital systems can reduce material depletion and provide an eco-friendly construction site (Lin et al., 2017). According to Chen et al., in 2020, driven databases will increase overall site security because they help supervisors store an organization's safety and security protocols across multiple stores. This is because management can provide feedback and access the complete record of all reports anytime, anywhere, reducing latency compared to manually checking incomplete archives.

Lastly, the availability of structured digital data enhances data-driven decision-making within organizations. Data-driven decision-making is enhanced when structured digital logs can identify risk patterns and help management better assess security performance (Chen et al., 2020). This level of analysis was previously unattainable in manual processes. The supervisor can quickly evaluate and survey the safety risk results from the digital dataset. Hence, data collection not only improves safety assessments but also provides insights into areas that need improvement, including trends and safety management strategies.

Limitations of the Proposed System

Despite substantial advances in safety management enabled by new technologies, several limitations remain due to operational, technical, and security factors. The proposed system is still at an early stage and not been tested on a real construction site. Thus, it is important to thoroughly understand and discuss the system's limitations for future development and long-term benefits.

Firstly, in the proposed system, the training datasets remain limited in size and diversity because the early-stage systems are not yet fully mature for development. Its detection dataset capability may still need refinement to be more accurate, stable, and flexible across different site environments. This is because the smaller datasets usually may not cover all potential PPE types, where the model performs well on training data but still poorly on uncertain data. In this study, the model is evaluated in a controlled environment rather than on the real construction site. The real construction may include factors such as occlusion, brightness, crowd density and camera angle. It could be uncertain and unfriendly to AI, as it is unlike humans, who have their own thoughts and make accurate detections in unpredictable situations. Early-stage AI prototypes exhibit model generalization problems when exposed to changes in lighting conditions, posture, or background noise (Gholizadeh et al., 2020). These problems occur in the testing environment and affect the PPE detection accuracy in real construction applications because the system is evaluated in a controlled environment rather than on a real construction site. To improve the proposed system, continuous retraining was required to add more quantity, improve quality, and augment data to enhance performance in safety regulations.

In addition, the proposed system is not conducting long-term site testing because it is still in an early stage, which limits the model's flexibility. However, the system introduced security vulnerabilities because the violation logs and reports were stored on Streamlit Cloud, an online platform. Such cloud-based storage solutions may expose the system to unauthorized access or data breaches if security configurations are poorly set (Hashizume et al., 2013). Thus, even if the model performs well in initial tests, it still fails to maintain the effectiveness of safety protocols and may destroy the system's long-term adaptability in workplace safety. To reduce the privacy and surveillance concerns, the proposed system should further develop data protection protocols, especially restricted access control and anonymization of violation records. It is also important to note that the workers are clearly informed of the monitoring objectives to ensure the system is run in accordance with informed worker consent. If there is any dispute, it can ensure their rights are protected. Also, compliance with the Personal Data Protection Act 2010 in Malaysia should be considered during the system deployment.

In conclusion, the inspection process for PPE must remain continuously updated, and improvements must be made going forward. Continuous updates can make their equipment more flexible and adaptable in the construction industry, ensuring on-site safety. For future development, developers should focus on the sustainability of AI models' safety measures to ensure good on-site performance and continued application in real-world environments. From an industry perspective, although the new system may involve a higher initial investment in camera systems, server infrastructure, and system integration than the traditional monitoring method, the benefits may exceed the costs in the long term. Reducing accident-related expenses, project delays, and penalties from DOSH Malaysia can help users save costs through site safety management. It may not only improve PPE compliance but also enhance productivity by reducing the disruption caused by site accidents. Hence, the proposed system shows strong potential for adoption across different project sizes within the Malaysian construction industry.

CONCLUSION

In conclusion, this study was conducted to address non-compliance with PPE use, delayed hazard detection, and disorganized safety records at construction sites by implementing an AI-based PPE monitoring system. The study found that integrating YOLO algorithms successfully identified safety helmets, vests, and boots with high accuracy. This finding directly met the study objectives. This study contributes to safety management on construction sites by using AI-based systems to accurately detect PPE use among employees, then alert the responsible person to obtain the information quickly and take action directly after receiving the alert if employees fail to comply with PPE requirements. This technology transforms the detected data into safety information that is easier to use, better organized, and more accessible to management. This study's results show that the proposed AI-based approach significantly improved PPE compliance inspection. Therefore, the study can facilitate safety management at construction sites by enabling monitoring solely through the system, without manual oversight, thereby helping organize digitized records. For further improvement, it is recommended that AI-assisted worker identification be added to enhance follow-up after violations, especially a penalty system based on merit. Also, the interface design should be improved, more aesthetically pleasing and flexible, to encourage the use of this system on PCs and mobile devices.

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