Civil Engineering Dimension
https://ced.petra.ac.id

Enhancing Construction Site Safety through Automated PPE Monitoring: A Computer Vision-based Approach

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DOI: https://doi.org/10.9744/ced.28.2.193-203

Article Info:
Submitted: Oct 23, 2025
Reviewed: Nov 24, 2025
Accepted: Feb 24, 2026

Keywords:
safety automation,
construction safety management,
automation in construction safety,
computer vision,
YOLOv5s.

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Abstract

The construction industry is known as one of the most accident-prone industries, where conventional Personal Protective Equipment (PPE) compliance checks remain laborious and inadequate for real-time safety monitoring. Although several sensor-based and AI-driven systems exist, many remain limited in scope, difficult to scale, or unsuitable for low-compute environments. This study developed a practical, multi-class, real-time PPE monitoring framework using an optimized YOLOv5s model aligned with industry insights. A PRISMA-based literature review and a semi-structured survey of 74 professionals identified critical PPE items and implementation barriers, informing dataset design and model requirements. Trained on hybrid datasets, the model achieved a mean average precision (mAP) of 86.5% at an Intersection over Union (IoU) threshold of 0.5, along with 91.4% precision, 87.5% recall, and an inference speed of approximately 140 frames per second (FPS). The resulting framework provides a scalable and easily deployable solution that integrates with existing CCTV systems to automate PPE compliance monitoring on construction sites.

INTRODUCTION

The Construction, Real Estate, Infrastructure, and Project Management (CRIP) industry is globally recognized as one of the most unsafe sectors, where workers face a high risk of accidents, injuries, and fatalities [1]. Although the industry employs nearly 7% of the world's workforce, it accounts for a disproportionate share of workplace accidents. Whether a construction project is small or large-scale, maintaining rigorous safety standards is essential; however, the complexity of large-scale developments presents unique challenges [2]. In the context of India, rapid urbanization and a surge in massive infrastructure projects have significantly intensified these safety concerns [3]. Construction sites are inherently dynamic and lack organized work zones; a significant proportion of frontline workers have limited formal education and often underestimate safety practices, which intensifies safety concerns [4].

Although unsafe behaviors contribute to nearly 60% of construction accidents [5]. The root causes often lie in poor safety supervision, inconsistent administration, and organizational shortcomings, rather than worker intent alone [6-8]. Technology-based PPE monitoring should hence be viewed not merely as a policing tool, but as a component that can support a stronger safety culture, consistent supervision, and improved organizational practices [9]. Numerous studies have emphasized that incorporation of correct PPE use, particularly safety helmets and safety shoes, significantly reduces accident severity by protecting against falling objects, injury to legs, and other common site hazards[10–12] . However, the enforcement of these laws has been inconsistent.

Note : Discussion is expected before November, 1st 2026, and will be published in the "Civil Engineering Dimension", volume 29, number 1, March 2027.
ISSN : 1410-9530 print / 1979-570X online
Published by : **Petra Christian University**

Traditional PPE monitoring approaches rely on manual examinations or prolonged reviews of surveillance footage, which are labor-intensive and prone to human exhaustion, leading to errors in judgment [13]. To address these shortcomings, researchers have explored sensor-based systems, including radio-frequency identification (RFID) [14], accelerometers [15], and force-sensing resistors [16]. While technically effective, these methods face resistance due to high cost, and worker discomfort linked to privacy and health concerns [17]. This has shifted attention toward computer vision techniques, which offer non-intrusive, cost-efficient, and scalable solutions [18] .

Recent vision-based studies have primarily focused on detecting safety helmets while overlooking other critical PPE items, such as safety shoes, reflective vests, and gloves [19–22]. Attempts to develop multi-class detection frameworks are limited [23–25]. Computer vision methods have clear advantages over sensor-based systems because of their scalability and ability to detect multiple PPE at once [26–28]. However, challenges remain in detecting reflective jackets, as variability in color, texture, and overlap with background features complicate consistent identification in real-life conditions [18,28]. Furthermore, many models rely on small or unbalanced datasets and lack validation on real construction sites, which restricts their generalizability [29].

The YOLO family of object detection models has gained importance in real-time applications owing to its single-stage architecture and high inference speed. Earlier versions, such as YOLOv3 and YOLOv4, have been applied for helmet detection and compliance monitoring [22]. Comparative evaluations indicate that YOLOv5 outperforms its predecessors, achieving up to 140 FPS and offering a model size nearly 90% smaller than YOLOv4, making it well-suited for dynamic construction environments [30-31].

Even though newer versions of the YOLO family, such as YOLOv8 and YOLOv11, have been released, they have introduced improved architectures and greater robustness, resulting in higher mAP scores, which are commonly used to evaluate computer vision models. Higher mAP values indicate both precise identification and correctly drawn bounding boxes, making it a critical metric for PPE detection tasks. In this study, YOLOv5 was selected for its optimal balance of accuracy, computational efficiency, and deployment flexibility. Unlike later versions that require higher processing power and often rely on proprietary or closed training pipelines, YOLOv5 offers a fully open-source solution, allowing easier customization, reproducible testing, and smooth deployment on low-compute edge devices. These conditions closely reflect real construction site environments. Furthermore, YOLOv5's stability, extensive documentation, and validated community benchmarks make it a reliable foundation for research that prioritizes accuracy and real-time performance. This makes it ideal for real-time monitoring applications in dynamic site environments[32–35] . Thus, YOLOv5 provides the most practical balance between technological advancement and field implementation for the intended application of automated PPE compliance monitoring in the construction industry. But even with this progress, there are still gaps. Most studies still lack balanced attention across the full range of PPE categories and rarely incorporate stakeholder-informed prioritization [36-44].

To address these gaps, this study presents a stakeholder-driven PPE monitoring framework that integrates systematic evidence, field input, and engineering adaptations to provide a deployable solution for construction sites. The contributions of this study are as follows: (1) stakeholder-informed prioritization of critical PPE (helmets, reflective vests, safety shoes) obtained from a semi-structured survey of industry professionals and used to shape model classes and operational thresholds; (2) conception and selection of a hybrid dataset (open-source and real construction site images) in line with the suitability for construction sites; (3) a set of data-handling and training adaptations (class-balancing augmentation, anchor recalibration for PPE size distributions, targeted augmentations for reflective clothing, and occlusion robustness) that tailor a YOLOv5s backbone to construction site environments; and (4) a practical system integration pipeline that implants the detector into existing CCTV streams and a real-time alerting mechanism for compliance enforcement. These elements together form the methodological bundle. The proposed solution is shaped by actual industry demands and has been refined for practical field application, which helps extend its relevance and effectiveness in diverse operational settings.

METHODS

The research methodology was intended to combine theoretical rigor with practical applicability and was carried out in three sequential phases: a Systematic Literature Review (SLR), an Industry Survey, and Model Development, as shown in Figure 1. This combined workflow ensured that the proposed system for automated PPE compliance detection was both scientifically grounded and aligned with the requirements of real-world construction.

Systematic Literature Review

An SLR was conducted using the PRISMA framework to build a structured understanding of automated PPE compliance detection in construction. The Scopus database was queried using the following search string: TITLE-

ABS-KEY("computer vision" OR "YOLO" OR "deep learning") AND TITLE-ABS-KEY("construction safety" OR "personal protective equipment" OR "PPE") AND (LIMIT-TO (LANGUAGE, "English"). This process initially gave back 140 records, which were systematically screened to remove duplicates and non-relevant entries, resulting in 61 studies for the final analysis. From these studies, several key insights were derived, including the identification of research gaps in PPE detection, benchmark metrics reported for other YOLO models, and an overview of the critical PPE categories that have been most frequently examined in prior studies. These outputs were not only essential for mapping the state of the art, but also directly guided the formulation of survey questions and informed the selection of dataset classes for model development.

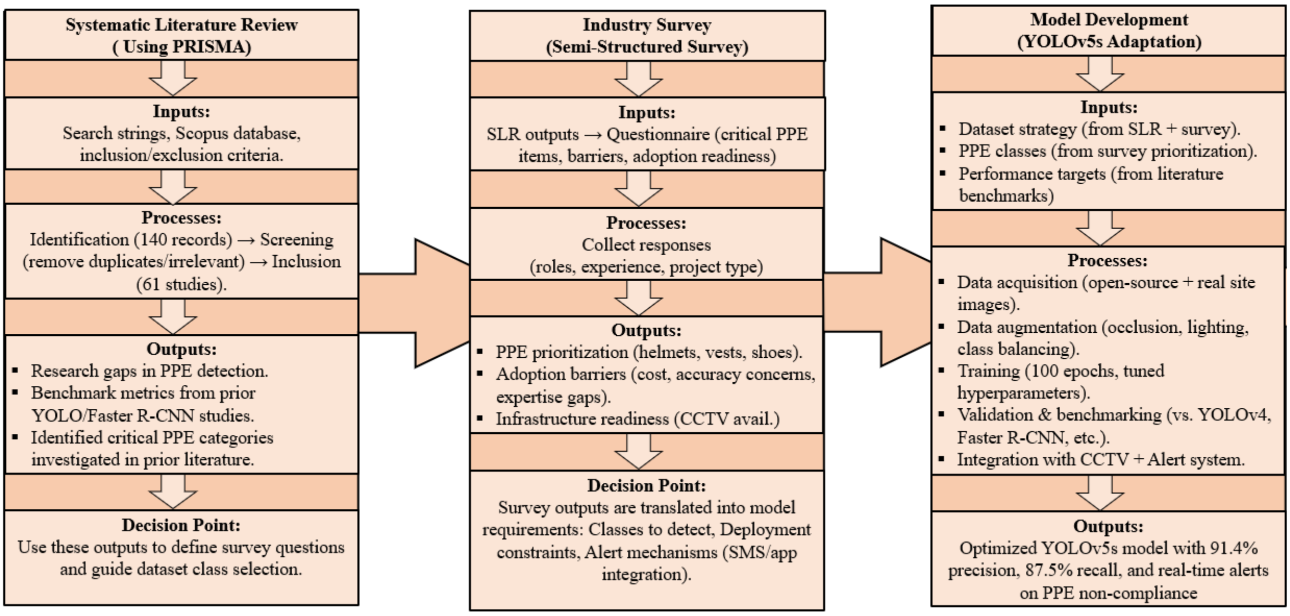

Figure 1. Integrated Methodological Workflow for YOLOv5-based PPE Detection System

Industry Survey

The second phase of the methodology involved a semi-structured survey that combines fixed-choice items with open-ended questions, allowing respondents to provide both quantitative ratings and qualitative insights designed to translate the findings of the literature review into industry-grounded requirements for PPE compliance monitoring, as summarized in Table 1. Based on the outputs of the SLR, a survey questionnaire of 15 questions: 12 closed-ended items using a 5-point Likert scale and 3 short open-response questions, was developed to assess critical PPE items, barriers to adoption, and readiness for technology integration. The survey was conducted in March 2025 among 74 construction professionals in and around Pune, who were engaged through purposive sampling via professional networks.

The target group of professionals was selected using purposive sampling, targeting individuals with direct execution and safety responsibilities. Inclusion criteria required respondents to (i) be employed full-time on an active construction project, (ii) have at least two years of experience, and (iii) hold a role involving safety supervision, site management, or daily coordination (project managers, site engineers, safety officers). This ensured that the responses reflected informed stakeholder perspectives rather than general opinions. The survey took approximately 5 to 7 minutes to complete and was administered online over four weeks. Responses provided key insights: safety helmets, reflective vests, and safety shoes emerged as the highest-priority PPE items for monitoring. Barriers included cost constraints, accuracy concerns, and a lack of expertise at the site. Approximately 78% of participants reported that CCTV infrastructure was already in place, although AI integration remained limited. These insights were systematically translated into model requirements that defined detection classes (helmet, vest, and shoes), deployment constraints (lightweight models for low-compute edge devices), and alert mechanisms.

The survey focused on five core aspects.
(i) Awareness and perception of computer vision in safety monitoring.
(ii) Flexibility of professionals/organizations in adopting automated PPE compliance systems.
(iii) Infrastructure readiness, particularly the availability of CCTV and surveillance networks.
(iv) Critical PPE prioritization, identifying items that are most essential for the safety of the worker.

(v) Adoption challenges and investment willingness, assessing barriers such as cost, technical expertise, and accuracy concerns.

Table 1. Structure and Execution Framework of the Semi-Structured Survey

Parameter	Details
Type of Survey	Semi-Structured Questionnaire-Based Survey
Target Group	CRIP Industry Professionals (Project Managers, Safety Officers, Site Engineers) of Pune
Sample Selection	Purposive sampling
Participant's Experience	2 to 20 years in construction site and safety management
Mode of Survey	Online (Google Forms)
Number of Participants	74
Number of Questions	15
Average Time to Complete	5 to7 minutes
Survey Execution Timeline	Conducted over 4 weeks across various construction sites in Pune (March 2025)
Evaluation Parameters	Awareness of computer vision, critical PPE prioritization, infrastructure readiness, and flexibility to adapt
Purpose of Survey	To identify stakeholder-led critical PPE elements and assess the feasibility of integrating automated computer vision–based PPE detection in real construction environments.

Although Pune represents one of India's mature real estate and construction sectors, the findings revealed that while 78.3% of respondents reported having CCTV systems, only 4.9% had adopted AI-integrated surveillance. Safety helmets (98.6%), safety shoes (87.8%), and reflective vests (75.7%) were consistently ranked as the most critical PPE items, directly informing the model prioritization approach. Additionally, more than 70% of the participants expressed willingness to invest in AI-based PPE detection if the systems were cost-effective and consistent, with 45.9% showing interest in pilot programs. These understandings establish both the necessity and feasibility of developing a scalable, real-time PPE monitoring framework.

Model Development

Based on the SLR and survey findings, a YOLOv5s-based object detection model was developed to monitor PPE compliance. The composition of the dataset is presented in Table 2. The model development workflow included the following steps:

(i) Data acquisition and preprocessing: images were selected from the open-source Kaggle [45] datasets and real construction sites. The data were annotated and pre-processed by normalizing the inputs, resizing them to 640 × 640 pixels, and applying augmentation techniques to enhance robustness.

(ii) Model Training and Optimization: YOLOv5s was fine-tuned using PyTorch [46] to balance the detection accuracy and inference speed. The optimizations included cross-entropy loss for classification and IoU loss for localization.

(iii) System Integration: The trained model was implanted into existing CCTV networks to analyze live video streams for PPE compliance.

(iv) Real-time Detection and Alerts: The system identified safety helmets, vests, and shoes, assigned confidence scores, and triggered instant alerts (audio and SMS) in case of violations.

(v) Validation and Testing: The model was evaluated under various site conditions in Pune, including low-light and cluttered environments, to ensure consistency.

The YOLOv5s architecture consists of three modules: a CSPNet-based backbone for efficient feature extraction, PANet neck for multi-scale feature fusion, and a detection head with anchor boxes for bounding box regression and classification [45,46]. The developed model enabled rapid and efficient multi-class detection while maintaining minimal computational need. Experimental evaluation demonstrated that the model sustained an implication speed of approximately 140 FPS on the Tesla V100 GPU, achieving a mAP between 44% and 52%, depending on dataset variability. Due to its compact structure of nearly 15 MB and accelerated training performance relative to earlier YOLO versions, the model exhibits strong potential for real-time monitoring applications at resource-constrained construction sites.

Table 2. Dataset Statistics

SrL No.	Item	Value
1	Total images (2 + 3 + 4)	2,400
2	Training images	1,600
3	Validation images	400
4	Test images	400
5	Open-source images (count)	1,600
6	In-situ (self-collected) images (count)	800
7	Total annotated instances (helmet)	2,700
8	Total annotated instances (vest)	2,100
9	Total annotated instances (shoes)	1,800
10	Per-class ratio (7: 8: 9)	1.0: 0.78: 0.67
11	Annotation tool	CVAT (Computer Vision Annotation Tool)
12	Annotation QC	Double annotation on 10% subset; Cohen's κ = 0.85

YOLOv5s was selected for its optimal balance of inference speed, lightweight architecture, and competitive detection accuracy in real-time applications [35]. Its small model size and capability to deliver over 100 FPS render it well-suited for deployment in existing CCTV-based monitoring systems. To adapt YOLOv5s for PPE detection in construction environments, several dataset-specific and task-oriented modifications were implemented to ensure the framework moved beyond a regular application.

(i) Anchor recalibration: The anchor configurations were redefined according to the bounding-box distribution in the training dataset, enhancing the localization precision for small PPE elements such as helmets and safety shoes.

(ii) Class balancing and augmentation: To mitigate moderate class imbalances, particularly for diminished categories like safety shoes, targeted data augmentations were applied, including scaling, photometric distortions, and synthetic occlusions. Additionally, standard mosaic and rotational transformations were utilized to strengthen model generalization.

(iii) Illumination and occlusion robustness: Reflective vests and helmets often exhibit variations in brightness and glare; the training pipeline incorporated brightness variation, shadow overlays, and partial occlusion simulation to improve detection reliability under complex lighting conditions.

(iv) Optimization and inference calibration: Key hyperparameters like the learning rate, Stochastic Gradient Descent (SGD) momentum, and weight decay were optimized using the validation performance. The non-maximum Suppression (NMS) thresholds and per-class confidence levels were fine-tuned to minimize false detections in cluttered scenes. Mixed-precision training and early stopping strategies were employed to achieve faster convergence and prevent overfitting.

These targeted modifications enhanced the model's stability and reliability when deployed in real-world construction settings, particularly in areas where lighting variability, worker overlap, and PPE occlusion occur frequently.

RESULTS AND DISCUSSION

Dataset Utilization

The dataset used in this study was designed to balance statistical diversity with real-world representativeness, as shown in Table 2. A total of 2,400 images were used, comprising 1,600 publicly available images sourced from established open-source repositories (including Kaggle and PPE detection datasets) and 800 images collected directly from active construction sites. This hybrid composition ensured that the model was exposed to both controlled benchmark scenarios and complex field conditions.

The dataset was split into 1,600 training images, 400 validation images, and 400 test images, following a standard 67:17:17 ratio to support robust learning and unbiased evaluation. Annotation focused on three stakeholder-prioritized PPE classes, which are safety helmets (2,700 instances), reflective vests (2,100 instances), and safety shoes (1,800 instances), resulting in a class ratio of 1.0:0.78:0.67. Although a slight class imbalance was present, it reflects actual site conditions where certain PPE items are less consistently worn.

All images were annotated using the CVAT. To ensure annotation reliability, a double-annotation quality check was conducted on a randomly selected 10% subset of images, yielding a Cohen's κ value of 0.85, which indicates strong inter-annotator agreement.

The in-situ images were intentionally captured under varying lighting conditions, shadows, occlusions, and cluttered backgrounds, thereby enhancing the dataset's ability to represent the uncontrolled and dynamic nature of construction environments.

Training Outcomes

The YOLOv5s model was trained for 100 epochs using an NVIDIA RTX 3090 GPU with a batch size of 16 and an input resolution of 640 × 640 pixels. Beyond reporting training configurations, learning effectiveness was evaluated using both training and validation metrics to assess convergence behavior and generalization.

Across epochs, training and validation loss curves exhibited a consistent downward trend, with no observable divergence between the two, indicating stable learning and the absence of overfitting. Validation mAP values plateaued after approximately 70 epochs, suggesting that the model reached performance saturation without excessive parameter tuning. This behavior confirms that the combination of data augmentation, class-aware sampling, and anchor recalibration contributed to controlled model generalization rather than memorization.

In addition to offline evaluation, the trained model was integrated into a live inference pipeline. During validation testing, the system successfully generated real-time alerts for missing PPE, confirming that the trained weights were not only numerically optimal but also operationally viable. The visual outputs presented in Figures 2 and 3 further demonstrate that detection confidence remained stable across different site conditions, reinforcing the model's readiness for real-world deployment.

Model Performance

To evaluate the performance of the proposed YOLOv5s-based PPE detection framework, a comparative benchmark analysis was conducted against previous YOLO model versions, as summarized in Table 3. YOLOv3 and YOLOv4 serve as classical benchmarks for real-time object detection, with YOLOv3 achieving a mAP@0.5 of 57.9% at an inference speed of 22 FPS using the Darknet-53 backbone. The standard YOLOv4 model improved this performance to 65.7% mAP@0.5 and 65 FPS, owing to its CSPDarknet-53 backbone. An enhanced YOLOv4 variant optimized for construction helmet detection achieved 92.78% mAP and 86.35% recall, although its inference speed was limited to approximately 43 FPS due to increased computational load [47-49].

In contrast, the newer YOLOv8 family demonstrates higher accuracy but at the cost of increased model complexity. The YOLOv8-small variant achieved 90.7% mAP and 93% precision, whereas YOLOv8-medium achieved 91.5% mAP and 92.3% precision [50]. However, these architectures have bigger model sizes and higher inference overheads, making them less suited for low-latency edge deployment in construction surveillance systems compared to the proposed YOLOv5s model. The model achieved 86.5% mAP@0.5, 91.4% precision, and 87.5% recall, and operated at approximately 140 FPS with a compact architecture ideal for CCTV integration. Although its accuracy is marginally lower than that of YOLOv8, its superior real-time speed and lightweight design make it more practical for large-scale deployment in resource-constrained site environments. This comparison validates YOLOv5s as an optimal trade-off between detection performance, inference speed, and deployment feasibility for monitoring construction safety in real-world environments.

Although the YOLOv5s model exhibited consistently high detection accuracy, a detailed analysis of the test outcomes revealed several performance limitations that offered valuable insights for future enhancements. The majority of missed detections were linked to small or distant PPE objects, accounting for roughly 18 to 20% of the false negatives. These errors mainly occurred when items such as helmets appeared disproportionately small within the frame, making accurate localization more difficult. An additional 12 to 15% of false negatives were attributed to partial occlusion, particularly in scenarios where PPE was obscured by construction materials, scaffolding, or overlapping workers. These cases highlight the visual complexity of real construction environments and underscore the challenge of detecting PPE under non-ideal visibility conditions.

In contrast, false-positive cases were less frequent, comprising approximately 10% of the total misclassifications. These mainly stemmed from visually complex environmental backgrounds, such as reflective surfaces, safety boards, or brightly coloured equipment that resembled reflective vests or other PPE components.

Overall, these findings align with prior studies where YOLO-based PPE detectors, despite achieving mAP exceeding 90%, reported similar challenges in handling small object detection and occlusion-prone scenarios within active construction environments.

Table 3. Comparative Performance of YOLO Models

Model Version	mAP@0.5 / Accuracy (%)	Precision (%)	Recall (%)	Inference Speed (FPS)	Model Size / Notes	Reference
YOLOv3	57.9	–	–	22	Baseline Darknet-53; standard object detection	[13]
YOLOv4	65.7	–	–	65	Model size 243.92, CSPDarknet-53; standard object detection and testing	[49]
YOLOv4 (improved version)	92.78	–	86.35	~ 43	Model size 41.88 MB, helmet detection use-case	[49]
YOLOv8 (small)	90.7	93	84.4	-	Model size ~16 mb	[50]
YOLOv8 (medium)	91.5	92.3	87	-	Model size ~25.9 mb	[50]
Proposed YOLOv5s	86.5	91.4	87.5	~140	Compact size, CCTV deployment ready	This Study

To address these limitations, targeted improvements were implemented, including synthetic occlusion augmentation, brightness normalization, and testing with higher input resolutions (up to 1280 × 1280 pixels) for enhanced small-object detection. To further enhance real-time detection stability, future versions of the model will incorporate temporal consistency filtering across successive frames. This approach aims to reduce frame-level noise and improve inference stability by leveraging information continuity over time. Such temporal smoothing techniques reinforce the field applicability of the model while outlining practical directions for its refinement.

Figure 2. (a) Single Worker Carrying Rebar, (b) YOLOv5s Detection Output Showing Identified Helmets and Vests with Confidence Scores, (c) Multiple Workers at a Reinforced Concrete Pouring Site, (d) YOLOv5s Detection Output Identifying Helmets and Vests with Confidence Scores, (e) Multiple Workers Engaged in Concrete Placement, (f) YOLOv5s Detection Output Highlighting Helmets, Vests, and Boots of Multiple Workers with Confidence Scores

Contribution in Relation to State of the Art

While prior studies have primarily focused on helmet detection [19–21], often neglecting vests, shoes, and gloves, this study demonstrates a multi-class PPE detection framework grounded in stakeholder-defined safety priorities. Unlike sensor-based approaches (RFID, accelerometers) that suffer from cost and worker resistance, the proposed computer vision model integrates seamlessly with existing CCTV systems, offering a non-intrusive, scalable solution. Compared to earlier YOLO versions and other single/multi-stage detectors, YOLOv5s shows a superior speed–accuracy trade-off, making it practical for large-scale deployment in dynamic construction environments.

These contributions go beyond simply copying existing work by delivering a framework that is guided by stakeholder needs, technically authorized, and scalable for real-time use. It effectively bridges the gap between academic AI research and practical applications in construction safety management.

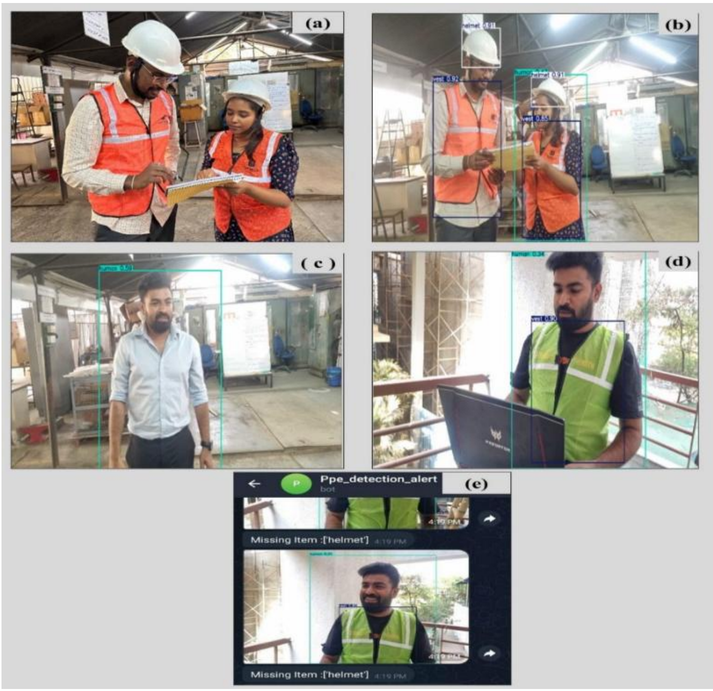

Figure 3. (a) Team Members Wearing Safety Helmets and Reflective Vests, (b) YOLOv5s Detection Output Showing Team Members Labelled with Helmets and Vests, Including Confidence Scores, (c) A Team Member without a Safety Helmet was Detected by the PPE Monitoring System, (d) Detection of a Team Member without a Helmet but Wearing a Vest, (e) Mobile Alert from the PPE Detection System Indicating a Missing Helmet

CONCLUSIONS

This study presents a practical and scalable framework for automated PPE compliance monitoring in construction by combining computer vision with industry insights. Through a literature review and surveys with professionals, key challenges such as cost, limited technical know-how, and infrastructure readiness were identified, while emphasizing the critical need for helmets, reflective vests, and safety shoes on-site. The YOLOv5s detection model was developed and validated using open-source and real-field images, achieving an mAP@0.5 of 86.5%, a precision of 91.4%, and a recall of 87.5%. The model operates at approximately 140 frames per second with a latency of 7 milliseconds, supporting efficient real-time monitoring.

Beyond the quantitative performance, the primary contribution of this study is methodological. It bridges the gap between academic object-detection research and on-site operational needs by (i) translating survey-based stakeholder priorities into defined model classes and alert thresholds, (ii) curating a field-representative, quality-controlled dataset, and (iii) applying targeted engineering adaptations to enhance the robustness of the model under real-world conditions. Theoretically, the study contributes to PPE-focused computer vision research by demonstrating how practitioner-driven class definitions, dataset structuring, and deployment constraints can systematically inform model design, thereby extending existing knowledge on the real-world detection generalizability. Practically, the findings highlight a replicable pathway for contractors and safety managers to operationalize low-cost, real-time computer vision systems within current site workflows, reducing manual supervision effort and enabling data-driven safety compliance management. Collectively, these elements establish a deployable, scalable, and resource-efficient framework designed for real-time PPE compliance in diverse construction environments.

Although the model performs reliably in various scenarios, certain limitations persist, particularly under low-light conditions, partial occlusions, and high worker density. Future research will focus on expanding detection capabilities to additional PPE items, such as gloves and goggles, integrating multimodal IoT and sensor data for richer situational awareness, and optimizing deployment for low-compute edge devices.

ACKNOWLEDGEMENT

This research was made possible through the valuable support and active participation of industry professionals who contributed at the grassroots level to ensure the practicality and effectiveness of the developed model. The author extends their sincere gratitude to Tarun K., Chinmay Kavatagimath, Shivani Radhakrishna, and Hruthik R. for their key contributions in facilitating data collection, providing site-level insights, and assisting in validating the system under real-world construction conditions. Their involvement was instrumental in bridging the gap between research and field implementation.

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