



UAV-based automated monitoring of personal protective equipment compliance on construction sites: a field performance evaluation

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Abstract. Ensuring compliance with personal protective equipment (PPE) requirements remains one of the most persistent challenges in construction site safety management, and conventional manual inspection struggles to provide continuous, site-wide coverage. This study evaluates the field performance of an unmanned aerial vehicle (UAV)-based monitoring system that combines drone imagery with computer vision to automatically verify PPE compliance among construction workers. The object of the study is construction-related PPE, and the subject of the study is the effectiveness of its detection by computer vision using a UAV camera. The system developed by the authors was tested using a DJI Matrice 4E UAV (Da-Jiang Innovations Science and Technology Co., Ltd., Shenzhen, China) at an active construction site. Based on the resulting video recordings, a dataset of more than 500 high-resolution images was compiled and manually annotated to support training and evaluation. Field performance was assessed across four scenarios monitoring four to seven PPE items simultaneously, using the percentage of matches against manually annotated reference images, descriptive statistics, and trend analysis, and the results were discussed against comparable field and benchmark studies. The average number of correctly detected objects ranged from 3.75 to 5.75 across the four scenarios, corresponding to a relative detection rate of 82.1% to 93.8% of each scenario's maximum, with a coefficient of variation not exceeding 17.8%, supporting the system's potential as a continuous, site-wide complement to manual safety inspection.

Keywords: construction safety, personal protective equipment, unmanned aerial vehicle, occupational health and safety monitoring, computer vision.

1. Introduction

The construction industry is one of the key drivers of national economic development, and occupational health and safety (OHS) remains a critical factor in determining the productivity, sustainability, and competitiveness of construction companies [1]. In Kazakhstan, particularly in the city of Astana, the rapid growth of high-rise construction, fast-changing site conditions, strong wind loads, and significant temperature fluctuations call for innovative systems capable of monitoring hazardous workplace factors directly on site. Traditional approaches to occupational safety management rely on technical regulations, normative documents, construction standards, and periodic inspections, and although effective safety management improves productivity, reputation, and investment appeal, unsafe conditions continue to cause workplace injuries, occupational diseases, and reduced process efficiency [2]. Construction companies therefore need proactive digital tools for continuous monitoring and forecasting of occupational risk, ranging from wearable sensors to vision-based monitoring systems [3].

International OHS management models, such as the UK's HSE model [4], the U.S. OSHA approach [5], and the model of the Korea Occupational Safety and Health Agency (KOSHA) [6], provide an important regulatory framework for worker safety, but rely primarily on periodic

inspections, record-keeping, and retrospective analysis of incidents, whose effectiveness can be limited on large, highly dynamic sites where risk varies within a single shift. Modern safety management thinking instead emphasizes digitalization, safety culture, and automated monitoring as complements to inspection-based regimes, although practical adoption requires investment in digital infrastructure and personnel training.

Traditional fixed video surveillance and manual inspection do not always provide adequate coverage of large construction sites, high-rise structures, and remote production zones. Unmanned aerial vehicles (UAVs), combined with artificial intelligence, offer a promising approach to occupational safety monitoring in Kazakhstan's construction industry [7]: autonomous drones can conduct regular site inspections, automatically detect PPE violations, and transmit data for near-real-time analysis [8], reducing reliance on manual inspection and providing access to hazardous or hard-to-reach areas [9]. Integrating detection results with contextual parameters, such as workers' location and shift duration, can further support dynamic risk profiling and a shift from reactive to predictive safety management [10].

The object of this study is personal protective equipment (PPE) for workers at construction sites; the subject is the process of automatically detecting PPE elements in UAV imagery and evaluating the effectiveness of the developed software in recognizing protective equipment under real-world construction conditions. Despite the mandatory use of PPE, violations related to the absence or improper use of safety helmets, high-visibility vests, and safety footwear remain among the leading causes of workplace injury in construction [11]. Traditional compliance monitoring is carried out by safety specialists, is time- and labor-intensive, and, being periodic, cannot provide continuous supervision of all workers on site. Advances in UAV technology, computer vision, and deep learning are creating new opportunities to automate this process, allowing near-real-time detection of workers and their PPE status [12].

Deep learning object detectors, most notably successive versions of the YOLO architecture, have been applied to PPE and hazard detection with reported accuracy exceeding 90% for helmet and vest detection under favorable conditions [12]. Building on this foundation, Kim and Park [13] combined YOLO-based detection with hazardous-area monitoring; Hayat and Morgado-Dias [14], Wu et al. [11], and Fang et al. [15] developed and benchmarked hard-hat detection models, including one of the few benchmarks based on far-field surveillance footage rather than close-range imagery; and Zhang et al. [16] and Han et al. [17] extended detection to face masks and used attention mechanisms to improve robustness to the partial occlusion typical of active work areas. Wang et al. [18] and Lung and Wang [19] evaluated detection speed and accuracy under real construction-site deployment rather than curated benchmark datasets alone, which is the more demanding and practically relevant test for a site-safety tool. In parallel, computer vision has been used to track unsafe worker behavior and posture [20], [21], [22] and to identify hazardous zones and worker proximity to hazards [9], [23]. Because the present study also uses a QR code to identify individual workers, it draws on a further, smaller body of work on robust QR-code recognition under difficult outdoor imaging conditions [24], [25].

A recent systematic review of computer-vision-based PPE compliance in industry practice [26] reports steady progress in detection accuracy alongside persistent field challenges, including occlusion, small object size, and variable outdoor lighting, and calls for more evaluation under real operating conditions rather than curated benchmark datasets. From a construction-management perspective, such systems are best understood not as a replacement for site safety personnel, but as a continuous, site-wide complement to periodic manual inspection, supporting the shift toward proactive, data-driven safety management discussed above. Despite the growing body of technical work, evidence on how such systems perform when deployed on an active construction site, across a realistic range of simultaneously monitored PPE classes, remains limited, and few studies discuss their field results against the accuracy levels reported elsewhere in the literature. Therefore, the goal of this study is to evaluate the field performance of software developed by the authors for the automatic detection of PPE worn by construction site workers, based on UAV imagery, to compare

this performance against related studies, and to identify the factors affecting recognition accuracy under real-world operating conditions.

As a visual illustration of the proposed approach, Figure 1 presents a conceptual storyboard for the intelligent monitoring system's presentation video, fully generated by the Gemini 3.6 AI (Google LLC, Mountain View, CA, USA) according to the authors' technical specifications, demonstrating the end-to-end operational stages of the algorithm, from panoramic site scanning and the detection of fully equipped personnel, complete with confidence-score bounding boxes, to the automatic logging of safety violations.

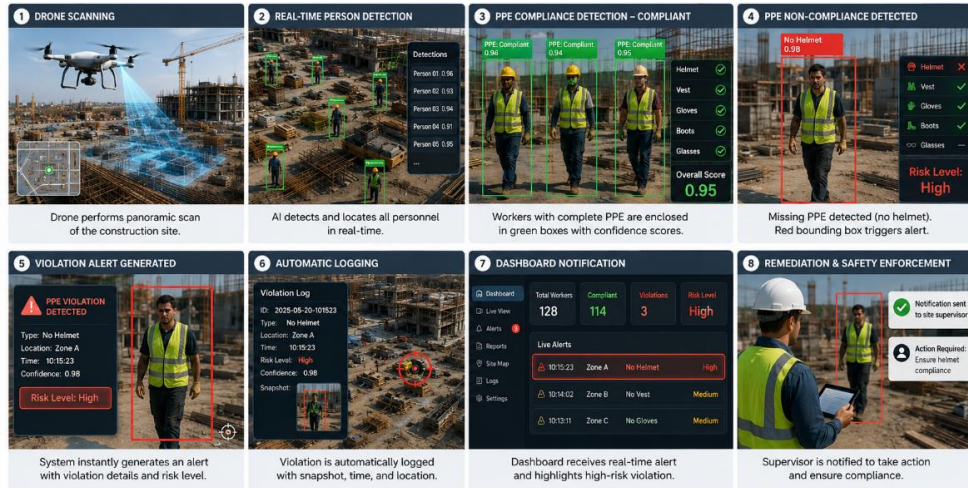


Figure 1 – AI-generated storyboard showcasing real-time PPE detection and violation logging workflows

2. Methods

The system evaluated in this study is intended to be flown as part of a routine site safety walk, supplementing the areas and shifts that manual inspection cannot continuously cover. It comprises proprietary software, “Intelligent System Based on Artificial Intelligence for Automatic Monitoring of Personal Protective Equipment Use at Construction Sites” (Copyright No. 76402, dated July 10, 2026), developed by the authors as part of research project AP26198207 [7], together with a DJI Matrice 4E UAV (Da-Jiang Innovations Science and Technology Co., Ltd., Shenzhen, China). The software uses computer vision and deep learning to detect workers and their PPE from UAV-captured photo and video footage; its modular architecture also supports facial recognition, site access control, and personnel condition assessment, so that it can operate either as a standalone PPE-monitoring tool or as part of a broader site safety management system.

The study targeted the four PPE items most commonly required on construction sites that are most frequently implicated in PPE-related safety violations: construction hard hat, high-visibility vest, protective gloves, and safety footwear. All PPE used during the experiments complied with current standards [27]; the applicable regulatory documents for each item are listed in Table 1.

Table 1 – Key characteristics of the PPE used

PPE	Purpose	Key Features	Regulatory Document
Safety helmet	Protecting the head from physical impacts	Shock absorption, puncture resistance, temperature resistance, lightweight, adjustable headband	[28], [29]
High-visibility safety vest	Improving an employee's visibility	Fluorescent material, reflective strips, high visibility during the day and at night	[30]
Safety footwear	Protecting the foot from mechanical injury	Safety toe cap, slip-resistant sole, puncture resistance, abrasion resistance	[31]
Protective gloves	Protecting the hands from mechanical and other hazards	Abrasion resistance, puncture resistance, flexibility, grip	[32]

These items were selected as detection targets because they are mandatory on most sites and possess visual characteristics well suited to computer-vision recognition [12], while differing sufficiently in size, shape, and color to allow a meaningful assessment of detection performance across object classes (Table 2). Three additional classes, safety goggles, protective masks, and a QR code used for worker identification, were introduced progressively in scenarios T2 through T4 (Section 3) to test how performance scales with the number of simultaneously monitored objects.

Table 2 – Visual characteristics of detected objects

PPE	Typical form	Primary Colors	Detection Features
Safety helmet	Hemispherical	White, yellow, red, blue, orange	Small size; partial overlaps are possible
High-visibility safety vest	Rectangular (following the body's contours)	Lemon or orange with reflective stripes	Clearly visible during the day and at night
Safety footwear	Low-top/high-top shoes	Black, brown	The most difficult object to detect due to its small size and frequent occlusion by other objects
Protective gloves	Hand-shaped, five-fingered	Orange, yellow, gray, black	Small, articulated shape; frequently occluded by tools or the worker's body position
Safety goggles	Small oval or rectangular lens shape	Clear, tinted, or dark frame	Very small object; low contrast against skin or helmet, easily occluded
Protective mask	Small curved shape covering nose and mouth	White, blue, black	Very small object; frequently occluded by the helmet strap or camera angle
QR code	Square, high-contrast pattern	Black and white	Fixed, rigid geometric pattern; more reliably distinguishable than the other classes due to its non-organic shape

Experimental data were collected with a DJI Matrice 4E UAV (20 Megapixels camera, 4K video, three-axis gimbal, up to 49 min flight time, GNSS/RTK positioning, up to 56× hybrid zoom), selected for the image quality and repeatable flight paths needed to reliably resolve small PPE items such as gloves and goggles. Video was recorded at an active construction site during ongoing construction and installation work, in daytime and evening light and including snow-covered conditions, both in open site areas and inside buildings under construction. Individual frames were extracted automatically, deduplicated, and compiled into a dataset of more than 500 images (3840×2160 pixels) spanning a range of distances, viewing angles, worker postures, and partial occlusion by structures or other workers, to reflect realistic monitoring conditions.

Images were manually annotated using the same software (Figure 2) with the classes Person, Helmet, Vest, Goggles, Mask, Gloves, Boots, and QR Code, recording the presence or absence of each PPE class per worker. The four core classes (Helmet, Vest, Gloves, Boots) were annotated in all images; Goggles, Mask, and QR Code were added for the relevant scenarios only. The annotated dataset was then split into training, validation, and test sets for model training and evaluation.

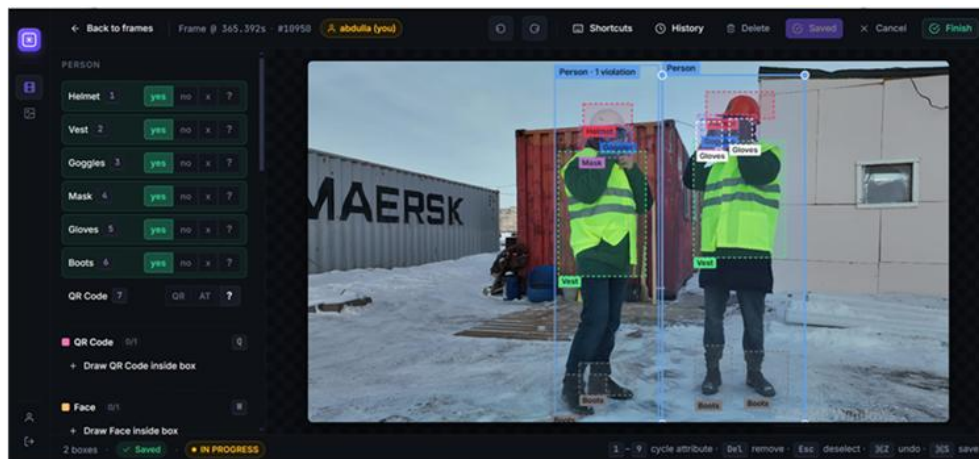


Figure 2 – User interface of the developed software for manually segmenting images and annotating objects using bounding boxes

Field tests (Figure 3) were conducted at the same site under real operating conditions, using fixed survey points that varied in distance from workers, viewing angle, and background. At each point, the UAV hovered and recorded video for a fixed duration before moving to the next point. The flight path and the sequence of survey points were held constant across all test series, and each checkpoint was surveyed at least three times to reduce the influence of random factors. For each flight, the software recorded the number of correctly detected PPE items, missed detections, and false positives.



Figure 3 – DJI Matrice 4E UAV and construction site workers before an experimental video recording session inside a building under construction

Detection performance was verified against a manually annotated reference set, using the percentage of agreement between automatic and ground-truth annotations for each scenario. Although standard metrics such as precision, recall, and mean average precision are more common in the computer-vision literature [33], a percentage-of-match metric was adopted here because it more directly reflects the practical question of interest to site safety management, namely, what share of the required PPE items are correctly flagged per inspection round:

$$P = N_{\text{correct}} / N_{\text{total}} \times 100\%, \quad (1)$$

where: P is the percentage of detection agreement, %; N_{correct} is the number of correctly detected objects; N_{total} is the total number of objects in the reference sample.

For each of the four scenarios, the number of correctly detected objects was recorded over 20 consecutive measurements, and the resulting series was examined for temporal trends. Descriptive statistics, mean, standard deviation, and coefficient of variation, were then calculated for each scenario to quantify central tendency and variability, and detection rates were additionally expressed relative to each scenario's maximum possible count to allow comparison across scenarios monitoring different numbers of PPE classes.

3. Results and Discussion

Figure 4 presents the number of correctly detected PPE items over 20 consecutive measurements for four scenarios: T1, detection of 4 items (safety helmet, high-visibility vest, protective gloves, safety footwear); T2, 5 items (adding safety goggles); T3, 6 items (adding a protective mask); and T4, 7 items (adding a QR code used to identify the worker).

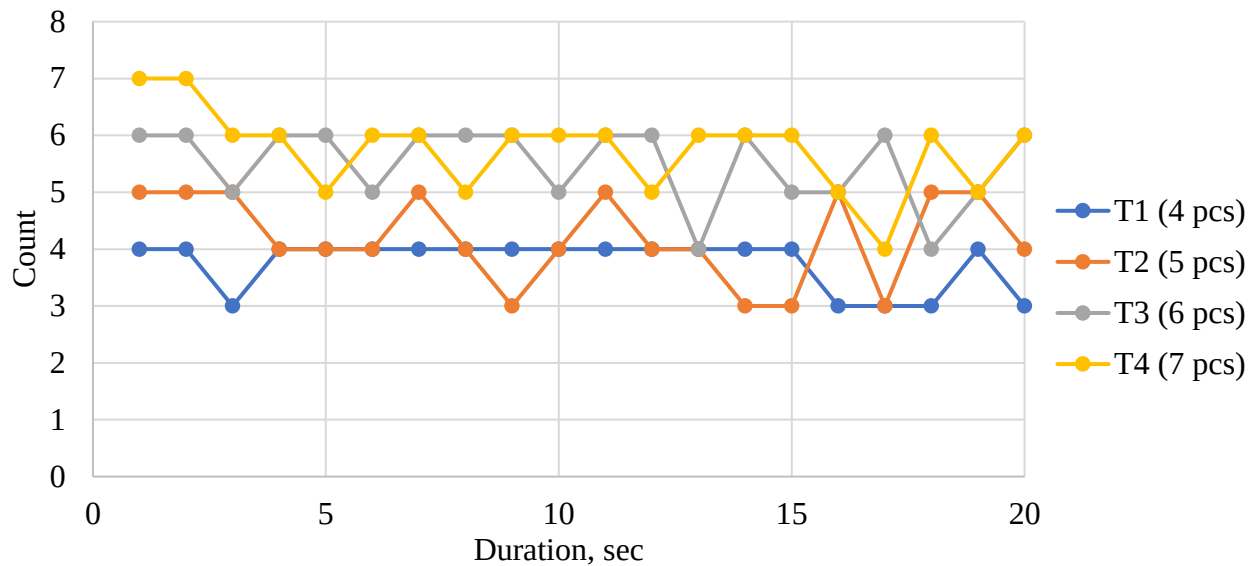


Figure 4 – Number of correctly detected pieces of PPE over 20 consecutive measurements for scenarios T1–T4

In Scenario T1, correctly detected objects ranged from 3 to 4; in T2, from 3 to 5; in T3, from 4 to 6; and in T4, from 4 to 7. Expressed as a percentage of each scenario's maximum, detecting 3 or 4 objects in T1 corresponds to 75% or 100%; the observed ranges in T2, T3, and T4 correspond to 60–100%, 66.7–100%, and 57.1–100%, respectively.

The frequency with which each scenario reached its own maximum, rather than only its range, distinguishes the scenarios more sharply than the ranges alone suggest. Detection reached the full scenario maximum in 75% of measurements for T1 (15 of 20) and 60% for T3 (12 of 20), but in only 40% for T2 (8 of 20) and 10% for T4 (2 of 20): full-set recognition became markedly less frequent as more, generally smaller, object classes were added, even though the shortfall rarely exceeded one or two objects at a time. The persistence of below-maximum readings followed the same pattern: in T1 and T3, consecutive below-maximum runs never exceeded three and two measurements, respectively, consistent with genuinely isolated and short-lived dips associated with workers being partially obscured by building structures or changes in position relative to the camera. In T4, by contrast, the software registered fewer than the full seven items for eighteen consecutive measurements, so operating below the theoretical maximum was effectively the norm for that scenario rather than an exception, even though the count itself remained stable at six or seven throughout.

Based on the descriptive statistics in Table 3, the average number of correctly detected objects was 3.75 for T1, 4.20 for T2, 5.50 for T3, and 5.75 for T4. Expressed relative to each scenario's own maximum, the average detection rate was 93.8%, 84.0%, 91.7%, and 82.1%, respectively; performance therefore remained high throughout, with a modest decline as the number of simultaneously monitored PPE classes increased from four to seven. In absolute terms, the standard deviation was highest in T4 (0.70), reflecting the larger number of objects monitored; however, once normalized by the mean, the coefficient of variation was highest in T2 (17.8%), indicating that relative variability was in fact greatest when five objects were monitored rather than seven. The coefficient of variation remained below 20% in all four scenarios, indicating good reproducibility.

Table 3 – Descriptive Statistics of Detection Performance by Scenario

Scenario	PPE items monitored	Mean correct detections	SD	CoV, %	Range	Relative detection rate, %
T1	4	3.75	0.43	11.5	3–4	93.8
T2	5	4.20	0.75	17.8	3–5	84.0
T3	6	5.50	0.67	12.2	4–6	91.7
T4	7	5.75	0.70	12.1	4–7	82.1

To test whether relative detection rate declined systematically with the number of monitored PPE classes, a linear regression was fitted to the four scenario-level relative detection rates against the corresponding item counts (4, 5, 6, and 7). The fitted slope was -2.72 percentage points per additional class ($R^2 = 0.38$); the negative direction is consistent with the pattern in Table 3, but with only four scenario-level observations it did not reach conventional statistical significance ($p = 0.38$) and should be treated as suggestive rather than conclusive. A one-way analysis of variance on the measurement-level relative detection rate (20 measurements per scenario, 80 in total) nonetheless confirmed a statistically significant effect of scenario ($F(3,76) = 4.33$, $p = 0.007$), indicating that the differences between scenarios visible in Table 3 are unlikely to reflect measurement noise alone, even though more scenarios would be needed to establish the functional form of the decline with confidence.

These relative detection rates are broadly consistent with the accuracy levels reported for helmet and vest detection under real, rather than curated, construction-site conditions elsewhere in the literature. Hayat and Morgado-Dias [14], Wu et al. [11], and Fang et al. [15] each report hard-hat detection accuracies above 90%, with Wu et al.'s benchmark reaching 83.89% mean average precision on far-field surveillance footage, matching the performance observed here for the four- and six-item scenarios (T1, T3), in which the larger, core PPE classes dominate the aggregate count. The comparatively lower relative rates in T2 and T4 (84.0% and 82.1%), both of which add safety goggles to the monitored set, echo the specific difficulty of small, low-contrast items noted by Zhang et al. [16] and Han et al. [17], who found that masks and similarly compact items required attention-based mechanisms to approach the detection accuracy achieved for helmets and vests. By comparison, Kim, Kim, and Jeong [12] report considerably higher mAP50 accuracy, 94.1% for YOLOv5 and 95.1% for YOLOv8, for safety risk factor recognition; however, that dataset was assembled through web crawling rather than captured on an active site, which plausibly explains why its reported accuracy exceeds the field performance observed here even for the best-performing scenarios. Because the present study reports aggregate, rather than per-class, detection counts, it cannot isolate which individual class drives the lower relative rate in T2 and T4 with statistical certainty, a methodological difference from studies reporting per-class precision and recall [16], [17], [33].

The results also support the broader observation, made in the systematic review by Vukicevic et al. [26], that PPE compliance systems tend to perform well under controlled conditions but face a persistent accuracy gap once deployed on active sites, driven by occlusion, variable lighting, and small object size. Wang et al. [18] and Lung and Wang [19] made a related methodological point, arguing that detection speed and accuracy should be evaluated under real deployment rather than curated benchmark datasets alone; the present results, obtained entirely on an active site, support that argument empirically, showing that a coefficient of variation below 20% in every scenario is achievable in field conditions, not only in laboratory settings.

The stability of the QR-code class in Scenario T4 is also noteworthy: unlike organic PPE shapes, a QR code is a fixed, high-contrast, rigid pattern, consistent with reports that such codes remain reliably detectable even under outdoor imaging conditions that degrade detection of irregular objects [24], [25]. This suggests that QR-code-based worker identification could be integrated into UAV-based monitoring with comparatively little additional accuracy risk, even as further PPE classes are added. More broadly, the operational case for UAV-based PPE monitoring rests on coverage and continuity as much as on raw detection accuracy: as argued by Jeelani et al. [9], UAVs extend inspection reach into hazardous or hard-to-access areas independent of detection accuracy, so even the comparatively weaker performance observed in T2 and T4 likely represents a net safety gain relative to the absence of any coverage between manual inspection rounds.

These findings should be read in light of several limitations. Detection counts were recorded in aggregate per scenario rather than per individual PPE class, so the specific contribution of any one class, such as safety goggles, to the lower relative detection rates in T2 and T4 cannot be isolated with statistical certainty; class-level precision and recall would allow a more direct comparison with studies such as [16], [17]. The dataset, although representative of the site studied, was drawn from a single construction site over a limited observation period and does not capture the full range of site

types, structural backgrounds, and extreme weather conditions found across the construction industry. The evaluation also used a percentage-of-match metric rather than standard object detection metrics such as precision, recall, or mean average precision [33], which limits direct numerical comparison with benchmark-based studies, although it was chosen deliberately for its relevance to site inspection practice. Finally, the 20-measurement observation window per scenario, while sufficient to characterize short-term stability and to support the statistical comparison above, does not address longer-term reliability under equipment wear, seasonal extremes, or extended operational use.

4. Conclusions

This study evaluated the field performance of a UAV-based, computer-vision system for verifying PPE compliance on an active construction site. Detection performance remained high across four scenarios monitoring four to seven PPE classes, with a relative detection rate of 82.1–93.8% of each scenario's maximum and a coefficient of variation below 20% throughout, declining modestly and, for the measurement-level relative rate, significantly (ANOVA, $p = 0.007$) as additional, smaller PPE classes were added, consistent with the class-specific accuracy patterns reported elsewhere in the literature.

For construction site management, these results support UAV-based PPE monitoring as a continuous, site-wide complement to periodic manual inspection rather than a replacement for it, particularly for the four core PPE classes that account for most PPE-related violations. Deployed as part of a routine safety walk, such a system can extend inspection coverage, generate a time-stamped compliance record, and support the shift toward proactive, data-informed safety management. These conclusions are nonetheless based on aggregate, not per-class, detection counts from a single site and a comparatively short observation window, and were evaluated using a practice-oriented match-percentage metric rather than standard object detection metrics.

Future work should address these limitations directly: recording per-class detection statistics, benchmarking against precision, recall, and mean average precision, extending data collection across multiple sites and seasons, and integrating the system into a real-time construction safety management platform with automated compliance reporting.

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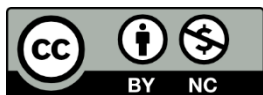
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