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Combining Computer Vision and Drones for Proactive Construction Site Safety Monitoring

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Abstract: Worksite accidents have long been the leading cause of occupational injuries and fatalities worldwide, primarily due to two factors: the open and dynamic nature of the worksite environment and the inadequacy and incompetence of on-site safety managers. Recent advancements in deep learning (DL) and computer vision (CV) offer promising solutions to long-standing challenges in construction safety management. This paper proposes a proactive, real-time monitoring model for construction site safety, inspired by recent research integrating unmanned aerial vehicles (UAVs) with DL-based CV techniques. Specially designed data matrix (DM) tags were affixed to the safety helmets and vests of workers. The model captures DM-tagged images on-site and applies DL-based image recognition algorithms to assess individual risk levels, thereby enabling the implementation of preventive safety measures. Preliminary experimental results show that the model achieved a recall of 97.3% and a precision of 98.3% in worker identification. These findings highlight the practical potential of the proposed approach. The study concludes with a discussion on how the proposed approach could be applied to future advancements in construction safety management.

Keywords: construction safety, UAV, computer vision (CV), proactive site management model.

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1. Introduction

Construction sites are extremely dangerous because of their open and dynamic work environment and because of their fragmented and temporary construction organization, which typically results in no one being responsible for worker safety. This aspect is particularly true for small and medium-sized enterprises (SMEs). In a long-term study from 2000 to 2014 on data from the Construction Industry Accidents Knowledge Platform (CIAKP) of Taiwan, Cheng and Lin (2017) reported that 17% of the fatal accidents during the study period occurred among workers on their first day at the worksite and 38% of these accidents occurred among workers who had been at the worksite for less than 1 month. In a similar study, Lin et al. (2013) reported that 19% of the fatal accidents during their study period occurred among unskilled workers. According to TOSHA (2024), approximately 70% of fatal accidents in the construction industry occur in SME construction firms with 10 or fewer employees. It reveals that workers with different characteristics face varying levels of occupational accident risk.

According to Lin et al. (2013), Cheng and Lin (2017), and Yu et al. (2022) construction site accidents typically occur among workers who have not received adequate safety training, are located in an unfamiliar work environment, or are inadequately protected. Identifying unsafe conditions in relation to specific worker characteristics and issuing targeted alerts are key to the effective prevention of construction site accidents. In the current practice, construction safety monitoring relied on human safety managers. However, according to the current occupational safety and health regulations and site practice, each professional safety manager is required to manage a construction site with numerous workers (MOL, 2025). Similarly, in South Korea, each safety manager is required to monitor the safety of up to 84 workers (Statistics Korea, 2018; KSEA, 2018). Therefore, passively preventing construction site accidents through manual inspections by safety management personnel is impractical and unfeasible. Therefore, a proactive model for construction site safety monitoring is required.

In this study, a proactive construction site safety monitoring model based on computer vision (CV) and drone (or unmanned aerial vehicle, UAV) technology was developed. In the proposed model, UAV are used to conduct aerial inspections and obtain real-time images. Subsequently, CV is used to recognize the identities of the construction workers. After the identity of each worker is confirmed, the risk of a construction site accident is immediately evaluated and predicted, and appropriate hazard prevention measures are taken to avoid accidents.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 explicitly presents and discusses the research problems. Section 4 describes the proposed model. Section 5 discusses the preliminary experimental results of the proposed model. Finally, Section 6 concludes the paper and provides suggestions for future research.

2. Literature Review

2.1. Theory of Accident Causation

Construction accident-causation theories have evolved significantly over time, moving from early behavioral models to more complex system-based frameworks (William et al., 2019). The Domino Theory, which was proposed by Heinrich (1931), is the most popular causation theory for occupational accidents, including construction site accidents. According to domino theory, occupational accidents are caused by events that occur in succession, similar to dominoes falling one after the other. If one domino can be prevented from falling, the final outcome (the accident) does not occur. The domino theory provides a means for preventing construction site accidents, that is, an early warning for domino-sequence construction site accidents.

To eliminate workers' unsafe behavior and avoid disasters, Widner (1973) and later scholars modified the original domino theory while retaining the fundamental concept of accident prevention. According to Fang et al. (2018), effective external intervention can eliminate unsafe behavior and gradually enhance the safety awareness and attitude of workers.

The risk of construction site accidents differs between workers. Therefore, if the risk level of each worker is identified and reported early, the first domino does not fall, and accidents are prevented.

2.2. Worker Protection in Dangerous Work Environments

Before workers can be warned against any hazards, dangerous work environments must first be identified. Teo et al. (2016) used the original working zoning concept proposed by Rasmussen et al. (1994) to develop a risk zoning theory (three zones of risk) for field workers (see Fig. 1). As shown in Fig. 1, work zones can be divided into three types: a safe zone (Zone I, in which workers can work safely), a dangerous zone (Zone II, in which risks arise when potential hazards are not entirely identified and controlled), and an out-of-control zone (Zone III, in which risks are beyond the control of safety management personnel).

The most effective safety management strategy for managing dangerous work environments is to keep workers out of Zone III and as long as possible in Zone I. If this strategy is not feasible, then the second priority is to control potential hazards so that they do not endanger workers. However, to achieve this goal, two tasks must first be completed. First, the level of hazard in each work zone must be accurately identified. Second, the proximity of workers to dangerous zones must be identified in real time. If these tasks are successfully completed, workers and safety managers can receive early warning messages for any potential hazards when they are close to a dangerous zone. Consequently, safety management personnel can implement measures to correct the unsafe behavior of construction workers and prevent construction site accidents.

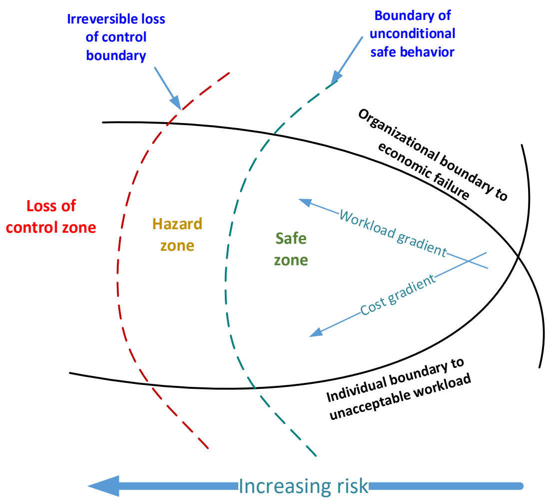

Fig. 1. Three zones of risk proposed by Teo et al. (2016).

2.3. Drones and Construction Site Safety

Unmanned Aerial Vehicles (UAVs), or drones, are increasingly utilized across various industries—including mining, agriculture, surveillance, and road monitoring—with construction emerging as one of the fastest-growing sectors in UAV adoption (Jeelani and Gheisari, 2021; Drone Deploy, 2018). In dynamic human-machine collaboration environments like construction sites, UAVs play a pivotal role in enhancing safety and operational efficiency, while also introducing new safety considerations (Chang et al., 2025; Al Omari et al., 2025). Innovative uses in the architecture, engineering, and construction (AEC) industry include aerial site photography for maintenance planning, real-time construction process monitoring, and structural inspections to identify defects and maintenance needs (Ersoz and Pekcan, 2025; Xu et al., 2025; Tan et al., 2025). UAVs replace high-risk manual inspections of bridges, exterior walls, and dams, significantly reducing workers' exposure to hazardous environments (Villarino et al., 2025; Xu et al., 2025). Equipped with advanced cameras and sensors, UAVs can perform non-destructive testing (NDT) to detect early-stage structural defects such as cracks and spalling, thereby preventing potential structural failures (Al Omari et al., 2025; Villarino et al., 2025; Xu et al., 2025). They are also capable of operating during adverse weather or disaster conditions when manual inspections are dangerous or unfeasible (Al Omari et al., 2025). In congested urban areas or active job sites, UAV path-planning algorithms consider safety distances and hazardous zones to minimize collision risks (Xu et al., 2025), while simultaneously offering high-resolution imagery to aid in trust-building and dispute resolution (Al Omari et al., 2025).

However, the integration of UAVs introduces several risk dimensions. Physical risks include the potential for collisions between drones and workers or equipment (Jeelani and Gheisari, 2021). Attentional risks stem from distractions caused by drone noise or their presence on-site, while psychological risks involve cognitive overload, stress, and sensory fatigue (Jeelani and Gheisari, 2021). Moreover, in human-robot collaboration settings, "inappropriate trust"—whether overtrust or distrust—can lead to the misuse of UAVs and increased injury risk (Chang et al., 2025). For example, overtrust may cause workers to reduce monitoring efforts, increasing the chance of being struck (Chang et al., 2025). Additional operational challenges include limited battery life, complex path planning that may lead to "path deadlocks," and mission failures in dynamic environments (Xu et al., 2025; Al Omari et al., 2025). To mitigate these risks, emerging research explores the use of physiological signals such as functional near-infrared spectroscopy (fNIRS), electrodermal activity (EDA), heart rate (HR), and head motion to dynamically assess and manage trust in UAV operations (Chang et al., 2025).

2.4. CV and Construction Site Safety

CV is an interdisciplinary field that focuses on how computers gain advanced knowledge from digital images or videos (Wikipedia, 2025a). CV relies on advanced deep learning (DL) and machine learning (ML) techniques, such as deep convolutional neural networks (CNNs) (Krizhevsky et al., 2012; Szegedy et al., 2013), region-based CNNs (Girshick, 2015), fast region-based CNNs (Girshick et al., 2016), faster region-based CNNs (Ren et al., 2015), and You Only Look Once (Redmon et al., 2016), to perform automatic recognition. With these DL-based techniques, CV provides a feasible solution to unsolved construction site safety monitoring problems (Dong et al., 2018; Yu et al., 2017). The applications of CV in construction site safety monitoring include automated visual tracking systems (Krizhevsky et al., 2012), automated personal protective equipment detection (Fang et al., 2018), dynamic on-site worker behavior tracking (Yang et al., 2016), and the monitoring of unsafe construction worker behavior and potential fall risk (Fang et al., 2018).

A key application of CV in construction safety is complex scene understanding (CSU), which enables systems to recognize objects, their relationships, and contextual factors in a human-like manner (Zhong et al., 2023; Zhang et al., 2024). CSU supports four core safety functions:

- Multi-object Recognition and Relationship Analysis – Identifying various objects such as workers and equipment, and understanding their spatial or functional relationships (e.g., "a worker is using safety gear") (Zhong et al., 2023).
- Attribute Recognition and Description – Determining specific characteristics like job roles, safety gear types, and environmental conditions, often generating natural language descriptions (Zhang et al., 2024).
- Context Integration – Incorporating contextual factors such as task type, location, and site conditions to evaluate whether worker behavior aligns with safe practices (Kim and Yi, 2024).
- Domain Knowledge Application – Integrating safety regulations, standards, and expert knowledge to assess compliance, such as checking for proper PPE usage or rule violations (Tang et al., 2020; Zhang et al., 2024).

By combining these capabilities, CSU enhances the accuracy and intelligence of automated safety monitoring systems in construction, supporting proactive risk management and decision-making.

3. Point of Departure and Research Problems

While prior studies have highlighted the potential of drones and computer vision (CV) in enhancing construction site safety, few have explored the integration of these two technologies for automated safety monitoring. Moreover, existing research has identified risks associated with their deployment in construction environments.

This study aims to bridge that gap by combining the aerial inspection capabilities of unmanned aerial vehicles (UAVs) with the automated image recognition capabilities of CV. The goal is to develop a proactive model for real-time safety monitoring and risk assessment on construction sites, thereby improving accident prevention and response. To achieve this, the following key research problems must be addressed:

- Defining safe and unsafe zones on construction sites—Construction areas must be dynamically segmented into zones based on hazard levels, following frameworks such as the three-zone risk model proposed by Teo et al. (2016).

- Identifying construction workers—Accurate worker identification must account for varying site conditions (e.g., face coverings during pandemics, workers facing downward) and should not rely solely on facial recognition. Integrating specialty and safety training data is also critical.
- Determining individual risk levels—The real-time probability of site accidents such as falls, struck-by, collapse, and electric shocks must be assessed using a historical accident database and contextual information on-site.

4. Proposed Model

To address the aforementioned research problems, this study develops a proactive construction site safety monitoring model that integrates the aerial inspection capabilities of unmanned aerial vehicles (UAVs) with the automated image recognition capabilities of computer vision (CV). The objective of this model is to deliver real-time accident risk information, enabling the timely implementation of preventive measures to mitigate potential incidents. Fig. 2 illustrates a conceptual safety monitoring scenario in which a UAV patrols the site at an altitude of approximately 5–10 meters. The key components of the proposed model are described in the following sections.

4.1. Site Aerial Inspection and Safety Zoning

To solve the first research problem, a stream of field images was captured by a UAV at a resolution of 1920 × 1080 pixels (a lower resolution might cause problems in image recognition). Fig. 2 depicts the aerial inspection scenario with the UAV over the construction site.

On-site safety zoning can be accomplished using virtual safety fences directly drawn on the safety monitor screen (Chang et al., 2023) or through the DL-based semantic segmentation of danger zones (Yu et al., 2021), as indicated by the red area in Fig. 3. In Fig. 3, the edge opening of the construction floor is identified as Zone III. The worker identified near the danger zone must be closely monitored and protected to prevent fall accidents.

Fig. 2. Conceptual scenario of the proposed model.

Fig. 3. UAV aerial inspection of an unsafe zone.

4.2. Data Matrix Tag Identification

Worker identification has emerged as a widely examined topic within construction academia (Angah & Chen, 2020). During the COVID-19 pandemic, construction workers were required to wear face masks. Most workers often face down while working. Therefore, video-based monitoring and facial recognition are unfeasible. In this study, to solve the second research problem, an automatic identification method was developed to label each worker with a data matrix (DM) tag.

A DM is a two-dimensional code of black and white cells or dots arranged in a square or rectangular pattern (Wikipedia, 2025b). In contrast to other automatic identification technologies, such as quick response (QR) codes, DMs allow for an error correction level of 30% (15% for regular QR codes) (Tremblay, 2019). In addition, in contrast to other automatic identification and optical character recognition techniques, DMs allow moderate irregularities in the shapes of DM labels (e.g., deformations) to be identified. This feature is useful for identifying the helmets or vests of construction workers, which might experience deformation over time.

During the identification of workers, the threshold of the recognized DM must be set. Although any value of truth above 0.5 can be used as a threshold, in this study, a relatively strict threshold of 0.9 was used; thus, the identified information was accepted only when the value of truth was 0.9 or higher. Fig. 4 depicts examples of DM and QR codes containing the same information, and Fig. 5 shows the DM tags on a worker's helmet and vest.

(a) QR Code	(b) Data Matrix

Fig. 4. DM and QR codes containing the same information.

As displayed in Fig. 5, a worker is identified from drone images through CV technology by using the *readBarcode* function of MATLAB's Computer Vision Toolbox (v.2021b).

Fig. 5. DM tags on a worker's helmet and vest.

4.3. Assessment of Worker Accident Risk Level

To solve the third research problem, the model of worker accident risk assessment originally proposed by Chang et al. (2021) was used in this study. In general, the likelihood of an accident occurring on a construction site is influenced by many factors, such as the worker's experience, worker's age, work type, project type, project scale, and company scale (Chang et al., 2021). Therefore, a risk model based on the concept of the superimposed effect of risks that was originally proposed by Yi and Langford (2006) was adopted in this study. In this model, the total risk of a construction accident is estimated by superimposing all relevant risk levels (e.g., type of work × experience, project type × experience, age × experience, project scale × experience, and company size × experience). Risk is calculated as follows:

$$TR_P = \sum_{i=1}^{n} RS_i \times k_i , \tag{1}$$

where RS_i is the individual risk level of the ith attribute, i is the attribute type, k_i is the weighting of the ith attribute, n is the total number of attributes in the model (i.e., five attributes), and TR_P is the estimated total risk level.

Attribute weightings are calculated by dividing the maximum value of each column by the sum of all maximum values of all columns:

$$k_i = \mathrm{M}ax(F_i) \Big/ \sum_{i=1}^{n} \mathrm{M}ax(F_i) , \tag{2}$$

where F_i is the maximum frequency of the ith attribute.

4.4. Metrics for Evaluating Model Performance

To evaluate the performance of the proposed model, a confusion matrix (shown in Table 1), which is commonly used to evaluate the performance of ML models in pattern recognition, information retrieval, and classification, was used. In general, each confusion matrix has two performance metrics: recall and precision. Recall is calculated by dividing the total number of relevant instances (true with target) by the number of actual retrieved instances (predicted with target).

$$\mathrm{Re}call = \frac{TP}{TP + FN} , \tag{3}$$

where *TP* is the number of true-positive observations and *FN* is the number of false-negative observations. Precision is calculated by dividing the number of relevant instances by the number of retrieved instances.

$$\Pr ecision = \frac{TP}{TP + FP}, \tag{4}$$

where *FP* is the number of false-positive observations.

Table 1. Definition of a confusion matrix.

	True with target	True without target	*Precision*
Predicted with target	*TP*	*FP*	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$
Predicted without target	*FN*	*TN*	
Recall	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$		

Each confusion matrix has four parameters: the numbers of true-positive observations (positive observations predicted as positive), false-positive observations (negative observations predicted as positive), false-negative observations (positive observations predicted as negative), and true-negative observations (negative observations predicted as negative). In this study, the performance criteria for inspection task acceptance were established by experts in construction safety management; the criteria were that recall and precision had to exceed 95%.

5. Testing Experiments

After model construction, preliminary experiments were conducted to evaluate the feasibility of the proposed model.

5.1. On-Site Data Collection

To test the viability of the proposed DM identification (DM-ID) technique on site, a case study was conducted at the site of a steel structure construction project in Changhua County, Taiwan. DM-ID stream images of workers were captured using a UAV navigated by one of the research team members. These images were used as system training and validation datasets.

Before field testing, the simulated construction scenes for workers on site were planned to include: (1) construction workers walking around, chatting, and looking up to observe the aerial camera (shooting-in-hover mode); (2) construction workers standing at different positions (flying-around mode); and (3) construction workers with different specialties, such as material-handling workers, scaffolding workers, site-cleaning workers, and supervisors (shooting-in-hover mode).

5.2. Testing of DM Tag Identification

To increase the accuracy of worker identification, DM-ID tags were attached at different points on the workers' helmets and safety vests. The UAV (or drone) was configured to capture videos with a resolution of 1920 × 1080 pixels at 60 frames per second. Seven videos were captured on site, with an image being captured every 6 s. To identify the DM-ID target, 2,000 images were selected as the dataset for framing. Of these 2,000 images, 1,950 were used as the training set and 50 were used as the testing set.

Table 2. Identification results for DM tags.

	Actual with target	Actual without target	*Precision*
Predicted with target	*284*	*5*	98.3%
Predicted without target	*8*	*0*	
Recall	97.3%		

In the 50 images of the testing set, 292 tags were detected. When the readBarcode function threshold was set as 0.9, 284 tags were recalled but eight tags were not detected. Therefore, the recall rate was calculated to be 97.3%; thus, the expected goal for recall rate was achieved. In terms of precision, five tags were misidentified, with the precision being 98.3%; thus, the expected goal for precision was achieved. The results of DM tag identification are listed in Table 2.

5.3. Risk Level Assessment

Table 3 presents raw historical accident frequency data (type of work × experience) obtained from the CIAKP (2025). Table 4 presents the transformation of these raw data into five risk levels. Each worker's accident risk level can be calculated using the accident frequency data and the risk level assessment method described in Eqs. (1) and (2). In the following subsection, an application example is described.

Table 3. Accident frequency data (type of work × experience) obtained from the CIAKP (2025).

Work Type / Experience	Masonry	Interior	Equip. operator	Concrete Tamper	MEP technician	Manager	Form work	Rebar	Steel component assembler	Misc.	Scaffold	Other	Sum
<1 month	62	19	31	8	41	30	83	35	59	209	21	396	994
1-3 months	17	3	16	3	30	19	50	12	26	54	5	183	418
3-6 months	15	2	11	3	25	10	28	11	10	45	8	117	285
6-12 months	7	3	9	2	11	17	22	6	11	27	5	105	225
1-3 years	9	4	16	3	36	26	18	2	19	26	7	139	305
3-5 years	3	0	8	2	10	19	6	0	9	17	2	58	134
5-10 years	4	1	6	1	16	18	9	0	6	8	1	45	115
>10 years	8	1	4	1	13	36	2	3	3	7	1	45	124
No record of experience	2	2	1	1	2	23	15	1	5	7	1	29	89
Sum	127	35	102	24	184	198	233	70	148	400	51	1117	2689

Table 4. Transformation of risk levels (type of work × experience).

Work Type / Experience	Masonry	Interior	Equip. operator	Concrete Tamper	MEP technician	Manager	Form work	Rebar	Steel assembler	Misc.	Scaffold	other	Sum
<1 month	5	4	5	3	5	5	5	5	5	5	4	5	5
1-3 months	4	2	4	2	5	4	5	3	4	5	2	5	4
3-6 months	3	1	3	2	4	3	4	3	3	5	3	5	3
6-12 months	3	2	3	1	3	4	4	2	3	4	2	5	3
1-3 years	3	2	4	2	5	4	4	1	4	4	3	5	3
3-5 years	2	0	3	1	3	4	2	0	3	4	1	5	2
5-10 years	2	1	2	1	4	4	3	0	2	3	1	5	2
>10 years	3	1	2	1	3	5	1	2	2	3	1	5	3
No record	1	1	1	1	1	4	3	1	2	3	1	4	1

5.4. Application Demonstration

To demonstrate the feasibility of the proposed model, a real-time on-site construction safety monitoring scenario is presented. The test was conducted at a residential building construction site in Changhua City, Taiwan, employing 57 workers with a contract value of USD $32 million. During the test, a UAV conducted aerial patrols at an altitude of approximately 5 meters. Live video footage captured by the UAV was transmitted to a server located in the site office, where it was processed by the proposed system. Once a worker was detected, their accident risk level was immediately calculated using Eqs. (1) and (2). Fig.e 6 shows a construction worker being monitored by the UAV. Using a DM tag, the worker was identified as a 51-year-old superintendent.

The first step in risk identification is to use CIAKP data to calculate the number of major accidents that have previously occurred and recorded in the data of CIAKP. As presented in Table 2, the individual in question is a superintendent, which corresponds to risk level 5. He is 51 years old, which corresponds to risk level 3. The project is a building construction project, which corresponds to risk level 5. Moreover, the firm of the considered individual has 57 employees, which corresponds to risk level 3. Finally, the contract value is USD$32 million, which also corresponds to risk level 3. As presented in Table 5, multiplying the risk levels by the weightings yields a total personal risk of 3.78, which is moderately high. Therefore, the considered individual must be closely monitored and instructed to leave the site.

5.4. Discussion of the Preliminary Results

5.4.1. System Strength and Advantages for Construction Safety Management

According to the preliminary experimental results, the proposed model can identify workers with a recall (97.3%) and precision (98.3%) of higher than 95% (i.e., human capability of image recognition). Within the context of COVID-19, this model can help identify workers while they are wearing face masks, which is rather difficult for on-site staff.

Fig. 6. Worker accident risk monitoring

Table 5. Accident risk level for a superintendent.

Attribute	Value of parameter	Risk Level	Weighting	Sum
Work type	Superintendent	5	18.95%	0.95
Age	51-year-old	3	7.51%	0.23
Project type	Building	5	20.00%	1.00
Company employees	57	3	33.64%	1.01
Contract price	32 million	3	19.90%	0.60
			Total risk level	3.78

The superimposed-effect-based model effectively estimates each worker's accident risk level and transmits this information to the appropriate safety manager or the worker. This capability underscores the model's strong potential for real-time safety monitoring and accident prevention on construction sites. By combining the capabilities of UAVs and CV, the proposed model can increase the performance of construction safety personnel because UAVs can conduct aerial site inspections at any time and computers can automatically recognize captured images through the CV algorithm without incurring additional labor costs.

Unmanned Aerial Vehicles (UAVs) offer several advantages for construction safety management. They significantly reduce human exposure to high-risk environments by providing a safer, more cost-effective alternative to manual inspections—particularly for elevated structures and hard-to-reach areas (Villarino et al., 2025). UAVs can rapidly collect high-resolution data, even under adverse weather conditions or during disasters when manual inspection is not feasible (Al Omari et al., 2025). Their ability to provide real-time visual evidence enhances communication, builds trust among project teams, and accelerates construction workflows by clarifying on-site conditions. Compared to traditional methods, UAVs can reduce inspection time by 25.9% to 65% and lower raw data volume by approximately 40% (Villarino et al., 2025; Tan et al., 2025), leading to substantial gains in efficiency. Similar improvements were observed during the preliminary testing in this study.

5.4.2. Limitations

Despite the advantages of using UAVs in construction safety management, several limitations and challenges must be addressed. Environmental factors pose significant operational constraints—UAVs often struggle under adverse weather conditions such as strong winds, rain, or fog, which can delay inspections and degrade data quality. In complex terrains or around obstructive structures, UAVs may encounter blind spots or reduced accuracy, limiting their ability to fully replace manual inspections (Xu et al., 2025).

Safety-related risks are also a concern. Jeelani and Gheisari (2021) identified three categories of risk associated with drone deployment in construction: (1) Physical risks, including potential collisions with workers or equipment that may lead to injury or fatality; (2) Attentional risks, where drones may distract on-site personnel and incur high hardware costs; (3) Psychological risks, including negative impacts on workers' mental health and privacy, potentially causing stress, cognitive overload, and sensory fatigue.

Another human factor is inappropriate trust in UAVs, encompassing both overtrust and distrust. Overtrust may lead workers to reduce attention toward drone operations, thereby increasing the likelihood of accidents (Chang et al., 2025). In addition, practical and regulatory barriers hinder widespread adoption. UAVs are limited by short battery life, which constrains mission duration. The high volume of high-resolution data they generate demands advanced computational tools, storage capacity, and technical expertise for processing (Xu et al., 2025). Furthermore, increasingly strict and inconsistent drone regulations—including flight permissions, altitude limits, and operator certification—pose additional obstacles to implementation (Villarino et al., 2025).

6. Conclusions, Limitations, and Recommendations

6.1. Conclusions

This study developed and successfully validated an innovative model that achieves proactive and real-time construction site safety monitoring by integrating Unmanned Aerial Vehicle (UAV) aerial inspection capabilities with deep learning (DL)-based computer vision (CV) technology. This model aims to address the challenges faced by traditional manual monitoring in open, dynamic, and densely populated construction environments, particularly issues such as insufficient safety managers and difficulties in identification

The proposed model contributes to the field of construction safety in the following aspects:

- Innovative Worker Identification Method—Unlike traditional monitoring methods that rely on facial recognition or single perspectives, this study specially designed Data Matrix (DM) tags and affixed them to workers' safety helmets and vests. These DM tags improves up to 30% of identification precision and posses good tolerance for shape deformation, allowing the model to confirm worker identities with high accuracy through DL-based image recognition algorithms, even when workers are wearing masks or working with their heads down.
- Precise Accident Risk Assessment Mechanism—After confirming worker identity, the model further integrated a superimposed-effect-based risk assessment model. This model considers multiple key attributes, including worker experience, age, work type, project type, project scale, and company size, thereby calculating and predicting each worker's accident risk level in real-time.
- Superior Model Performance—Preliminary experimental results showed that the model demonstrated outstanding performance in worker identification, achieving a recall of 97.3% and a precision of 98.3%. These results significantly exceeded the established 95% performance acceptance criteria, proving that its image recognition capability has reached or even surpassed human levels. In a practical application demonstration at a construction site in Changhua County, Taiwan, the model successfully conducted aerial inspections, worker identification, and real-time risk calculations, for instance, accurately identifying a superintendent and calculating their risk level as moderately high (3.78), fully verifying the model's practicality and feasibility.

6.2. Limitations

Despite the promising preliminary experimental results, the proposed model has the following limitations:

- UAVs can fly outdoors only and it's difficult to be used for indoor safety monitoring.
- Sunlight affects the recognition accuracy of DM labels. Excessive brightness or darkness might reduce the precision and recall of image recognition.
- Drones have low battery life. Currently, the battery life of drones used at construction sites is between 30 min and 1 h. Battery replacement is the operator's responsibility.
- On-site obstacles, such as completed structures, temporary facilities, and mobile crane booms, might interfere with the operation of drones.

- Government regulations on drones are becoming increasingly stringent, mandating that drone pilots obtain a drone license. In addition, in some restricted areas near sensitive zones, such as military bases or government agencies, drones are prohibited, which increases the difficulty of operating drones in nearby construction sites.

6.3. Recommendations

Despite the promising preliminary experimental results, actual site implementation of the proposed model was not realized. In addition, the difficulties that might arise during field implementation are unknown. Therefore, field testing is the next step of the current investigation.

Future studies must address the limitations of the proposed model, including the effects of sunlight, the low battery life, the interference of on-site obstacles, and the recognition of DM tags under different weather conditions.

Although the proposed model yielded promising results, some potential risks, namely physical, attentional, psychological, and privacy infringement risks, must be addressed. Moreover, the increasingly stringent drone use regulations issued by governments worldwide must also be considered. All of the aforementioned problems merit additional research.

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Author Contributions

As the principal investigator, Dr. Wen-der Yu planned and supervised the execution of the research project and drafted the manuscript. Dr. Bing-Hui Fan was responsible for finalization of the manuscript to update it to the most recent technical developments. Dr. Hsien-Kuan Chang was responsible for ML programming and contributed to the development of the superimposed-effect-based risk model. Dr. Wen-ta Hsiao was responsible for conducting expert interviews and processing construction-related data. Mr. Hung-Sheng Chiang was responsible for the field experiments and data processing. Professor Alexey Bulgakov assisted with the resolution of drone-related problems.

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