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Automated Detection of Safety Harness Usage Using Computer Vision Technology to Prevent Fall Accidents Among Construction Workers

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ABSTRACT: Fall accidents are a major threat to worker safety, especially in high-altitude environments such as construction sites. Falls remain the leading cause of workplace fatalities and injuries, making safety at heights a critical industry challenge. Traditional safety measures focus solely on checking harness fastening before work begins, making it difficult to determine whether the harness is actually worn. Furthermore, the lack of real-time monitoring increases the risk, leaving workers vulnerable. This paper presents an advanced safety monitoring system that ensures real-time compliance with harness usage. Using the YOLOv5 object recognition model, the system continuously verifies proper harness use, significantly reducing fall risks. Testing under varied conditions, including different clothing colors and measurement distances, demonstrated high reliability, with precision and recall rates of 87% and 78%, respectively. The system maintained stable performance across varying conditions, while slight accuracy differences were observed depending on clothing color. These variations highlight the system's limitations, while also pointing to areas for further improvement. By automating safety monitoring, the system addresses workforce shortages in construction and enhances workplace safety by reducing accidents and improving compliance. This real-time system offers a promising solution for preventing fall-related accidents, strengthening high-altitude workplace safety, and filling gaps in traditional practices.

1. INTRODUCTION

Fall accidents are a significant and persistent hazard in industrial and construction settings, posing serious risks to worker safety. Despite advances in automation and technology aimed at reducing physical workloads, work-related injuries continue to occur at alarming rates. Among these injuries, slips, trips, and falls (STFs) are particularly concerning because they represent a primary cause of harm across various environments (Yang et al. 2017; Yoon & Lockhart 2006; Kemmlert & Lundholm 2001). Although STFs are a pressing issue in industrial contexts, their impact extends beyond workplaces, affecting individuals in everyday life.

Fall accidents are particularly prevalent in construction. Construction workers are at a more than sevenfold higher risk of suffering fatal injuries from falls compared to workers in other industries (National Safety Council, n.d.; U.S. Bureau of Labor Statistics, 2024; Choi and Koo 2023). These accidents are the leading cause of death in this sector, resulting in severe economic and human losses. Beyond fatalities, falls are significant contributors to nonfatal injuries such as contusions and fractures, which can cause long-term disabilities (Courtney et al. 2002). The associated physical and financial costs are substantial, highlighting the importance of effective fall risk management strategies.

The construction industry in Korea exemplifies the gravity of this issue, recording the highest rates of workplace injuries and fatalities across all sectors. In 2022, 46% of all workplace accident-related deaths occurred in the construction industry, with fatality rates in general and specialty construction sectors more than double the national average (2.06% and 2.99%, respectively, compared to 1.10% across all industries). Falls from heights are a major contributor, accounting for 215 out of 402 construction-related deaths (53%) in 2022 (KOSHA, 2023). Despite ongoing efforts, such as safety regulations, mandatory training, and risk assessment protocols, fall accidents have continued to rise.

Several preventive measures have been implemented, including regular risk assessments for high-altitude work, the deployment of safety managers, and worker-participatory practices such as Tool Box Meetings (TBM) (Jung et al. 2023). These meetings allow workers to identify and discuss potential hazards before starting tasks. However, the construction industry still faces persistent challenges, such as the inherent risks of construction work, worker complacency, and a shortage of safety personnel (Lee and Ahn 2021). These factors contribute to the high frequency of fall accidents, leading to tragic losses of life, project delays, cost overruns, reputational damage, and diminished trust in the industry.

In addition, despite effective safety measures, such as proper lanyard fastening and safety harnesses, many accidents occur due to non-compliance or faulty equipment. Compounding the issue is a critical shortage of safety managers. In 2023, the Korea Construction Industry Research Institute estimated a requirement for 3,914 safety managers in small- to medium-sized construction sites, but the annual increase in safety managers was only 734. This significant shortfall underscores the compelling need for alternative technologies to enhance safety monitoring and address unsafe behaviors on construction sites.

Considering the frequency and severity of fall accidents, substantial research has focused on their causes and preventive strategies. Wearable sensing technologies have been explored for automatic fall detection, real-time monitoring, and improved workplace safety (Yang et al. 2017; Courtney et al. 2002; Cattledge et al. 1996; Huang and Hinze 2003; Chi et al. 2005). However, existing studies on construction site safety have limitations, as wearable sensors and surveillance-based monitoring systems have inherent weaknesses and limited effectiveness. This highlights the urgent need for alternative technologies to enhance construction site safety.

In response to these challenges, this paper introduces a smart safety harness detection system using computer vision technology to prevent fall accidents. The system utilizes object detection algorithms to verify the use of safety harnesses, ensuring compliance with safety regulations. By automating the monitoring of unsafe behaviors, the proposed system complements the limited availability of safety managers, offering a scalable and reliable solution to reduce fall hazards in real-time.

This paper is organized as follows. Section 2 presents a literature review to contextualize the research. The following section details the development of the safety harness detection system based on a YOLOv5 object recognition model. The performance of the system is evaluated in a simulated environment, and its results are analyzed. Finally, this paper discusses the potential applications, expected benefits, and future directions to improve safety in the construction industry.

2. LITERATURE REVIEW

Several studies have explored the use of surveillance cameras on construction sites to identify risky behaviors through object recognition technologies. Sadiq et al. (2022) examined the application of video analysis for behavior detection, while Fang et al. (2018) proposed a safety harness detection model based on Faster R-CNN. This model enabled rapid object detection with minimal delay, making it suitable for real-time applications. Xu et al. (2023) developed a safety harness detection system that analyzes workers' actions in real time using surveillance camera footage. These studies are significant as they allow safety managers to continuously monitor safety harness usage, enabling the prompt identification of risky behaviors and contributing to fall accident prevention.

In addition to video-based approaches, wearable sensor technologies have been assessed as complementary solutions. Chu (2022) introduced a wearable sensor-based safety harness detection model that automatically identifies high-altitude workers and confirms whether they are wearing their safety harnesses. This system enables real-time monitoring, addressing the challenges posed by the shortage of safety personnel. Jeon et al. (2020) improved convenience for safety managers by integrating a smart safety harness detection model with a management application. This system detects whether a harness is fastened and provides proactive notifications to safety managers, ensuring timely intervention during high-altitude tasks. Similarly, Lim et al. (2022) developed a computer vision process tailored to specific construction environments to detect the fastening of safety harnesses.

These studies have established a solid foundation for using AI and computer vision technologies to prevent fall accidents on construction sites. The primary approaches include wearable sensor-based models focusing on safety harness fastening detection and the application of object recognition technologies to surveillance camera footage for monitoring safety harness usage.

Despite these advances, limitations remain. First, wearable sensor-based studies often emphasize detecting whether the safety harness is fastened correctly, focusing primarily on the hook or D-ring connection to an anchorage point. However, these models frequently fail to verify whether the harness straps around the worker's body, such as the shoulders and waist, are worn correctly. This oversight can lead to safety gaps, as a worker may fasten a safety harness without properly wearing the straps, leading to misclassification as safe despite being at significant risk.

Second, studies relying on surveillance camera footage for safety monitoring face practical challenges. Surveillance cameras are typically mounted on fixed tower cranes, often with limited coverage. These cameras primarily monitor the upper levels of buildings, leaving tasks such as external wall construction, window installation, and finishing work unmonitored. Furthermore, the small size of objects in footage, such as safety belts or harnesses, complicates accurate detection, reducing system reliability.

This study addresses these limitations by proposing an enhanced safety monitoring system that focuses on verifying whether workers are correctly wearing safety harness straps rather than solely assessing the fastening of locking hardware. The proposed system employs advanced object recognition technologies to eliminate blind spots in traditional surveillance setups and ensure a more comprehensive assessment of worker safety. This approach complements existing safety harness detection systems, providing a robust and precise mechanism for preventing fall accidents. Ultimately, the aim is to develop a holistic safety management solution that significantly improves the accuracy and reliability of monitoring high-risk activities on construction sites, ensuring better protection for workers and minimizing fall-related incidents.

3. RESEARCH METHODS

In computer vision, object detection is a fundamental task that involves identifying and locating meaningful objects within images or video sequences. This process not only recognizes objects but also determines their precise location by drawing bounding boxes around them (Redmon 2016). Advanced algorithms such as Convolutional Neural Networks (CNNs) are commonly employed for this purpose. CNNs extract hierarchical features from images, learning patterns and representations of objects during training, enabling accurate detection and classification of objects in new images or video frames. Prominent object detection models include R-CNN, YOLO, and SSD, each offering distinct advantages depending on the application.

Among these models, YOLOv5 was selected for this study due to its optimal balance between accuracy and real-time detection capabilities. YOLO, or "You Only Look Once," is a deep learning model known for its speed and efficiency. Unlike traditional object detection methods that use sliding windows or region proposals, YOLO divides an image into a grid and predicts bounding boxes along with class probabilities in a single forward pass. This approach makes YOLO highly efficient for real-time applications. The

YOLOv5 variant was chosen for its lightweight architecture, making it particularly suitable for deployment on hardware with limited computational resources, such as mobile devices, embedded systems, and surveillance cameras. Furthermore, its low memory usage enhances its integration into resource-constrained systems while maintaining high detection accuracy (Jeon 2023).

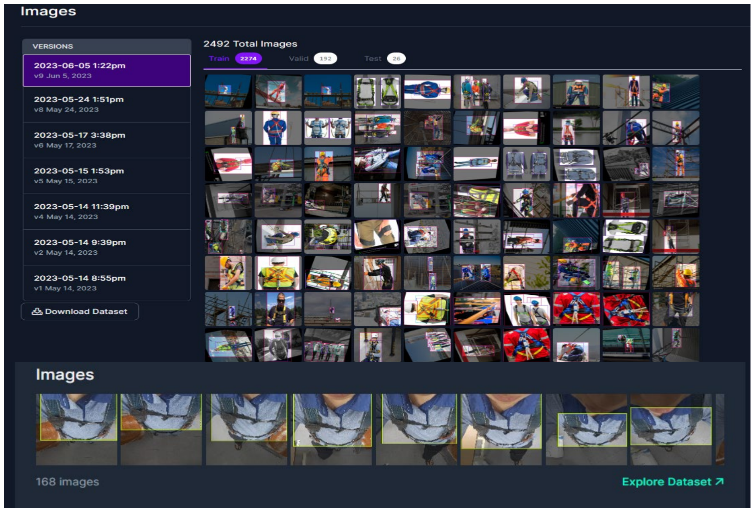

Figure 1: Built Image Dataset

For detecting safety harness straps, a dataset of 2,660 images was curated. This dataset encompassed a diverse range of construction environments, various types of safety harnesses, different worker postures, lighting conditions, and viewing angles. The images were sourced from the Roboflow dataset, supplemented by additional images captured by the authors. Each image was meticulously annotated to mark the location of safety harness straps, ensuring comprehensive training data for the YOLOv5 model.

The dataset was then used to pre-train the YOLOv5 model. Pre-training involves initially training the model on a large, general-purpose dataset before fine-tuning it for a specific task. In this case, the model was trained specifically to detect safety harness straps and the upper bodies of workers wearing them. During training, YOLOv5 learned to identify distinguishing features of safety harnesses, including their shape, structure, and relative positioning on the worker's body.

Once trained, the YOLOv5 model was capable of performing object detection by predicting bounding boxes around both the safety harness straps and the upper bodies of workers. These bounding boxes visually represent the detected objects' positions and dimensions. The model's performance was evaluated using the Intersection over Union (IoU) metric, a standard measure in object detection tasks that assesses the overlap between predicted bounding boxes and ground truth annotations. IoU is computed as the ratio of the overlapping area to the total combined area of the predicted and actual bounding boxes.

In this study, the IoU score was a key factor in determining whether a worker was correctly wearing a safety harness. If the IoU score indicated a positive overlap between predicted bounding boxes and ground truth labels, the worker was classified as wearing a safety harness. This approach ensured that detection was not solely based on the presence of bounding boxes but also on their precise alignment with actual safety harness straps.

Following training and evaluation, YOLOv5 was implemented using Python for real-time object detection. The implementation utilized pre-trained weights fine-tuned for detecting safety harness straps in live video streams. Python's powerful libraries, including OpenCV and PyTorch, facilitated seamless execution of the YOLOv5 model on incoming video frames. This real-time detection capability was crucial for promptly identifying unsafe situations on construction sites, where timely intervention is essential to prevent serious accidents.

4. RESULTS

The camera used in this study captures the worker's upper body, while the YOLOv5 model analyzes the live video stream using pre-trained data from Roboflow to determine if the worker is wearing a safety harness. To evaluate the system's robustness across different environmental conditions, multiple tests were conducted, varying factors such as background colors, clothing colors, harness colors, and distances.

In a series of 300 object detection trials, six distinct test datasets (Test Data Set 1 to 6) were created, each corresponding to a different clothing color. Specifically, Test Data Set 1 included gray clothing, Test Data Set 2 black, Test Data Set 3 orange, Test Data Set 4 brown, Test Data Set 5 blue, and Test Data Set 6 white. For each dataset, 50 detection trials were performed, ensuring a comprehensive assessment of performance across varying conditions. The results of these trials are summarized in Table 1.

Table 1 300 Object Detection Results

	Mean Confidence Score	Standard Deviation
Test Data Set 1 (The color of the worker's upper clothing: gray)	0.910	0.029
Test Data Set 2 (The color of the worker's upper clothing: black)	0.889	0.033
Test Data Set 3 (The color of the worker's upper clothing: orange)	0.919	0.028
Test Data Set 4 (The color of the worker's upper clothing: brown)	0.918	0.028
Test Data Set 5 (The color of the worker's upper clothing: blue)	0.918	0.030
Test Data Set 6 (The color of the worker's upper clothing: white)	0.899	0.052
Total	0.910	0.041

Figure 2 illustrates examples of detections from each test dataset. The confidence score, which reflects the likelihood that a particular object exists within a bounding box, was calculated using the Intersection over Union (IoU) metric (Redmon 2016). Tests conducted under different background colors demonstrated that confidence scores remained consistent across these variations. This indicates that the proposed system is highly robust against background interference and can reliably detect safety harness usage across diverse scenarios.

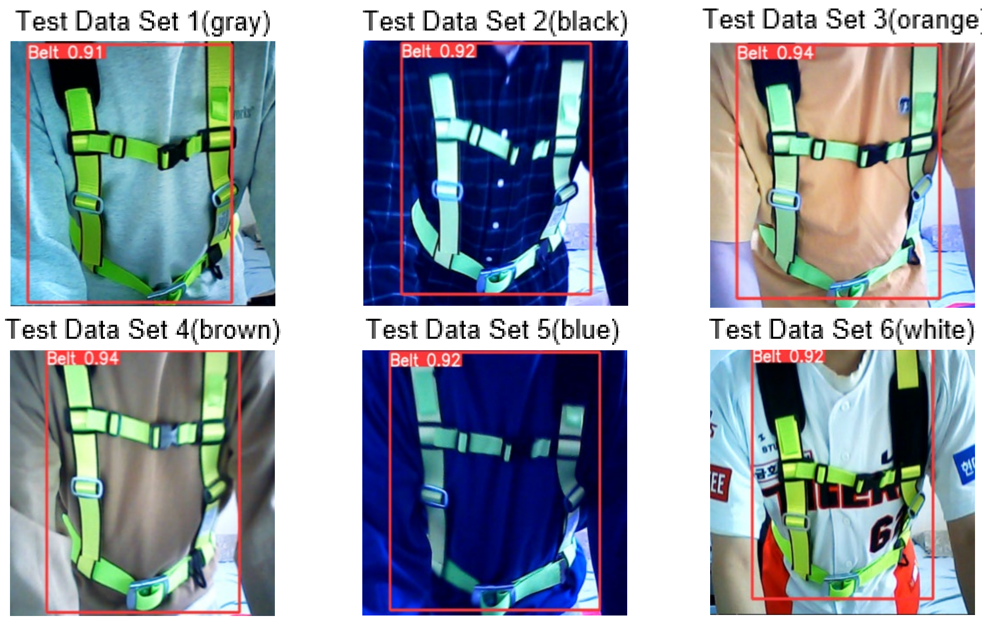

Figure 2: Screenshots of Safety Harness Detection Tests with Test Data Set 1-6

To further examine detection reliability, additional tests were conducted by varying the camera angle and distance. The camera angle was adjusted from a direct frontal shot (0°) to a downward angle of 30°. The average confidence scores for different clothing colors were calculated from 50 trials at each angle and distance variation, as depicted in Figures 4 and 5. The results revealed that detection accuracy decreased as the camera angle deviated from the frontal view. Conversely, distance variations (ranging from 20 cm to 60 cm, simulating a helmet-mounted camera) had minimal impact on detection accuracy. These findings highlight that camera angle plays a more significant role than distance in determining detection effectiveness.

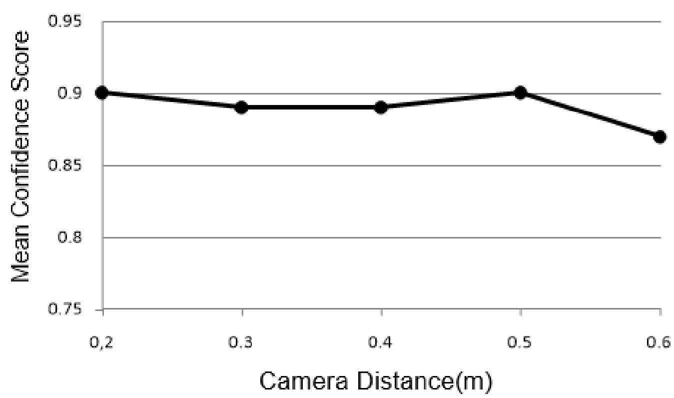

Figure 4: Confidence Score Curve as a Function of the Camera Distance (meters)

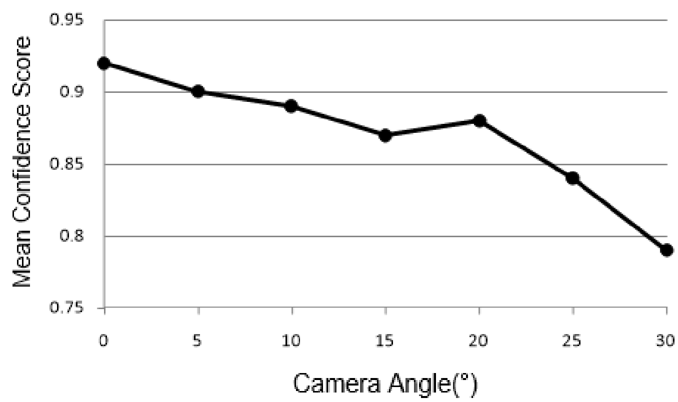

Figure 5: Confidence Score Curve as a Function of the Camera Angle (°)

Table 2 presents the Precision-Recall-Accuracy (PRA) chart after 200 object detection trials. Performance evaluation metrics were employed to assess and validate the system's effectiveness. Precision and recall were the primary metrics used in this analysis.

Table 2 Precision-Recall-AUC (PRA) Chart

	Predicted Positive	Predicted Negative
Actual Positive	True Positive 78	False Negative 22
Actual Negative	False Positive 12	True Negative 88

- **Precision**: The probability that a worker identified as wearing a safety harness is indeed wearing one. The system achieved a precision of approximately 87%.
- **Recall**: The proportion of workers actually wearing a safety harness who were correctly identified. The recall value was calculated at 78%.
- **Accuracy**: The percentage of correctly classified cases (both harness-wearing and non-harness-wearing workers). The system achieved an accuracy of **88%**, meaning that it correctly identified and potentially prevented accidents for nine out of ten workers at risk of a fall due to not wearing a safety harness.

These results confirm the system's capability in identifying unsafe behaviors and preventing potential fall accidents in construction environments. The proposed safety harness detection system demonstrates strong reliability, making it a valuable tool for improving worker safety on construction sites.

5. DISCUSSION AND CONCLUSIONS

This study proposed a smart safety harness detection system leveraging object recognition technology to prevent fall accidents on construction sites. The PRA chart analysis confirmed the system's ability to accurately detect workers wearing safety harnesses and identify those who were not. Furthermore, the successful integration of the YOLOv5 object recognition model with Python enabled real-time monitoring of unsafe situations, contributing to a more proactive safety management approach.

Despite these advancements, certain limitations remain. Detection performance may decline under low-light conditions, such as nighttime work environments, and recognition accuracy can be affected by camera angles. However, our evaluation demonstrated that the system remains robust against variations in clothing and background colors, ensuring stable and reliable detection across diverse settings. To address these remaining challenges, we propose the incorporation of the following advanced techniques:

1) EOFE-NET: This technique sequentially processes visual input by analyzing color, texture, edges, and semantics before classification. By storing redundant features, EOFE-NET minimizes detection errors and enhances accuracy. This method can significantly improve object recognition performance, particularly in complex and cluttered construction environments.

2) CLCFPN: This method mitigates resolution loss caused by variations in lighting conditions. It structures images in a hierarchical pyramid format, enabling the transfer of high-resolution semantic details to low-resolution images and vice versa. This bidirectional information exchange helps unify detection accuracy across different lighting conditions, improving precision in object recognition.

Despite the system's successful ability to detect safety harnesses, one limitation is its current inability to fully identify incorrect harness usage. While the system can detect whether the harness is being worn, confidence scores may decrease when the harness is improperly worn (e.g., not fastened securely). However, the system is not yet capable of fully distinguishing between correct and incorrect usage of the harness.

We believe that incorporating this feature will significantly enhance the system's ability to detect unsafe work conditions more comprehensively. As we continue to improve the system, we aim to integrate more advanced techniques to better identify incorrect harness usage, thereby providing a more robust solution for construction safety monitoring.

The implementation of this smart safety harness detection system marks a substantial step forward in enhancing construction site safety through AI-driven monitoring. Real-time detection, accurate classification of unsafe behaviors, and seamless integration with existing safety protocols offer a powerful solution to reducing fall accidents. If applied across various industrial settings, this technology has the potential to revolutionize safety management systems by fostering safer and more efficient work environments. Future research will focus on refining these AI-driven safety systems, further expanding their capabilities, and integrating them with broader industrial safety frameworks to ensure maximum protection for workers in high-risk environments.

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