Research Article

Computer Vision Process Development regarding Worker's Safety Harness and Hook to Prevent Fall Accidents: Focused on System Scaffolds in South Korea

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In South Korea, industrial accidents continue to increase in frequency, with construction accidents accounting for more than a third of all industrial accidents. Specifically, by preventing fall accidents, the death rate from accidents can be reduced by 50%. Fall protection is required to prevent fall accidents, and investigating the reinforcement of the worker's safety harness and hook fastening becomes imperative. This requires automation of computer vision confirmation of the safety harness and hook fastening. As the accident risk can be reduced by an effective safety culture in the system, it is necessary to monitor safety on site through a construction safety automation system. Therefore, the objective of this study is to develop a computer vision process for safety harness and hook for preventing fall accidents in South Korea's construction industry. This study focuses on system scaffolds that are widely used at construction sites. The application of this methodology to sample sites and field cases established its applicability. The proposed computer vision application methodology will serve as the foundation for visualization research in the construction industry, and image recognition will help reduce the safety accident rate. Accidents caused by failure to use a safety harness and hook can be reduced in South Korea as well as globally. Additionally, this methodology is applicable to roof construction, tower crane installation and dismantling work, as well as steel tower installation and dismantling.

1. Introduction

To prevent fall accidents, the South Korean construction industry invests significant effort and resources in fall prevention measures such as construction safety education, high place work management guidelines, and fall prevention protective equipment [1]. Industrial accidents continue to rise in South Korea, with construction accidents accounting for more than a third of all industrial accidents [2]. According to the Korea Occupational Safety and Health Agency's 2009–2017 industrial accident status and analysis, fall accidents accounted for 47.7%–52.1% of the total accident deaths in a year and for roughly half of all construction-related fatalities, which is an extremely high rate [3]. That is,

fall accidents are major disasters with a high rate of occurrence and severity of injuries that can occur anywhere at a construction site [1]. Even if a worker falls from the second floor while working, caution is required because serious injury or death is frequently the result [4, 5].

In the United States, employers are permitted to use any of the three fall arrest systems (guardrails, safety nets, or personal arrest systems) under Occupational Safety and Health Administration (OSHA) regulations, while it is more strictly regulated in other countries. For example, in China, it is mandatory for personnel working at a height of 2 m or greater to wear fall arrest equipment in all circumstances [6]. In South Korea, it is required to take necessary precautions to avoid falling hazards at construction sites including the

provision of walk platforms (work platforms), fall protection nets, and safety harnesses. Thus, various measures can be taken to prevent fatal accidents caused by falls; however, research on strengthening the safety harness and hook of workers is first needed to directly prevent accidents.

Many studies investigated factors influencing falls from heights in construction workplaces [7–10]. Evanoff et al. [11] and Kaskutas et al. [12] regarded safety culture as one of the basic causes contributing to workplace falls. In other words, safety accidents can be reduced by an effective safety culture of the system [13]. Falls from heights are the leading cause of occupational deaths in the construction industry, accounting for approximately 54% of all accidents [14]. These deaths can be significantly reduced due to the use of personal protective equipment. However, monitoring personal protective equipment is complex and difficult for field managers. Hence, construction safety automation can provide multiple solutions for monitoring safety on site.

As one of the largest industrial sectors in the world, the construction industry remains labor-intensive [15]. Currently, passive observation is adopted as the main method for monitoring worker productivity and safety at construction sites. If construction objects are recognized correctly, many construction monitoring tasks can be automated [16]. Continuous detection of machines and workers can prevent potential collisions and provide timely advance warning to construction engineers [17]. Therefore, promoting construction automation can speed up processes, increase productivity, and reduce safety risks. [18–20].

Various algorithms have been proposed for computer vision-based construction safety management, which can be classified as deep learning methods or shallow learning methods [17, 21]. And deep learning methods mean convolutional neural network (CNN), and shallow learning methods mean histogram of oriented gradients and support vector machine. CNNs are most commonly used to support computer vision because they can detect objects reliably and accurately [22]. Shallow learning methods rely on manual features that need to be created manually, thus negatively impacting detection accuracy [23]. In other words, deep learning can automatically extract sophisticated features from data with multiple levels of end-to-end representation compared to shallow learning approaches [24, 25].

Through the use of image recognition, it is possible to confirm the safety harness and hook fastening by using a camera at the construction site. Existing studies are primarily focused on image recognition and computer vision [26–28]. However, the concept is unclear and the method for applying the process in the field is not explained in detail; instead, the existing studies focus only on application examples. In other words, previous research has focused on computer vision algorithms and technologies and thus overlook detection targets. It is critical to determine what to recognize and in what order, how to review the law governing the recognized targets, and then apply the law during detection. Hence, it is necessary to make specific recommendations regarding the issue to be considered at each stage.

As such, the purpose of this study is to develop a computer vision process for safety harness and hook detection and prevention of fall accidents in the construction industry in South Korea. The scope of this study is limited to the system scaffolding that is used at a large number of construction sites. The study is organized as follows: Section 2 reviews existing studies on computer vision and object detection algorithms. Section 3 conducts a review of the field manager's onsite notice regarding the failure to secure the safety harness and hook when working on the system scaffolds and analyzes the accident case. Section 4 establishes a computer vision process for the safety harness and hook. Section 5 analyzes South Korean laws and standards regarding system scaffolds, safety harnesses, and hooks, and analyzes computer vision objects by image recognition target derivation process to secure the safety harness and hook in place while working on the system scaffolds. Section 6 validates the efficacy of the computer vision process through field application and sampling.

2. Literature Review

2.1. Construction Safety. Digitization enables construction sites to provide faster, cheaper, and smarter services [29]. Despite the many applications of deep learning, the applications of deep learning in the construction industry have not been fully utilized [30]. Li and Leung [31] defined the construction site as one of the most dangerous places and suggested using a high-speed R-CNN object detection method and using mixed reality so that artificial intelligence can detect the danger. Li et al. [32] set the detection model for a hard hat and hook based on You Only Look Once v5 and applied the object detection model and OpenPose algorithm to 1200 including unsafe behaviors and safe behavior. Luo et al. [33] investigated construction safety research in developed and developing countries, major organizations that conducted construction safety, and future research directions. And deep learning, machine learning, visualization, and building information modeling are the main factors in the future construction industry. Application is expected. Fang et al. [34] verified the safety device recognition accuracy of 89% using the object detection network YOLOv5 and the human body posture estimation network OpenPose to detect workers wearing safety devices.

Existing papers focused on the introduction of computer vision-related algorithms and data utilization technology and overlooked the detection targets of PPE. It is important to recognize in what order and how to apply for the law review on the recognized targets and the method for detecting the reviewed law. It is necessary to provide a detailed presentation of the matters to be considered at each stage. In addition, it is necessary to present a data utilization method according to the form in which the targets to be recognized are displayed.

2.2. Computer Vision. Luo et al. [33] stated that research on construction safety and computer vision was being actively conducted. Computer vision has recently gained increased attention as a result of its potential to overcome the limitations of manual observation of field hazards. Several

computer vision approaches have been proposed for automatically and continuously extracting visual information from field images or videos to detect unsafe behaviors or hazardous working conditions [35–37]. The development of deep learning algorithms further enhances the capabilities of computer vision to process and analyze visual images [38]. However, as a form of end-to-end learning, computer vision approaches have limitations in certain areas that require knowledge and reasoning [39]. Construction safety management requires a high level of knowledge [40].

Computer vision has garnered considerable attention in the construction industry, particularly in the areas of productivity analysis [41], work progress monitoring [42], and health and safety monitoring [43–45]. Historically, performing safety inspections was a time-consuming and labor-intensive process that required engineers and site managers to walk around the site trying to detect hazards. Due to the inefficiency of manual safety inspection, computer vision is considered an effective method for automatically identifying hazards in images or videos [18, 36, 46].

When performing site safety inspections, site managers and engineers must rely on their perceptual abilities to extract visual data. This data must be inferred to identify potential hazards and associated mitigation measures based on existing safety regulations and experience [28]. Thus, consideration must be given to the limitations and domain knowledge of the computer vision system that extracts the visual data captured by the camera [47, 48]. That is, an image recognition application process should be developed based on an analysis of South Korean laws and standards.

2.3. Object Detection Algorithm. Among a variety of detectors, the R-convolutional neural network (CNN) is a two-stage algorithm that initially garnered considerable attention. R-CNN proposed a region using a selective search method [31, 49]. Selective search is a technique for quantifying the correlation between individual pixels in an image and grouping similar pixels based on their numerical value. In comparison to the sliding window method, this method increased the speed because the area to be searched was reduced. However, the amount of computation required was very high because it had to go through CNN for all the proposed domains. Further, the region proposal method based on selective search was slow. It required the use of a central processing unit (CPU) because it did not employ a CNN network [50].

To address this issue, Fast R-CNN created a single feature map by running the CNN through the entire image without passing it through all the proposed regions. To connect the region of interest (RoI) pooling layer and the fully connected layer to locate a region within the created feature map and classify it, two branches were created connecting the fully connected layer and the SoftMax to detect the object. While this method was possibly faster than the R-CNN, it was still slow because the region proposal was performed outside the network. Thus, the region proposal method is incorporated into the CNN in the faster R-CNN. To propose a location, a region proposal network (RPN) is created within a CNN network. By searching the feature map through CNN in a sliding window method, RPN generates k distinct anchors of a specified size for each location. These anchors can be regarded as the initial values of the bounding box. Following this, a regression layer is created to obtain the coordinates of the corresponding location, and a classification layer is created to verify the existence of an object. A fixed-size feature map is advantageous for classification, and thus RoI pooling is performed on the RoI generated in the RPN to create a fixed-size region and perform classification [51].

Due to its high performance, the two-stage detector has been extremely popular. Although the two-stage detector performed well, it was relatively slow because it had to go through two stages to detect objects. Thus, a first-stage detector was developed, a concept distinct from the two-stage detector. The first stage detector operates within the network without requiring a distinct regional proposal method. Although the first-stage detector performs poorly in comparison to the second-stage detector, its complexity is low, enabling rapid object detection. You only look once (YOLO) [52], single-shot multibox detector (SSD), and RetinaNet all serve as examples of first-stage detectors. In this paper, the fast speed and competitive performance of the first-stage detector were studied.

Many research projects have been carried out to advance object detection algorithms for detecting construction objects such as construction machines and labor [16]. Kolar et al. [53] achieved an accuracy of 95.6% in the test to detect safety railings in construction sites. Kim et al. [54] combined transfer learning techniques with region-based fully convolutional neural networks (R-FCNs) for robust detection of construction equipment. Arabi et al. [55] provided a comprehensive solution for the detection of construction equipment, including development and mobile-end deployment. Roberts and Golparvar-Fard [56] proposed a deep learning-based end-to-end method for detecting, tracking, and analyzing excavator activity on a construction site. Object detection algorithm has been studied in construction work, but a system that can be effectively applied to the field has not yet been prepared. This shows that practical research through communication with field workers is still lacking. Therefore, field-applicable research should be conducted rather than research for experiments.

In particular, Xiao and Kang [16] conducted a study to recognize image data sets for construction machines using four algorithms: YOLO-v3, Inception-SSD, R-FCN-ResNet101, and Faster-RCNN-ResNet101. YOLO-v3 showed the highest detection speed at 26.3 fps. As this study aims to quickly recognize dangerous situations, an algorithm with high image processing speed is required. Therefore, YOLO-v3 was selected among several object recognition algorithms.

2.4. Fall Accidents of South Korea. South Korea has made efforts to prevent construction-related safety incidents, led by the Korea Occupational Safety and Health (KOSHA). In South Korea, the Occupational Safety and Health Act was

enacted on December 31, 1981, and KOSHA has made numerous efforts to prevent fall accidents in the construction industry since 1981, including reforming laws and implementing policies. In particular, the Ministry of Employment and Labor's 3-year industrial safety advancement plan (1997–1999) designated eradicating disaster-type construction accidents such as falls and collapses as one of the eight priority tasks, and the government implemented a plan to reduce fall accidents [57]. Additionally, various policies such as technical guidance and project support have been established in the Industrial Accident Prevention 5-Year Plan (2000–2019) to assist in the preparation of fall disaster prevention measures [58]. Despite ongoing efforts to reduce fall accidents, the number of deaths due to fall accidents continues to be a significant proportion in the construction industry [5].

Despite the trend of gradually decreasing industrial accidents in South Korea, the number of deaths from industrial accidents was 969 in 2016 and 964 in 2017, and the economic loss due to the accident amounted to about $21 Billion. The number of deaths in the construction industry declined until 2013 but increased again after 2014. And fatal accidents caused by falls account for about 50% of the deaths in the construction industry. In addition, it accounts for 32%–34% of the total number of injured in the construction industry. The Ministry of Employment and Labor in South Korea conducted inspection on 753 construction sites that are at high risk of major accidents from November 19 to December 7, 2018. As a result, 690 (91.6%) sites were detected because of violations of the laws, and safety management officers and corporations at 346 sites that neglected the risk of accidents were criminally charged. A fundamental solution is needed to prevent fall accidents through the automation of on-site safety inspections using computer vision.

2.5. Analysis of Relevant Laws and Standards in South Korea

2.5.1. Laws and Standards Related to Safety Harness and Hook. Table 1 summarizes the laws and standards governing safety harness and hook [59]. In Article 32 of the rules on occupational safety and health standards, the act on the provision of protective equipment was amended to allow for the provision and wearing of protective equipment suitable for the working conditions of more than the number of employed workers. This rule stipulates that the safety harness and hook be fastened when working in an area where there is a risk of falling from a height of more than 2 meters. In 2017, Article 42 amended the content of fall prevention. This stipulated that if installing a walking platform is difficult, a safety net should be installed, and if in-stalling a safety net is difficult, workers must wear a safety harness and hook to prevent a fall accident. The safety net must be placed as close to the workspace as possible, and the vertical distance between the workspace and the safety net must not exceed 10 meters. Article 44 specifies a maximum risk of the falling height of 2 meters, as well as the requirement to install a safety harness and hook attachment facility. When a support rope is installed as a safety harness and hook attachment facility, it is specified that necessary measures should be taken to prevent sagging or loosening. The laws governing this safety harness and hook should be reviewed during the image recognition process to determine potential hazards.

2.5.2. Laws and Standards Related to the System Scaffolding. Table 2 summarizes the laws and standards governing the system scaffolding [59]. Article 56 of the rules on occupational safety and health standards specifies the scaffolding structure. Scaffolding material must be sufficiently robust to withstand the load imposed by the work. Additionally, the width of the walking platform must be at least 40 cm, and the gap between scaffolding materials must be no more than 3 cm. The load must not damage the work platform's support, and the material of the walking platform must be connected or fixed to two or more supports to prevent overturning or falling.

Article 57 outlines the regulations that must be followed when assembling, disassembling, or changing scaffolding that is 5 meters or more in height. The time, scope, and procedure of assembly, disassembly, or change shall be communicated to workers engaged in the work, and the entry of persons other than workers engaged in the work area must be prohibited, and the contents must be posted in an easily accessible location. When the weather is extremely bad due to rain, snow, or other inclement weather, work must be halted, or it requires that precautions be taken to avoid falls. When workers are required to raise or lower materials, or tools, they must use a rope.

Article 58 provides that items be inspected before beginning work if work is resumed on the scaffolding following a stop due to rain, snow, or other deterioration of weather conditions, or following the assembly, disassembly, or change of the scaffolding. It requires that if an abnormality in the scaffolding is discovered, it must be repaired immediately. Inspection must check whether the scaffolding material is damaged, attached, or jammed, whether the connection or connections of the scaffolding are loose, whether the connection material and connection hardware are damaged or corroded, whether the handle has fallen off, the subsidence, deformation, displacement or swaying state, rope attachment state, and suspending device swaying state. When erecting or dismantling the scaffolding system, the worker's safety harness and hook can help to reduce the fatality rate at the construction site. However, the safety harness and hook are used to prevent fatal accidents, and all applicable laws must be followed. Laws and standards about these system scaffolding must be reviewed during the image recognition process to determine risk factors.

3. Accident Case Analysis through Reviewing of On-Site Notice by the Field Manager

Figure 1 shows the case in which the safety harness and hook are not fastened while working on the scaffolding. The worker is wearing a safety harness and the hook hanging

TABLE 1: Rules on occupational safety and health standards related to safety harnesses and hooks [59].

Laws	Details
Article 32	Safety harness and hook must be provided and worn by workers who work in places where there is a risk of falling from a height of over 2 meters
Article 42	If it is difficult to install a walking platform, a safety net must be installed. If it is difficult to install a safety net, workers must wear safety harness and hook
Article 44	If a worker wears a safety harness and hooks at a height of 2 meters or more, the safety harness and hook facilities must be installed

TABLE 2: Rules on occupational safety and health standards related to safety harnesses and hooks [59].

Laws	Details
Article 56	The material, structure, and specifications of the walking platform are prescribed, and measures necessary to prevent danger when working or moving on the walking platform must be taken
Article 57	The matters to be observed when assembling, disassembling, or changing scaffolding with a height of 5 meters or more
Article 58	When an employer stops work due to rain, snow, or other weather conditions, or after assembling, disassembling, or changing scaffolding, he or she must inspect the scaffolding before starting the work

from the horizontal reinforcing bar is a safety hook, as shown in Figure 1(a). Figure 1(a) shows that the work is being carried out in an unstable state on the upper portion of the scaffolding, and Figure 1(b) shows that the workers are in the process of installing the scaffolding. Figure 1(c) shows that the work is being carried out on the system formwork, and on the scaffolding adjacent to the formwork, installation work as shown in Figure 1(d). As shown in Figures 1(a)–1(c), there is a high risk of accidents due to workers who have not fastened the safety harness and hook in the arrangement where the walking platform is not installed.

When working on scaffolding, safety accidents can occur if the safety harness and hook are not properly fastened. According to a 2007 safety accident report of the Korea Occupational Safety and Health Agency (KOSHA), when a laborer climbed onto the scaffolding to dismantle the external scaffolding, the scaffolding's horizontal member disengaged from the clamp. As the scaffolding was tilted, the laborer fell approximately 25 stories to the floor and died [60]. This accident could have been avoided if the work had been carried out after inspecting the connection of the scaffolding for looseness before dismantling the scaffolding and while wearing the safety harness and hook. It is possible to determine when a person judges a situation as dangerous based on experience. Recognizing dangerous situations with a computer, on the other hand, must be done sequentially through algorithm input.

4. Computer Vision Process for Safety Harness and Hook

As illustrated in Figure 2, the image recognition inference process is divided into two stages: image object recognition and accident prediction. When the current work and incoming materials, workers, and equipment are input, all types of objects are analyzed in the image object recognition stage. Additionally, the state data is analyzed to derive hazard factors. The accident prediction stage determines the likelihood of an accident and derives actions to be taken at

the site based on the accident type. The database (DB) is used for analysis in all processes.

This methodology can be explained using an example of a safety accident that could occur as a result of a worker failing to secure the safety harness and hook during the system scaffold installation work.

(1) It is entered into the system scaffold installation process and analyzed the types of materials, laborers, and equipment brought to the construction site.

(2) Among the analyzed objects, the object position is determined and it is analyzed to determine if it is fixed and that the hazard factors are determined by confirming that it is not connected. In the case of the workers, the cause of the accident is analyzed by measuring the object position, verifying that the safety equipment is worn, and confirming that the safety harness and hook are securely fastened. In the case of equipment, it analyzes hazard factors by determining whether it maintains a safe distance from other objects and confirming that it is currently operating.

(3) As a result of the hazard factors analysis, the possibility of an accident is determined, and the possibility of a fall accident is deduced.

(4) Depending on the type of accident, appropriate instructions are given to the site, and the stop order is delivered.

It is possible to derive the image detection target for the nonfastening of the safety harness and hook at the construction site by analyzing laws and standards, as shown in Figure 3. This corresponds to the "Analysis of object type" of the CVA methodology in Figure 1. This can be explained as follows.

(1) To recognize the image, it is necessary to analyze the elements to be recognized in the image by dividing it into ① system scaffolding installation work and ② work on the system scaffolding and dismantling work.

(a)

(b)

(c)

(d)

FIGURE 1: Safety harness and hook not fastened when working on the system scaffolds. (a) Formwork on the top of the scaffold. (b) Scaffold installation work. (c) Work on the Scaffoldings. (d) Moving on to the scaffold.

(2) It is necessary to conduct compliance checks, and this process is incorporated into the laws and standards governing the safety harness and hook, as well as the system scaffolding. It is necessary to inspect the walking platform for proper installation, as well as the safety hook attachment facility. Additionally, it must be verified that the worker is wearing a safety harness and using the safety hook to attach to the attachment facility.

(3) The information gathered during the review of laws and standards can be used to analyze the image recognition elements in terms of their process. When installing the system scaffolding, the exterior wall is first identified, followed by the scaffolding when working on and dismantling the system scaffolding. Additionally, it is possible to verify that the walking platform has been installed, that the safety hook attachment facility has been installed, and that the safety harness has been worn and the safety hook has been connected.

(4) Using the preceding procedure, it is possible to establish the order in which the target should be recognized on the image of the safety harness and hook fastening. When installing system scaffolding, it is necessary to first identify the location of the scaffolding, followed by the walking platform, safety hook attachment facility, safety harness, and safety hook in sequence. Working on system scaffolding and dismantling work is identical except that the installed scaffolding first, and, as with scaffold installation work, safety hook attachment facility, safety harness, and safety hook are recognized in that order.

5. Application of Methodology

5.1. Sample Site Application. In this study, Python, C++ Language, and YOLO v4 algorithm were used to recognize the worker in images or videos. YOLO is designed to reduce the amount of computation required to detect objects in real time by dividing the image into regions rather than using the sliding window method, which includes each pixel in multiple windows [52]. YOLO can estimate the location of an object in a single network by turning the location and class probability of an object in an image into a single regression problem [50]. Object detection is, in general, a combination of a method of object localization and a method of object classification. The region proposal method
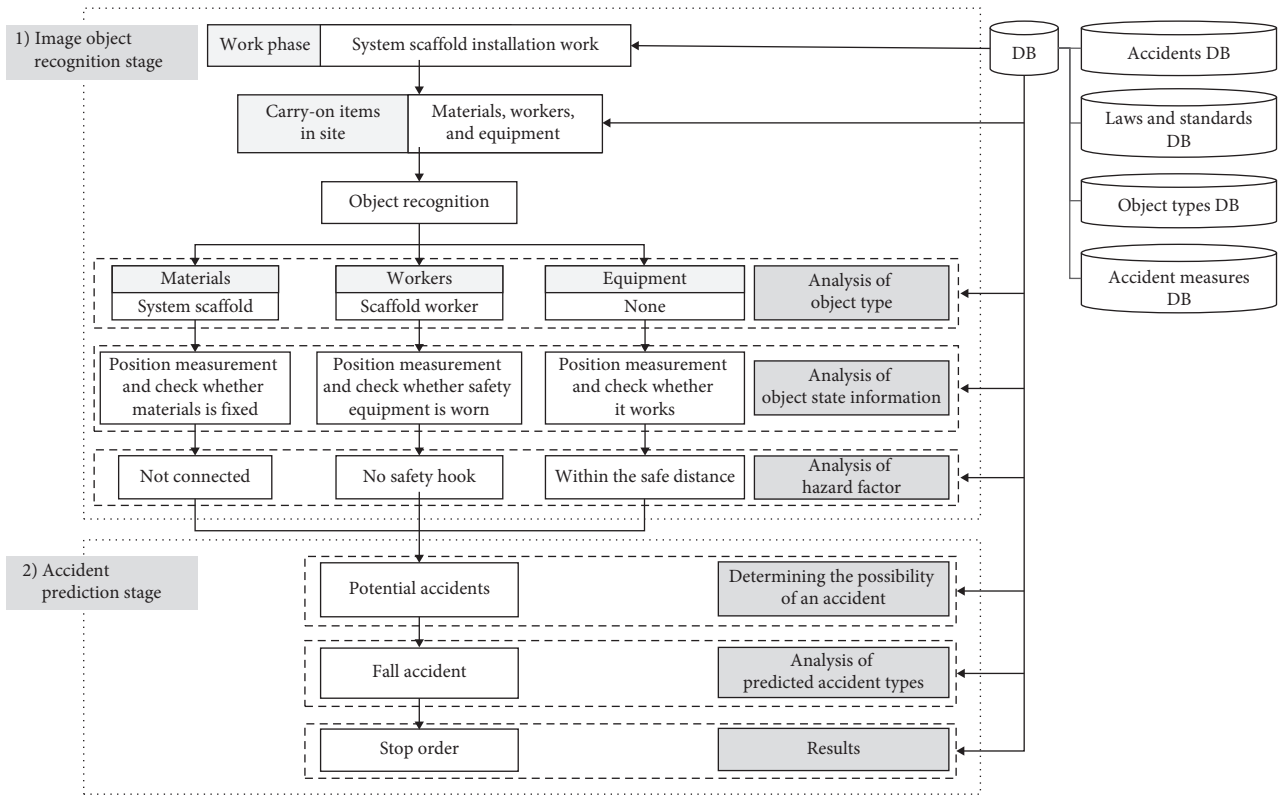
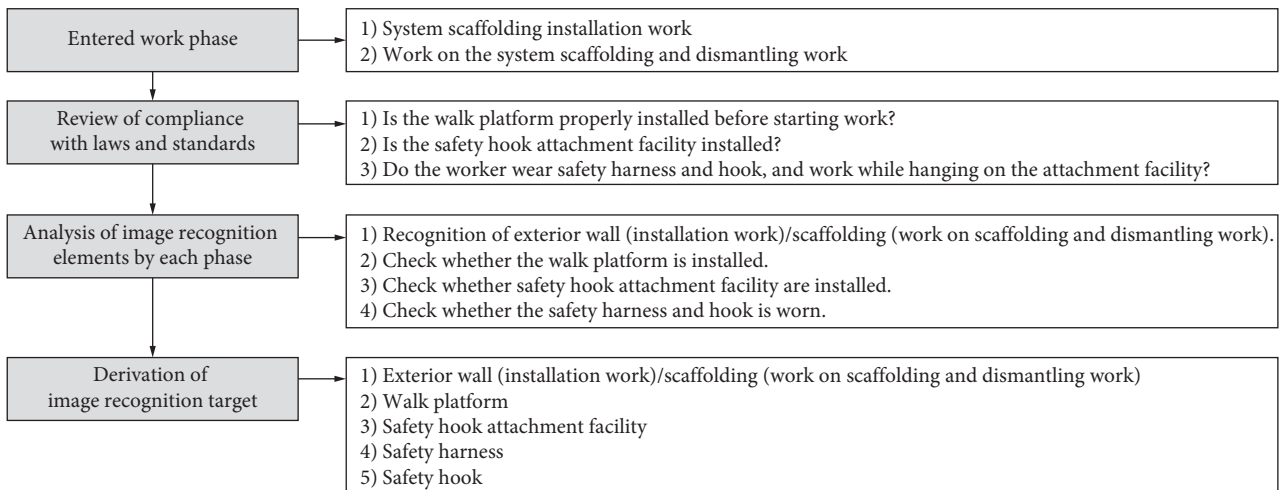FIGURE 2: Computer vision application (CVA) methodology.

FIGURE 3: Image detection target derivation process.

is commonly used to find the location of an object. In other words, YOLO performs both region proposal and classification at the same time. A sample site was created for the development of Artificial intelligence (AI) for hazard identification in this study, and it can be applied to two situations using the CVA methodology, as shown in Figure 4. The image that the equipment has not yet been brought in was used to apply the CVA methodology developed from a simple piece of work.

5.1.1. Worker with Safety Harness and Hook. Figure 4(a) shows that the worker moving on the walking platform between the system scaffolding, with the recognition of the worker's safety harness and hook analyzed as follows:

(1) Input of Work Phase and Field Carry-On Items. The work phase is "Work on the system scaffolds," which is entered by dividing all materials, workers, and equipment brought to the site. The system scaffolding [61] consists of steel stair, guardrail, vertical diagonal brace, vertical,

(a)   (b)

Figure 4: Worker detection at the sample site. (a) Worker with the safety harness and hook. (b) Climbing worker on the system scaffoldings.

horizontal, walk platform, wall tie, and base jack. It is input to recognize a safety hat, safety boots, safety harness, and hook in the case of workers.

(2) Object Recognition and Type Analysis. It is determined whether the objects entered are recognized at the sample site location. Additionally, the recognized objects are classified into materials, workers, and equipment, and their associated types are analyzed.

(3) Analysis of Object State and Hazard Factors. Before analyzing the object's state, it is necessary to understand the field data. When installing a walking platform and a safety hook attachment facility, it must be checked for the location of each object. Before beginning work, it is necessary to verify the availability of additional space using shop drawings and site photographs [14]. In addition, information from shop drawings and site photographs should be incorporated when creating the computer vision system. In Figure 4(a), the worker is moving between the system scaffolding by wearing a safety harness and hook. As such, before working on system scaffolds, it is necessary to check that measures have been taken to minimize the sagging and shaking of the ropes installed as safety hook attachment facilities.

In the case of carry-on materials, the position of the system scaffolding is measured, and the degree of shaking is recognized to determine its stability. It is determined to be safe by checking whether the safety guardrail was installed, as well as the location of each member of the system scaffolding. Because the width of the walking platform exceeds 40 cm and the gap between the walk platform materials is 3 cm or less, it was determined that the walking platform does not pose a hazard. Because the distance between the ground floor and the walking platform is less than 10 m, no safety net is required. Because the work is being performed in an area with a risk of falling more than 2 meters, the safety harness and hook must be fastened. In the case of the worker, it was determined that there is no hazard factor by measuring the location and determining whether or not to wear safety equipment (safety harness and hook, safety shoes, safety hat). As a result of applying the CVA

methodology used in this study, the worker was detected but not the safety hook. The reason for this is that the safety hook is a member small in size.

(3) Prediction of Accident Types. As a result of the hazard factor analysis, it is determined that there is no possibility of an accident, and no instructions are given to the workers, to complete the computer vision process.

5.1.2. Worker Climbing the System Scaffolding.
Figure 4(b) shows that the worker is climbing the system scaffolding. The following procedure is used to inspect the safety harness and hook fastening:

(1) Input of Work Phase and Field Carry-On Items. The work phase is entered as "Movement on the system scaffolds," and it is divided into all materials, workers, and equipment brought to the site. It should be entered as a system scaffolding composed of numerous components similar to Figure 4(a). Additionally, the walking platform is entered, and the workers' items, such as safety hats and safety boots, are recognized.

(2) Object Recognition and Type Analysis. It is checked to see if the input objects are recognized. Furthermore, the recognized objects are classified into materials, workers, and equipment, and their types are analyzed.

(3) Analysis of Object State and Hazard Factors. As illustrated in Figure 4(a), the location of each object must be verified using shop drawings and site photographs [14]. By measuring the position of each member of the system scaffolding including the guardrail, all materials were analyzed and it was determined that there was no hazard factor [61]. Because the width of the walking platform exceeds 40 cm and the gap between the walk platform materials is 3 cm or less, it was determined that there is no hazard factor for the walking platform. In the case of the worker, it was analyzed that there was no accident occurrence factor by measuring the worker's position and checking whether or not to wear safety equipment (safety harness, safety shoes,
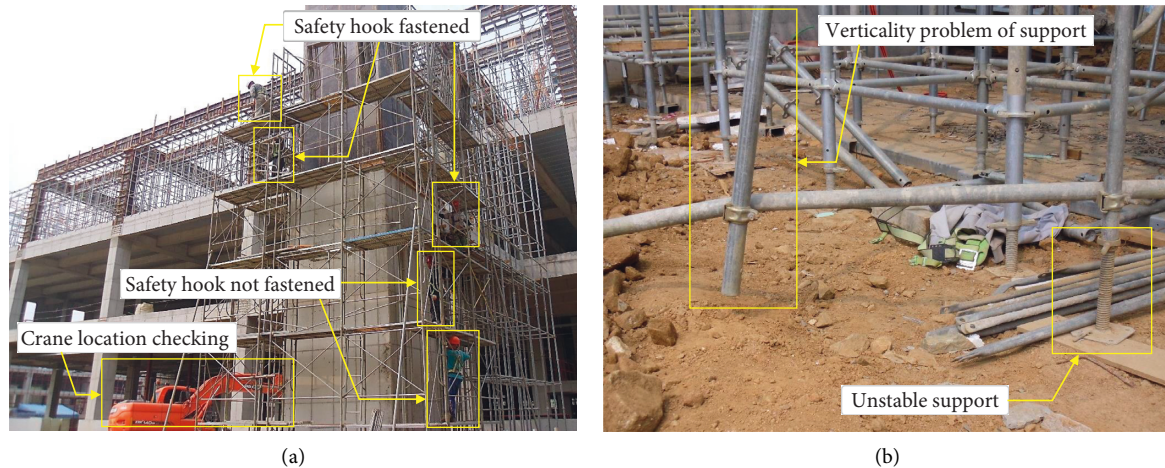
FIGURE 5: System scaffolding installation work. (a) Objective detection. (b) Support problems.

and safety hat). However, it was analyzed that there were risk factors because the safety hook was not secured, and the foot was resting on the guardrail outside the system scaffolding rather than on the walking platform.

(4) Prediction of Accident Types. The hazard factor analysis revealed that the possibility of a potential accident exists, and the type was classified as a "fall accident." It was decided to issue a "work stop order" instruction to the workers to halt work at the site. This concluded the computer vision process.

5.2. Field Application. Figure 5 shows the installation work of the system scaffolding. And checking whether the safety harness and hook are fastened is analyzed as follows.

5.2.1. Input of Work Phase and Field Carry-On Items. The work phase "System Scaffolding Installation Work" is entered by dividing all materials, workers, and equipment brought to the site [61]. In Figure 5(a), the input system scaffolding is shown and classified as forms for column and beam as material, five workers as workers, and a crane as equipment.

5.2.2. Object Recognition and Type Analysis. It should be checked that the material, worker, and equipment are recognized as input objects.

5.2.3. Analysis of Object State and Hazard Factors. The construction progress must be analyzed using drawings [14] and on-site photographs to ensure that the structure is completely up to the third floor, and that column and beam forms are installed on the third floor. In addition, the elevator zone scaffolding was installed. As illustrated in Figure 5(a), a hazard exists because two of the workers wore a safety harness but did not secure the safety hook. Additionally, a safe distance between the crane and the system scaffolding was not maintained by measuring the distance. However, because the crane was not operational, there was

no hazard factor. As shown in Figure 5(b), the lower support was determined to be dangerous due to its unsteady installation on a wooden plank. There was a hazard factor due to the presence of more than 5 supports and safety harnesses. Additionally, as the support verticality was not maintained at 90 degrees, there was a risk factor involved in the scaffolding installation process.

5.2.4. Prediction of Accident Types. A hazard factor analysis is necessary because reluctance to wear personal protective equipment and lack of awareness of on-site safety hazards are the main causes of safety accidents at construction sites (Liaudanskiene et al., 2009; [62]. Hazard factor analysis identifies potential accidents. It was classified as "falls from heights" as a result of failing to secure the safety hook, "collapse" as a result of unstable support and verticality issues, and "slip and falls" as a result of neglected safety harnesses and supports. It is decided to issue a "work stop order" instruction to the worker who does not have a safety hook, as well as a "work change order" instruction to correct the location of support installation. It is also decided to terminate the computer vision process by issuing a "removal order" instruction for the neglected supports and safety harnesses.

6. Conclusion and Future Research

Fall-related injuries accounted for 32.1% of all injuries at construction sites in 2009 and 33.8% of all injuries in 2017, accounting for 32%–34% of all injuries. Additionally, falls account for approximately 50% of all fatalities in the construction industry [5]. In other words, because fall accidents are the most serious type of construction accident [4], they must be managed systematically. Thus, by preventing falls at the construction site, the accident rate can be reduced by 30%. This has the potential to reduce the death rate from safety accidents by approximately 50%. The purpose of this study was to develop a CVA methodology that can be used at a construction site to prevent fall accidents. The developed methodology was used to secure the safety hook of the

system scaffold. Additionally, the risk factors and possible accident types at the construction site associated with the case-by-case process were analyzed. The following are the conclusions of this study.

First, this paper was reviewed by the construction site's field manager for safety harness and hook-related points. The risk of an accident is greatest if workers are working without fastening the safety harness and hooks in the state in which the work platform was not installed. It was through this process that the accident case that occurred at the site, as documented in the KOSHA safety accident report, was analyzed. As a result, it was determined that the fall and death accident could have been avoided if the work had been completed after the safety harness and hook attachment facility was installed, confirming the critical nature of the safety harness and hook.

Second, laws and standards governing safety harnesses and hooks, as well as system scaffolds, were examined in terms of fall accidents. The safety harness and hook were analyzed for their relationship to Articles 32, 42, and 44 of the rules on occupational safety and health standards, while the system scaffolds were analyzed for their relationship to Articles 56, 57, and 58. Specifically, in the laws and standards governing system scaffolds, it was stated that the purpose of the safety harness and hook was to prevent fatal accidents. The analyzed laws and standards can be used to determine the risk factors associated with the object.

Third, a process for deriving an image detection target at a construction site was developed using the information gleaned from an analysis of the laws and standards related to safety harnesses and hooks, as well as system scaffolding. It was confirmed during the process that it is possible to derive the image detection target for the safety harness and hook not being fastened properly on the system scaffolds.

Fourth, the CVA methodology was developed by separating the stages of image object recognition stage and accident prediction. This methodology was used at sample sites and in field cases. By analyzing the risk factors on the system scaffolds and forecasting accidents in advance, this methodology was demonstrated to be applicable in the real world.

The CVA methodology of this study will serve as the foundation for future computer vision research. Additionally, this methodology can help researchers better understand the data that must be gathered at construction sites when they are developing computer vision programs or systems to help reduce the rate of safety-related accidents. Finally, this method will help reduce the number of fall accidents not only in South Korea but also globally, as a result of the safety harness and hook being left unfastened. Additional studies are required to apply the CVA methodology to a wide variety of fields.

First, the worker and the safety harness were recognized using the algorithm developed in this study, but the safety hook was not recognized. This is because the safety hook is a relatively small component. To address this, a method for detecting when a small member is applied should be developed. Additionally, a computer vision system should be established to verify the connection of the safety hook, which

was not done in this study. In other words, an algorithm development study that can recognize the safety harness and safety hook of Figure 1(a) should be additionally conducted.

Second, this study established the CVA methodology and demonstrated only how to apply it to a prepared sample site and a real-world construction site. Building a computer vision system should be done in the same way as the method described in this study: (1) one worker wearing the safety harness and hook should be placed at the sample site where the system scaffoldings are installed, and (2) the system should be tested to ensure that it continues to work properly as the number of materials, several workers, and equipment increases. In addition, the CVA methodology should be modified and proposed to enable the construction of a computer vision system that is more suited to the field by utilizing the algorithm for system construction. To determine the most appropriate algorithm, a system should be developed by experimenting with various algorithms.

Third, it is necessary to investigate not only fall accidents that occur during work on scaffolding systems but also fall accidents that occur during construction projects involving a variety of equipment and materials. In other words, this methodology applies to a variety of scaffolding work, formwork, reinforced concrete work, roof work, tower crane installation, and dismantling, as well as steel tower installation and dismantling work. It is necessary to analyze the laws governing various types of works, materials, and situations, and all data will be stored in a database for the construction of a computer vision system.

Fourth, it is necessary to classify and define each type of object in terms of its state (materials, workers, and equipment), risk factors, predictable accidents, and site orders in response to predictable accidents. It is also necessary to study detailed definitions of predictable accidents, such as exposure to dangerous chemicals or toxins, electrocution, collapse, slip and falls, crashes, burns, fire, and overturning accidents, with the exception of falls from heights defined in this study.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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