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Correlation Extraction from KOSHA to enable the Development of Computer Vision based Risks Recognition System

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Abstract: Generally, occupational safety and particularly construction safety is an intricate phenomenon. Industry professionals have devoted vital attention to enforcing Occupational Safety and Health (OHS) from the last three decades to enhance safety management in construction. Despite the efforts of the safety professionals and government agencies, current safety management still relies on manual inspections which are infrequent, time-consuming and prone to error. Extensive research has been carried out to deal with high fatality rates confronting by the construction industry. Sensor systems, visualization-based technologies, and tracking techniques have been deployed by researchers in the last decade. Recently in the construction industry, computer vision has attracted significant attention worldwide. However, the literature revealed the narrow scope of the computer vision technology for safety management, hence, broad scope research for safety monitoring is desired to attain a complete automatic job site monitoring. With this regard, the development of a broader scope computer vision-based risk recognition system for correlation detection between the construction entities is inevitable. For this purpose, a detailed analysis has been conducted and related rules which depict the correlations (positive and negative) between the construction entities were extracted. Deep learning supported Mask R-CNN algorithm is applied to train the model. As proof of concept, a prototype is developed based on real scenarios. The proposed approach is expected to enhance the effectiveness of safety inspection and reduce the encountered burden on safety managers. It is anticipated that this approach may enable a reduction in injuries and fatalities by implementing the exact relevant safety rules and will contribute to enhance the overall safety management and monitoring performance.

Keywords: KOSHA rules, computer vision, objects correlation, risk recognition, safety inspection

1. INTRODUCTION

A safe environment is mandatory in all industries, while in construction, it is of particular importance because of the fourth highest fatal injury rates among all industries [1]. The construction industry reports show the incident rate of 36% in Singapore, 29.3% and 27% in South Korea and UK respectively, which is approaching to double than other industrial averages [2], [3]. Strong enforcement of safety regulations is a vital way to enhance construction safety and minimize accidents. Moreover, these safety regulations play a basic role in construction risk identification in the pre-construction and during construction.

Onsite safety monitoring is pivotal as it is the last safety management layer to prevent accidents. Since accidents happen during the physical construction work, so, extensive exertions had been given to enhance the effectiveness of inspection on job site during work. Unfortunately, current construction safety monitoring still relies on manual inspections, which are expensive and not always possible, thus, need to be improved and ultimately automated. In recent years, several approaches and techniques based on safety regulations, accident cases, training, and education have attempted new ways to enhance safety management. Among various methods to manage effective construction safety, application of advanced techniques such as computer vision, machine learning, blockchain, smart sensors, motion tracking technologies, augmented reality holds huge potential for proactive prevention of accidents and automatic risk identification.

Considering the recent construction context, computer vision and machine learning hold the ginormous potential to enhance the efficiency of the various tasks in construction safety monitoring, progress checking, defect detection and so on. The unprecedented increase in the visual data from the job site enables a unique opportunity for computer vision systems to be deployed widely which could improve safety performance and safety monitoring [4]. For instance, absence of helmet, wrong position or absence of fire extinguishers, absence of guardrails at the edges of excavation and floors, are handled with object detection systems. Also, object trackers systems or action recognizers are used to detect dynamic hazards such as moving equipment and workers. However, far as the scope and application of existing systems are still limited, thereby mostly consider some specific activities, equipment, worker behavior, and hazard types.

To eradicate potential hazards at the right time, continuous job site monitoring is required for unsafe acts. The unsafe acts include actions such as, but not limited to, positive and negative relationships between the construction entities which could be a direct reason for the accident. For instance, considering welding activity: fire extinguisher with welding machine, gloves and safety glasses (helmet) with the person shows a positive correlation. The example of a negative correlation could be the relation between electric wire and water, use of a ladder on scaffolding and many more. To fill the gap, this paper envisions to enhance construction site safety monitoring by introducing a safety rule compliance computer vision-based correlation recognition system with a larger scope. Deep learning supported computer vision technology is considered a feasible solution due to high performance, simple structure, and cost-effectiveness, as most of the construction job sites are currently equipped with the CCTVs. Rather than the traditional safety monitoring process whereby safety manager inspects the safety rule compliance in Jobsite physically, computer vision-based job site safety monitoring provides a reliable approach which allows automatic recognition of objects, hazards, and unsafe behavior.

2. LITERATURE REVIEW

2.1. Current Safety Monitoring Status

Generally, the construction sector and its clients are widely linked with high risks due to the nature of micro, meso and macro environments specific to the construction [4], unfortunately, due to ineffective dealing with that unique hazardous environment, construction industry has not a good reputation globally. The standard current practice to deal with the safety hazards in construction involved monitoring of job site environment. In order to identify any potential hazard or safety rule incompliance during construction, the safety manager must be present physically. The success of these physical visits for safety compliance depends on the experience and competence of the safety manager. In addition, existing inspection methods are painstaking and time-consuming [5]. In the recent decade, researchers have focused on enhancing the safety management process by using new technologies. Generally, the safety management process includes safety planning in the pre-construction stage and safety monitoring during construction stage. Many researchers proposed an advanced safety planning process by extracting relevant safety rules from the regulation database and then integrating that domain-specific rules with Building Information Modeling BIM [6], [7]. BIM is also utilized for hazard location detection in safety monitoring stage by several researchers which reduces cost and time. However, this approach still needs a manual inspection for generating safety reports from the field. In fact, researchers have recently introduced vision-based automated safety monitoring during construction which can minimize the existing problems in manual safety inspection [5], [8]–[10]

2.2. Computer Vision (CV) based Technologies in Construction

Unlike other industries such as manufacturing industries, the construction industry comprises a complex working environment and sometimes non-standardized operating procedures. Consequently, this unique nature creates challenges for safety monitoring and occupation health. Computer vision-based technology has been adopted in various areas of construction such as hazard recognition, defect detection, progress monitoring, productivity analysis, and automated documentation. Recent research in vision-based monitoring of the construction sites has focused on the development of the simple inspection system for the detection of basic hazards, for example, hard hats detection [11] and safety harness recognition for fall hazard [9]. Resources detection such as human resources, materials, and machinery/equipment is another development in the same domain which has been made in the near past [12]–[14]. Nevertheless, the “objects” detection ability of the trained models in these research studies is noticed limited. One reason could be the limited dataset used to train the models. Many researchers have focused on exploiting descriptors for machine learning classifier and only a few have explored the neural networks application for object detection in construction. In this paper, a science of design research methodology was adopted [15] to develop a risk detection system by employing neural networks algorithm that could be used to automatically recognize positive and negative correlation among the objects.

3. CORRELATION EXTRACTION FROM KOSHA REGULATIONS

In 1953, labor standard law led the foundation for industrial safety and health policy in Korea. Thereafter in 1987, Korea Occupational Safety and Health Agency (KOSHA) was established with regards to the rapid development of industries in 1970 to 180. The related acts were revised in order to meet the mandatory demand for safety and health standards required for various industries having a toxic and complex environment. Since then KOSHA collected and analyzed many accident cases, thereby resulted in the expert knowledge database. Based on that, Substantial amendments have been made to ameliorate the past polices for modern industry compliance and global competition.

The vital point to consider is that despite strong enforcement of occupational safety regulation and expert knowledge around the globe, the construction safety management process still relies on traditional practices. Computer vision can enhance the construction safety enforcement and implementation process, thus, by converting the expert knowledge, in this case, the rules into practicality by using deep learning algorithms. Therefore, the KOSHA regulations were analyzed and relevant rules having relationship information, either positive or negative were extracted. The KOSHA regulations standards on occupational safety and health are manually investigated by the authors manually at a basic clauses level.

Table 1. Analysis of KOSHA Regulations

Description of Construction Related Articles from KOSHA	**No of Articles**	**Percentage (%)**	**Technology Application**	
Correlation between the resources explained by articles	305	36.90	Computer Vision	
Limited access zone and numerical related articles	171	20.70	Computer Vision	
Miscellaneous articles	106	12.80	ICT excluding Computer Vision	
Remaining articles	245	29.6	Unable to be covered using technologies	
			Computer Vision	**Others**
Total	**824**	**100**	**57.60 %**	**42.40 %**

The KOSHA regulations consist of 13 chapters which include various sections followed by 671 standards, out of which 277 are related to the construction sector. These 277 standards further contained clauses that were thoroughly investigated and classified. The first step was to determine the standards which reflect the construction industry and then the potential of computer vision adoption was examined on the extracted standards. Subsequently, the object relationships based on the correlation, whether positive (+) correlation (objects relation is compatible with each other) or either negative (-) correlation (objects relation is not compatible with each other) within the articles were studied.

The analysis of 824 articles, as illustrated in Table 1, revealed that 57.6% of articles could be handle with computer vision while 12.8 percent were expected to be dealing with other information and communication technologies (ICT). In addition, 29.6 percent of articles were not able to cope with the technologies. With this regard, this study focuses on those risks mentioned by KOSHA regulations which could be tackle through computer vision. The scope of the paper is limited to the detection of positive and negative correlation of a worker with mobile scaffolding explained in article 68(1). Two case scenarios are explained to elaborate the proposed research concept.

4. CASE SCENARIOS

To identify the benefits of the proposed system, a construction entity (mobile scaffolding) which is almost used in every building construction site, was preferred for the experiment. The aim was to apply a computer vision-based risk recognition system developed for the detection of correlation between the construction entities.

The Article 68 (1): (Movable scaffolding) extracted from KOSHA said that “when the movable scaffolding is assembled by the employer, to prevent unexpected sudden movement or turning of the wheels of the movable scaffold, fix the wheel with a brake, wedge, etc., and fix the part of the scaffold to a solid facility or install an outrigger". This article in KOSHA demonstrates the two correlation (positive and negative) between the mobile scaffolding and worker. The extracted case scenarios from this article can be mathematically written as follows

Case 1: For instance, if a person “A” is working on the mobile scaffolding “B” with outriggers installed, then the relation between the two entities is concluded as positive relationships and is safe for work.

Case 2: On the contrary, if the person “A” is working on the mobile scaffolding with no outriggers installed then the relationship between A and C is supposed to be negative. consequently, the negative relation shows the unsafe arrangement and the system need to generate a warning message to the concerned safety manager automatically. Thus, the safety manager responsible for the mobile scaffolding safety will no more physically visit the job site.

5. DATASET ESTABLISHMENT

In order to train a CNN classifier, a huge number of labeled images are needed. Though, obtaining labeled images of construction objects from open-source databases is yet challenging. Thus, raw images of persons, mobile scaffolding (without outrigger and with outriggers) with an extensive range of variations such as lighting, shadow, etc. were collected. The raw images were taken from the Google database and one of the Tornado group's construction sites for higher secondary college of technology located in Abu-Dhabi, United Arab Emirates.

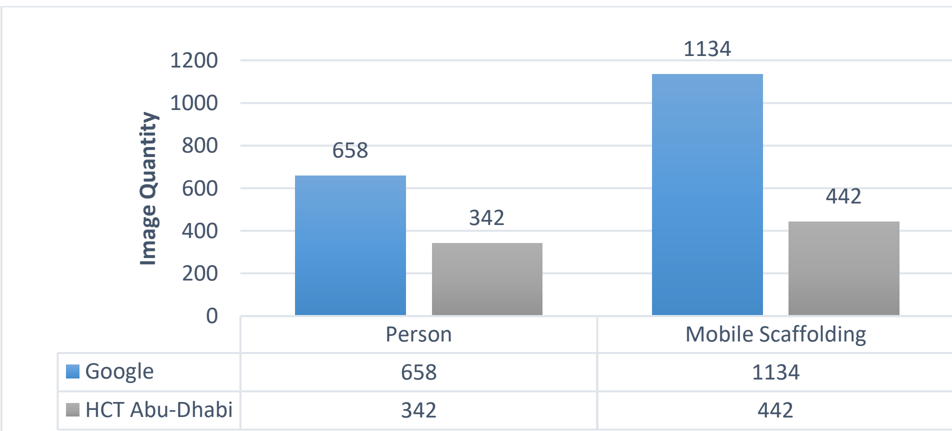

Figure 1. Distribution of image data source

A total of 3865 images were collected. Figure 1. depicts the detail statistics of each construction objects collected from two sources. To avoid overfitting, similar images from the identical scene were eliminated from the dataset during the annotation process. To detect the correlation among the resources in selected scenarios as a case example, three classes were defined: "scaffold" for mobile scaffolding, "safescaffold" for mobile scaffolding with having outriggers and "person" for a person. All the images (jpg, jpeg, png) in the database were labeled and saved as .json file format using standalone manual annotation software runs in a web browser called VGG Image Annotator (VIA) (see Figure 2.).

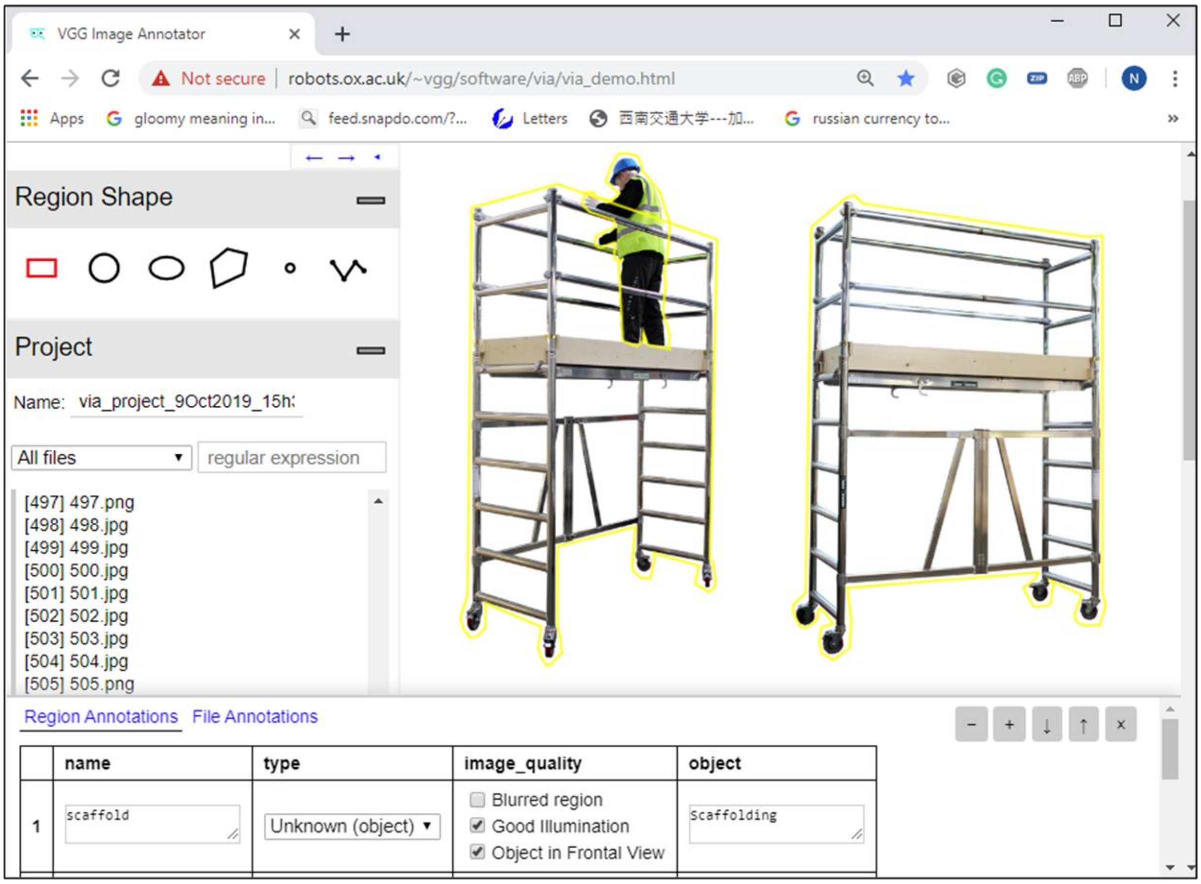

Figure 2. VGG Image Annotator (VIA): annotation tool

6. CONVOLUTION NEURAL NETWORKS APPLICATION

In recent years, many researchers have tried to focus on developing automated techniques for resource detection and tracking in a complex environment of construction [8], [9], [14]. The goal of these studies is to support operational effectiveness, increase productivity, safety enhancement and minimize idle time.

Convolution Neural Networks (CNN) have been used widely in object detection and classification due to the significance gained in the extraction of an image feature since rapid development witnessed in deep learning and other technologies. In the detection field, the accuracy and speed of object detection and classification are very important. Hence, many algorithms such as Region-CNN (RCNN), Fast RCNN, Faster RCNN came into existence, however, these algorithms require two-step processing [16] results in slow athematic speed, consequently, makes detection difficult in real-time. However, Faster RCNN has been found the best detection approach due to its ability of high accuracy. A major challenge confronting the CNN is its large dataset requirements for training. Likewise, the Mask R-CNN has been identified to outperform all the developed object detection approaches claimed by He et al. in 2017 [17].

Thus, to attain higher accuracy in terms of detection in a complex construction environment, the Mask-RCNN approach is applied in this research. Figure three shows the process flow chart of the proposed system. The annotated data is trained using the Mask R-CNN algorithm with 80 epochs and 300 steps per epoch. The results are quite impressive and can be seen in

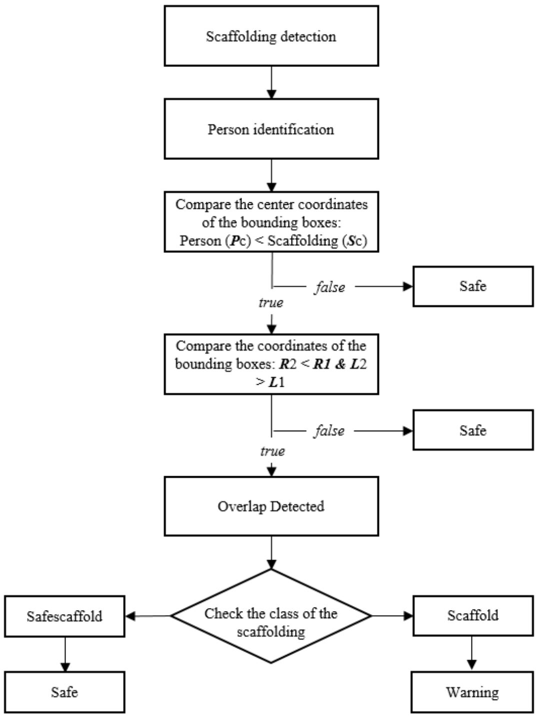

Figure 3. Process flow chart for correlation detection

7. Correlation Detection

This research introduces the overlapping method for correlation detection between the construction entity. Initially, the system detects and mask all the persons and scaffolding in a given image. After detection and segmentation, the center coordinates of both the bounding boxes are compared as shown in the figure......., if the person center coordinates "Pc" is greater than the mobile scaffolding "Sc", this means that the person is working on the ground and is safe to work. With the condition that person center "Pc" is lesser than the mobile scaffolding "Sc" then this implies the doubt of the relationship between the mentioned construction entities and will compare the corner coordinates of the two bounding boxes such as "L2" is greater than "L1" and "R2" is lesser than "R1", if both conditions satisfied then the system will detect the correlation else the action will be ignored. In order to identify the positive and negative correlation, the system will need to check the class of the scaffolding and decide accordingly.

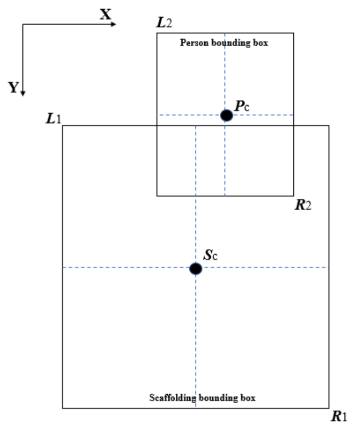

Figure 4. Example of bounding boxes coordinates

8. RESULTS AND DISCUSSION

The experiment was conducted on i7-9700k CPU, Ubuntu 16.04 LTS operating system, 32 GB memory, and Ge-Force RTX 2080 TI graphics card. A total of 3865 images were collected and manually annotated for model training. The qualitative results of the detection are illustrated in the below figures. It is clearly described from Fig.5 and Fig.6 that the trained model could localize the construction objects accurately.

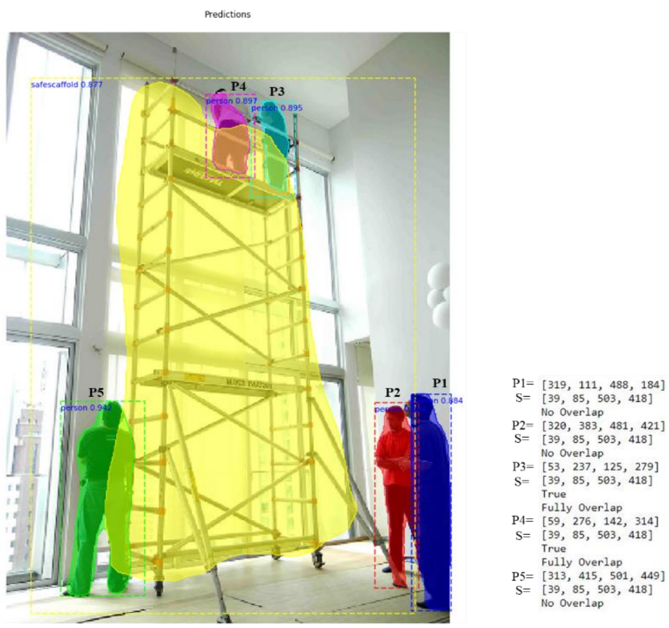

Figure 5. Case 1: Persons and Mobile scaffolding with outriggers having a positive correlation

Fig.5 exemplifies case 1 which includes the detection of persons and scaffolding with outriggers. The system initially detects the scaffolding and persons followed by determining the relationship using the overlapping methods discussed in section 7. Apart from construction entity detection, Figure 5. also illustrates the results of the correlation such as fully overlap for two persons P3 and P4. The detection results of case 2 are demonstrated in Fig. 6, which shows the negative correlation between the person and mobile scaffolding with having no outriggers.

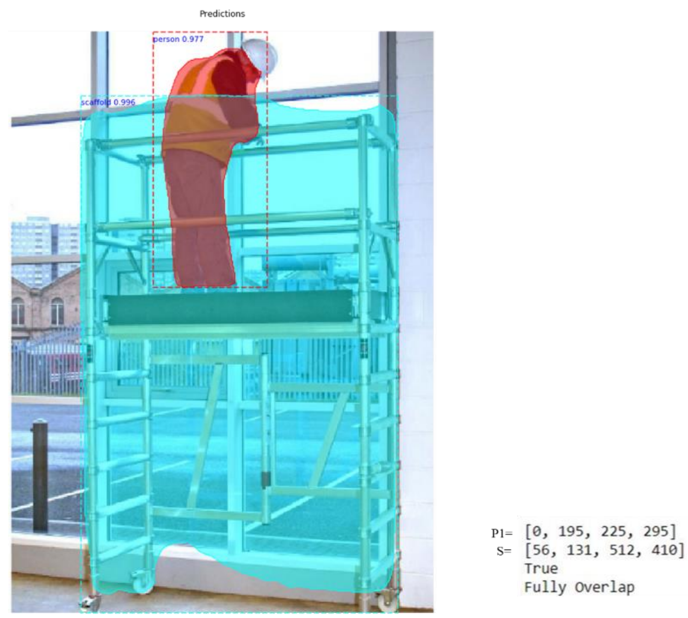

Figure 6 Case 1: Persons and Mobile scaffolding with no outriggers having negetive correlation

9. CONCLUSION AND FUTURE WORK

Safety in construction is directly proportional to the lives of the worker. Generally, construction safety consists of two phases: safety planning and safety monitoring. The latter is of utmost importance due to its nature as a final layer of safety management. To improve that final layer of safety management, this paper proposed a novel system based on the extracted KOSHA rules leveraging deep learning algorithms to enhance risk recognition and accident prevention. To achieve this goal, KOSHA regulations are investigated and the relevant safety rules having relationship information are used as a base for image data collection. Images were collected from two different sources for the creation of dataset and model training. The developed correlation dependent risk recognition system has been successfully implemented on the two real scenarios taken from the accident reports. The preliminary results of the detection using Mask R-CNN algorithms are presented. In the future, a larger dataset from the real construction site will be created for the better detection of construction objects. In order to get a real reflection of the construction job site and more practical results in the end, the same framework will be extended to the accident cases from the database. It is further expected that the developed system could assess the safety performance if integrated with other technologies such as blockchain and IoT automatically.

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