Real-time Identification of Worker's Personal Safety Equipment with Hybrid Machine Learning Techniques

Wen-Der Yu, Hsien-Chou Liao, Wen-Ta Hsiao, Hsien-Kuan Chang, Ting-Yu Wu, and Chen-Chung Lin

Abstract—**This paper presents an application of the hybrid Machine Learning (ML) techniques to real-time detection of unsafe personal safety equipment (e.g., helmet and safety vest) of construction workers on site, so that the unsafe behaviors can be corrected timely to reduce safety risks. Three different Convolutional Neural Network (CNN) based Deep Learning (DL) techniques were adopted for worker position locating, object classification, and subtle feature detection, including Faster R-CNN, YOLO and DenseNet. The lab testing showed high detectability with the Recall of 95% and the Precision of 90%. In in-situ implementation of a real-world construction site, a moderately acceptable detectability was achieved, with the Cleanness of 85% and Correctness of 80%. It is concluded that the proposed method quotes profound potentials to enhance the current safety management practice of construction site.**

Index Terms—**Construction safety management, computer visualization, machine learning, convolutional neural networks.**

I. Introduction

Construction accidents on site play the major role in vocational disasters of all industries worldwide [1]-[5]. Personal safety equipment, *e.g.*, helmet and safety vest, provide the first line protection to the workers [6], [7]. Due to the harsh and hot environment of construction site, it usually makes the workers uncomfortable and thus refusing to wear such personal safety equipment correctly. Traditional safety management practice requires experienced safety personnel in monitoring and correcting the unsafe behaviors of the workers. However, the limited experienced safety personnel available for most construction projects, the traditional safety management practice is usually ineffective in improving such workers' unsafe behaviors.

Thanks to the advancement of the state-of-the-art Deep Learning (DL) based Machine Learning (ML) techniques for auto-identification by computer visualization, such as Deep Convolutional Neural Network (DCNN) [8], [9], Region based Convolutional Neural Network (R-CNN) [10], Fast Region based Convolutional Neural Network (Fast R-CNN) [11], Faster Region based Convolutional Neural Network, Faster R-CNN) [12], YOLO [13], etc. It provides a promising solution to the unsolved long existing safety monitoring problems on the construction site [6], [14]-[16].

Although the previous works showed promising results on successful application of the state-of-the-art DL techniques for construction site safety management, some studies also show that the complicated and dynamic environment of construction sites cause difficulties in real-world implementation [6], [14]. To attack such a limitation, this research proposed a model of hybrid ML techniques for real-time identification of construction worker's personal safety equipment, e.g., helmet and safety vest, etc. With such an improvement, many hazards due to construction worker's unsafe behaviors during construction phase can be reduced and prevented, and thus the construction safety management practice can be improved.

II. Model of Safety Accident Prevention

The earliest work on analyzing the causes of occupational safety accidents (including construction accidents) was conducted by the American researcher, Herbert William Heinrich, in his famous Domino Theory [17]. In that theory, Heinrich addressed that 88% of all accidents were caused by unsafe acts of people, 10% by unsafe actions and 2% by "acts of God". He suggested the "Five-Factor Accident Sequence", shown in Fig. 1, and described as follows: 'Ancestry and social environment'→'Worker fault'→'Unsafe act together with mechanical and physical hazard'→'Accident'→'Damage or injury'. Each factor in the previous step would actuate the next step in the manner of toppling dominoes. By eliminating any of the first four factors can stop the occurrence of the last one— 'Damage or injury'.

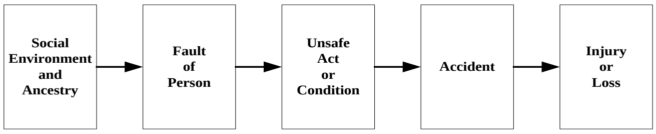

Fig. 1. The five-factor accident sequence of domino theory [17].

Widner [18] and some other researchers modified Heinrich's original theory, but maintained the essential concept for accident prevention by eliminating the unsafe behaviors of the worker in actuating the end result. It is believed that effective external supervision can not only prevent unsafe behavior in the first place, but can also gradually improve the level of safety awareness and attitude

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of workers [6], [19].

Some previous studies suggested that video surveillance system for monitoring unsafe behaviors of workers on construction may provide a solution to improve the safety awareness and attitude of workers and offer an effective tool to timely correct the unsafe behaviors, thus reduce the probability of accident occurrence [14], [16]. As a result, a DL-based computer visualization surveillance system for unsafe behavior detection can offer an effective method to stop the domino that actuate accidents on construction site.

III. Challenges Facing Construction Visual Recognition

As described previously, there were existing works on development of DL-based computer visualization surveillance systems for unsafe behavior detection. However, challenges still exist with the available visual recognition systems, including [6], [14], [16], [20], [21]: (1) the effects of complicated and dynamic environment of construction sites that affect the detectability of unsafe behaviors; (2) the requirement on the real-timeliness of unsafe behavior detection; (3) the difficulty in detecting subtle features that are meaningful for safety management.

There are several factors that may contribute to the complicated and dynamic environment of construction sites, e.g., the moving construction equipment and workers, changing temporary facilities, changeable weather conditions, sunlight and shadows that affect computer visualization, the dusts and fogs that block video images, etc.

The real-timeliness of unsafe behavior detection affects the effectiveness and usefulness of the unsafe behaviors detected, since there is usually limited time for preventing the occurrence of a construction accident after an unsafe behavior is detected. A primary challenge to the real-timeliness of visual recognition resides in computational efficiency of the visual recognition algorithm as well as the associated hardware. The state-of-the-art DL-based visual recognition methods combined with GPU computational device may be efficient in object identification (*e.g.*, human worker or moving equipment), but the time required to accurately determine the behavior types (especially the subtle feature difference of target images) is usually the bottleneck to real-time unsafe behavior detection. Although some complementary techniques (*e.g.*, the real-time image-skeleton-based method proposed by Yu *et al*. [16]), the results reported were still unstable.

The subtle features of target image are most difficult to detect. However, the subtle feature difference of an image usually implies significantly in identifying unsafe behaviors. For example, the fastness of chin strap on helmet is a subtle feature of a helmet image (see Fig. 2); while it tells the difference between the safe and unsafe helmet wearing behaviors. Traditional CNN methods are efficient in detecting features in a bounding box, but they are very inefficient in identifying subtle features. Regressing based methods, such as YOLO [13], [22] is efficient in determining the specific type of the features but is unable to detect the subtle difference of a feature in the image. A newly developed DL technique, namely DenseNet [23], is inefficient in locating the position of target object in a wide image frame, but it is very efficient in finding the subtle difference of features in an image.

Fig. 2. Samples of unclear and undetectable helmet wearing images.

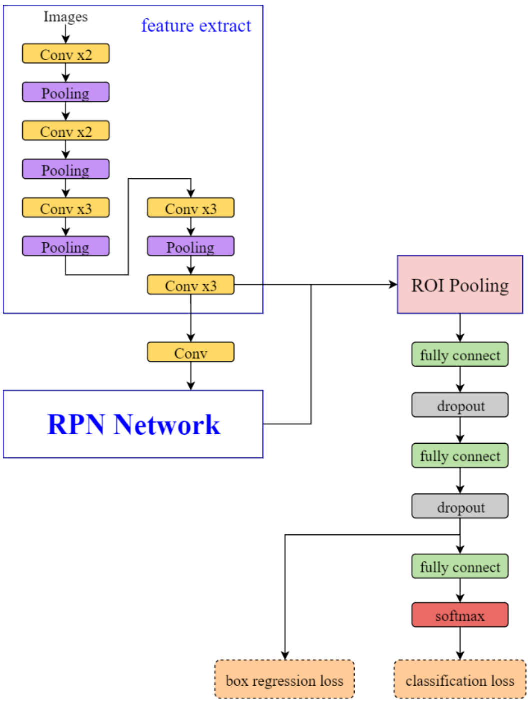


Fig. 3. The Faster R-CNN model for worker position locating.

IV. Hybrid Machine Learning Model for Real-Time Identification of Personal Safety Equipment

Base on the discussion in previous sections, the complicated construction site environment causes challenges for real-time visual recognition of the worker's unsafe behaviors. In order to overcome such challenges, this paper proposes a hybrid ML model that combines the following three different CNN-based DL techniques:

A. The Faster R-CNN for Fast Worker Position Locating

The adopted Faster R-CNN [12] is shown in Fig. 3 with the following network structure:

1) Input Layer—RGBs channels with image size of 1280×720;
2) Hidden Layers—5 layers of 'convolutional + ReLU + 3 × 3 Max Pooling', 32 3 × 3 Fiters, Padding =1, Stride =2;
3) Output Layer—1 fully connected layer with size = 256, 1 ReLU layer, 1 fully connected classification layer with size = 2 ('worker' or 'non-worker') and activation = 'Sigmoid'.

B. The YOLO v3 for Objects Classification

The adopted YOLO v3 [22] is adopted for objects (*e.g.*, helmet and safety vest) classification and shown in Fig. 4 with the following network structure:

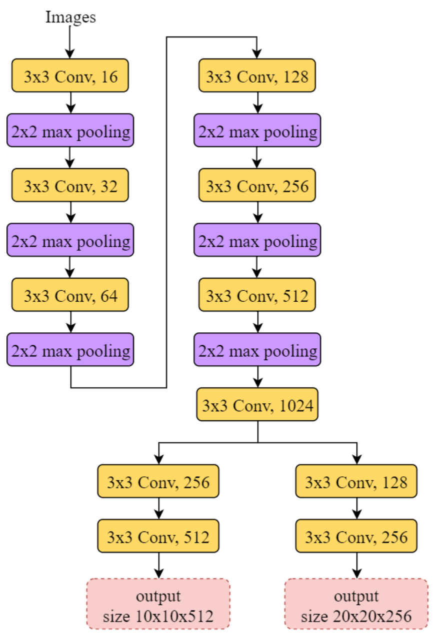


Fig. 4. The YOLO model for helmet and safety vest classification.

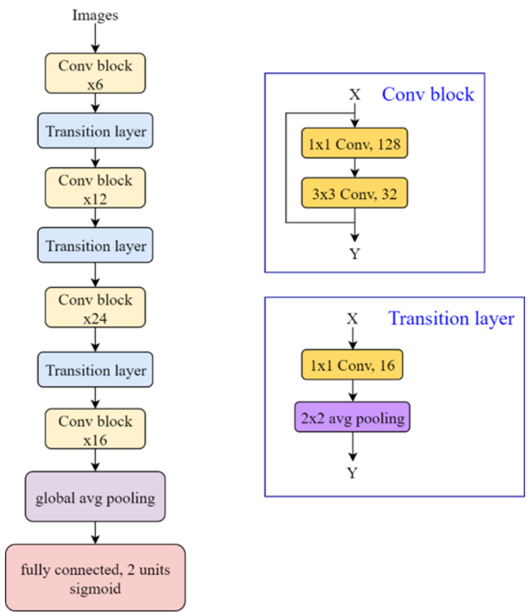


Fig. 5. The DenseNet model for fastness of chin strap on helmet recognition.

1) Input Layer—RGBs channels with image size of 240×150;
2) Hidden Convolutional Layers—6 layers of '3×3 conv, stride 1, filters 16' + '2×2 max pooling stride 2';
3) Output Layers—2 output branches—Branch (1): '3×3 conv, stride 1, filters 256' + '3×3 conv, stride 1, filters 512' + 'Output size 10×10×512'; Branch (2): '3×3 conv, stride 1, filters 128' + '3×3 conv, stride 1, filters 256' + 'Output size 20×20×256'.

C. The DenseNet v1.2.1 for Subtle Feature Detection

The adopted DenseNet v1.2.1 [23] is adopted for subtle feature detection (*e.g.*, fastness of chin strap on helmet) and shown in Fig. 5 with the following network structure:

1) Input Layer—RGBs channels with image size of 64 × 64;
2) Hidden Layers—1 layer of '7 ×7 conv, stride 2' + '3 ×3 max pool, stride 2' + 4 Dense Blocks + 3 Transition Layers;
3) Output Layer—1 classification layer of '7 × 7 global average pool' + 'fully connected, activation = Sigmoid'.

V. Model Training and Testing

The proposed hybrid ML model has been trained with sample datasets collected from real-world construction sites. The details of model training and testing are described in the following.

A. Data Acquisition

The training image datasets were collected from real-world projects via camera of mobile phone, videos of IP Cams, CCTV and the installed PTZ devices. Totally, 3,108 clear helmet images were collected, with 83% (2,639 images) used for training and the rest 17% (528 images) for testing; 1,173 clear safety vest images were collected, with 65% (762 images) used for training and the rest 35% (411 images) for testing.

B. Parameter Setting

Following training parameters were selected: (1) for helmet recognition— the initial learning rate was set as 7×10^{-5}, iterations = 13, an exponential decay coefficient is selected as 0.1 for iteration = 10, the minimum learning rate = 1×10^{-5}, the image size was normalized to 64 × 64 × 3 (RGB), batch size = 128; (2) for safety vest recognition—the initial learning rate was set as 1×10^{-3}, iterations = 13, the minimum learning rate = 5×10^{-4}, batch size = 2, other parameters were selected similar to (1).

C. Detectability Analysis

In order to measure the performance of the proposed model, the *Confusion Matrix* with 2 performance indexes, *Recall* and *Precision*, were calculated for both helmet and safety vest recognitions. The *Confusion Matrix* is shown in Table I. The *Confusion Matrix* shown in Table I is commonly adopted measure for evaluating the performance of pattern recognition, information retrieval and classification (for machine learning) tasks. In Table I, *Recall* is defined in Eq. (1) as: "the fraction of the total amount of relevant instances ('Actual with target') that were actually retrieved (or

‘Predicted with target’); *Precision* is defined in Eq. (1) as: “the fraction of relevant instances among the retrieved instances.” There are four parameters defined in Table I: (1) True Positive (TP)— Observation is positive, and is predicted as positive; (2) False Negative (FN) —Observation is positive (‘Actual with target’), but is predicted as negative (‘Predicted without target’); (3) True Negative (TN)—Observation is negative (‘Actual without target’), and is predicted as negative; and (4) False Positive (FP)—Observation is negative, but is predicted as positive (‘Predicted with target’). The performance criteria for the two detection tasks were set via a focused group meeting with the domain experts in construction safety management. The acceptance performance level for *Recall* is 95% and *Precision* is 90%.

TABLE I: THE CONFUSION MATRIX

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

$$\mathrm{R}ecall = \frac{TP}{TP+FN} \quad (1)$$

$$\mathrm{Pr}ecision = \frac{TP}{TP+FP} \quad (2)$$

TABLE II: THE CONFUSION MATRIX OF HELMET DETECTION

	Actual with target	Actual without target	*Precision*
Predicted with target	187 (TP)	9 (FP)	93.9%
Predicted without target	12 (FN)	308 (TN)	
Recall	95.4%		

D. *Training Procedure*

The training procedure consists of the following: 1) collecting data—collecting data from cameras and mobile phones, *e.g.*, IP Cams, CCTV, PTZ, etc.; 2) data cleaning—screening out the dirty, unclear or fuzzy images to preserve the clear and identifiable data (via human judgement); 3) bounding and labeling targets—selecting the targets in the image using ‘bounding box’ and labeling the targets; 4) separating training and datasets—randomly selecting training and testing datasets; 5) setting training parameters—setting the training parameters as described previously; 6) counting the frequencies of the four parameters in Confusion Matrix; 7) calculating the performance indexes—calculating *Recall* and *Precision*.

The testing results of training processes for helmet and safety vest are shown in Table II and Table III, respectively. It is found that both the *Recall* and *Precision* of the two *Confusion Matrixes* have meet the preset performance criteria. As a result, the trained models were accepted and adopted for in-situ testing of real-world projects. The system interface for implementation of the proposed model is shown in Fig. 6, where the detected targets are captured in the sub-windows on the right-hand side of the interface.

TABLE III: THE CONFUSION MATRIX OF HELMET DETECTION

	Actual with target	Actual without target	*Precision*
Predicted with target	163(TP)	12(FP)	93.1%
Predicted without target	0(FN)	435(TN)	
Recall	100%		

Fig. 6. System interface of the proposed model.

VI. IN-SITU IMPLEMENTATION OF REAL-WORLD CONSTRUCTION PROJECT

The pre-trained hybrid ML models were used for testing on real-world construction site to evaluate their applicability. A real-world case was selected from a public high-rise social residential building of the Taoyuan City Government, Taiwan, for the implementation and in-situ testing.

A. *In-situ Performance Evaluation*

A *Confusion Matrix* similar to the one defined in Table I was adopted for evaluating the model performance of the proposed method, excepting that *Cleanness* is used to replace *Recall* and *Correctness* is used to replace *Precision* for the in-situ testing. The acceptance criteria for in-situ detection testing were set via a focused group meeting with the domain experts in the construction safety management as *Cleanness* ≧ 85% and *Correctness* ≧ 80%.

B. *Case Project Selection*

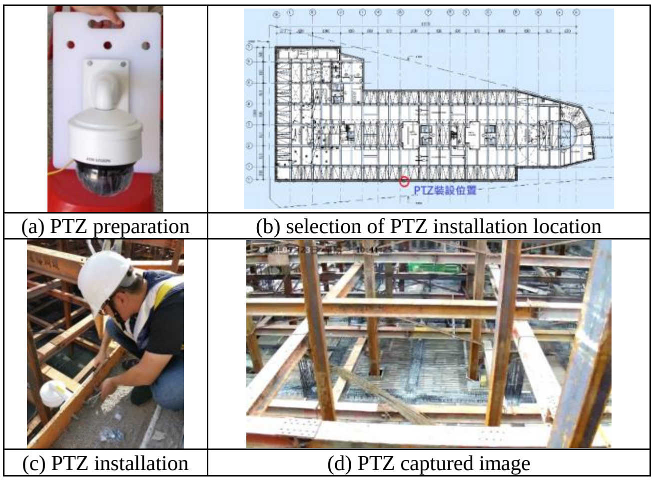
The selected case project is located in Taoyuan City near the intersection of the National Highways No. 1 and No. 2, namely the Chung-Lu No.3 Social Residential Building. The project aims at constructing a 20-story high-rise (3-floor basement) public social housing with 437 housing units for rent-only purpose to meet the shortage of housing in Taoyuan City. Total building area is 49,226.55 m^2. Total budget equals USD$ 56,278,944. During the in-situ testing of the proposed method, the construction phase of the project proceeds to the 2^{nd} basement underground.

C. *Establishment of Data Center for Construction Safety Management (DCCSM)*

In this case study the Data Center for Construction Safety Management (DCCSM) was located in Chaoyang University of Technology (CYUT), Taichung City, Taiwan. The computational device of DCCSM was equipped with the following hardware capacities: (1) CPU—Intel(R) Xeon®, E5-2620v4 @2.10GHz; (2) RAM—2400MHz 40GB RAM; (3) OS—Microsoft Windows 10®; (4) GPU—NVIDIA Quadro P2000 (5GB); (5) Hard drive capacity—2 tera bites.

D. In-situ Testing Procedure

The in-situ implementation testing procedure consists of: (1) DCCSM establishment—established the Data Center for Construction Safety Management (DCCSM); (2) data collecting and processing—video streaming data collected on-site were transmitted via internet to the DCCSM in CYUT, the interested images were captured from video streaming data; (3) target detecting—the captured images were processed with the pre-trained DL-CNN models to count the TP, TN, FP, FN frequencies in the *Confusion Matrix*; (4) calculating performance indexes—the two performance indexes, *Cleanness* and *Correctness*, were computed to evaluate the model performance; (5) model improvement—if the model performance indexes were not satisfactory, go back to step (2) and (3) to enhance the model by adding training datasets and modifying the parameters; (6) model acceptance—stopped the training procedure while the performance indexes met the preset criteria. Fig. 7 shows the installation of PTZ device on site for the in-situ case project.



(a) PTZ preparation (b) selection of PTZ installation location

(c) PTZ installation (d) PTZ captured image

Fig. 7. PTZ installation on site.

TABLE IV: IN-SITU PERFORMANCE EVALUATION OF HELMET DETECTION

	Actual with target	Actual without target	*Correctness*
Predicted with target	28(TP)	6(FP)	82.4%
Predicted without target	3(FN)	14(TN)	
Cleanness	90.3%		

TABLE V: IN-SITU PERFORMANCE EVALUATION OF SAFETY VEST DETECTION

	Actual with target	Actual Without target	*Correctness*
Predicted with target	39(TP)	9(FP)	81.3%
Predicted without target	1(FN)	2(TN)	
Cleanness	97.5%		

E. In-situ Testing Results

The two pre-trained hybrid ML models were not performing well in the beginning of the in-situ testing, with unacceptable Cleanness and Correctness performance indexes. The results were discussed and analyzed by the research team and found that the training datasets collected previously were from construction site above the ground floors, while the construction work of the in-situ case project was still in underground level. It is suggested to collect some sample images to enhance the training datasets and re-train the models. After model improvements, the in-situ testing results are shown in Table IV and Table V for helmet and safety vest detections, respectively. It is found from the two *Confusion Matrixes* that both *Cleanness* and *Correctness* performance indexes have met the preset criteria and thus the in-situ testing were accepted.

VII. SUMMARY

Due to the complicated environment conditions of construction sites and the requirements on real-timeliness of construction safety management, the application of the traditional Machine Learning (ML) based computer visualization techniques for construction site safety management has faced several unsolved challenges. This paper presents a hybrid ML-based model integrating three Convolutional Neural Network (CNN) based Deep Learning techniques—including Faster R-CNN, YOLO, and DenseNet—to overcome the challenges of the complicated and dynamic environment conditions of construction sites, the requirements on real-timeliness of unsafe behavior detection, and the difficulty in detecting subtle features that are meaningful for construction safety management. Both the training and in-situ testing results show a profound potential of the proposed models in improving the practice of construction safety management.

Although the preliminary results showed a promising potential, several future works need to be conducted in order to further validate the applicability of the proposed method, including: the evaluation of the detectability of videos under unfavorable conditions, *e.g.*, nights, fogs/dusts, changeable weathers (*e.g.*, raining), etc. Moreover, the *Cleanness* and *Correctness* performance indexes were set relatively low compared with human detection capability. Model improvements are desirable to meet the industry requirements.

CONFLICT OF INTEREST

The authors declare no conflict of interests with other parties, including copyrights and intellectual properties.

AUTHOR CONTRIBUTIONS

Yu and Lin proposed the original research idea; Yu laid out the research framework and concluded the research; System analysis was conducted by Liao; Hsiao and Chang analyzed the in-situ implement results; Wu programmed the system; Yu and Chang wrote the paper; all authors had approved the final version.

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