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HAZARDOUS DETECTION MODEL AT CONSTRUCTION SITE USING IMAGE DETECTION

Madihah Mohd Saudi[1],Obsatar Sinaga[2], Mohd Haizam Saudi[3], Aiman Azhar[1]*

Cyber Security and Systems (CSS) Research Unit, Islamic Science Institute (ISI), Universiti Sains Islam Malaysia (USIM), Nilai, Malaysia[1]

Padjadjaran University, Indonesia[2]

Widyatama University, Indonesia[3]

*madihah@usim.edu.my

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ABSTRACT:
Many factors lead to an incident for workers at construction sites. They were exposed to a different type of hazardous such as fall from scaffolding, electric shock, and hit by a crane. Yet, at the moment, we are still lacking a solution to mitigate such incidents by using image detection and machine learning algorithm with a cost-effective and real-time solution. Hence, this paper presents a hazardous detection model at a construction site by using image detection to ensure worker safety at a construction site. This experiment was conducted by using the Faster Region-based Convolutional Neural Networks (R-CNN) algorithm embedded in TensorFlow, 6000 images for training dataset from the MIT Places Database (from Scene Recognition), and 600 anonymous dataset images from construction sites for testing. Based on the experiment conducted, the model can detect possible hazardous incident at the construction site with a more than 70% accuracy rate.

INTRODUCTION

Many industries are categorized as high risk and construction is one of these. Injuries and deaths are among the components to be measured to know either the construction site is safe or dangerous. Apart from that, the workers are exposed to permanent disability and accidents at their workplace, even though the precaution and prevention mechanism already in place [1-4]. Surprisingly, in 2019, there were 326 cases reported to the Department of Occupational

Safety and Health (DOSH) with 84 deaths and 15 became disabilities permanently[5]. Hence, this paper presents a new model to detect possible hazardous objects that could lead to an incident at the construction site by using image detection. We integrated a machine learning algorithm called a Faster R-CNN algorithm to detect the image. For this model, a hazardous object consists of a scaffold, fall, electric shock, heavy machines, and cranes. This paper is organized as follows. Section II explains related works, Section III presents the method used in this research, Section IV consists of the findings and their evaluation, and Section V concludes the paper and makes suggestions for future work.

RELATED WORKS

Existing works by [6-7] focused on personal protective equipment (PPE) by using Faster R-CNN. This works algorithm is the same as our proposed algorithm but in different scope. While work by [8-9], focused the excavator, crane, and truck. Moreover, other existing works by [6-10], were related to the quality of project management at the construction sites. Based on the above existing works, we can conclude that accidents can occur even the workers obey all safety regulations. Yet we are still lack of detection and prevention against possible hazardous objects or incidents such as fall, scaffold, and electric shock. As for Table 1, we summarized other existing works related to object detection at the construction sites. It can be concluded that the existing works used more than 1000 images to train and evaluate their datasets with the majority were using Faster R-CNN. This indicated that Faster R-CNN is one of the established algorithms and we have integrated it in our proposed model in this paper.

Table 1. Object Detection at the Construction Sites

Author	Dataset	Detection Method
[10]	Training: 4483 images Evaluation: 1281 images	Used Stacked Hourglass Network (HG), Cascaded Pyramid Network (CPN), and an ensemble model (HG-CPN)
[11]	Training: 1000 images Evaluation: 365 images	Used Unmanned Aerial Vehicle (UAV)
[13]	Training: 317 annotated videos Evaluation: 317 annotated videos	Used YOLOv3
[12]	Training: Make a video of a construction site Evaluation: Make a video of a construction site	Used Improved YOLOv3
[14]	Training: 2700 images Evaluation: 1500 images	Used YOLO
[15]	Training: 81000 images Evaluation: 19000 images	Used: Deep CNN and Faster RCNN
[16]	Training: ImageNet dataset & Microsoft COCO 2014 Evaluation: ImageNet dataset and Microsoft	Used Faster R-CNN and ResNet-152
	Training: 10000 images	Used Enhanced Faster R-

[17]	Evaluation: 1500 images	CNN
[18]	Training: 1208 images Evaluation: 27 images	Used Google inception V3
This research	Training: 6000 images Evaluation: 600 images	Used: Faster RCNN

METHOD

To build this new model, the setup for the experiment as follows.

TABLE II. EXPERIMENT SETUP

Hardware/ software	Description
Notebook	PC specification
RTX 2060	Graphic card specification to run Tensorflow.
16 GB DDR4-2666 (1333 MHz)	RAM and central processing unit(CPU) specification
TensorFlow 1.15	Open-source software is used for training and testing the images. It consists of the Faster R-CNN algorithm. TensorFlow ran inside Anaconda for the usage of TensorFlow-GPU, which is faster than TensorFlow-CPU.
Anaconda	Virtual environment for Python code
LabelImg	A tool is written in Python code for graphical image labeling, and image training and testing.

A total of 15,000 images were collected from the MIT Database and being filtered based on our paper scope [19]. As a result, a total of 6,000 images consist of scaffolding, fall, crane, heavy machine and electric shock were used for the training and 600 images for evaluation. Then, by using LabelImg, the images were labeled and stored as XML files and trained by using Faster R-CNN Inception v2 COCO in TensorFlow (as shown in Fig.3). The strength of this algorithm lies in its classification capability[20]. With this algorithm, we were able to build our new model for hazardous object detection faster and more accurate (as depicted in Fig. 4).

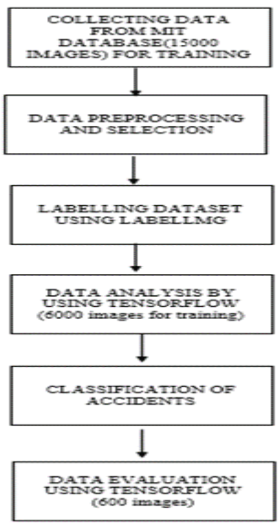

Fig. 1. Research Processes

Fig. 2. Dataset Labelling

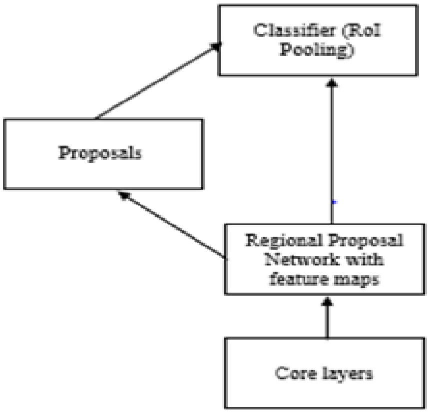

Fig. 3. Faster R-CNN Algorithm

Fig. 4. Hazardous Object Classification

The evaluation of this paper is based on an average precision (mAP) metric. First, The IoU is calculated. Next, precision and recall are calculated where TRP (true positive) is correctly classified to the class, FAP (false positive) is incorrectly classified to the class, and FAN (false negative) is incorrectly classified to another class.

$$Precison = \frac{TRP}{TRP + FAP} \qquad (1)$$

$$Recall = \frac{TRP}{TRP + FAN} \qquad (2)$$

Next, the mean Average Precision is calculated as follow:

$$AP = \frac{1}{11} \sum_{r\epsilon\{0,0.1,\ldots,1\}} \rho interp(r) \qquad (3)$$

FINDINGS

Our findings as follows. The mAP of the models is 70% from the 600 images evaluated with an accuracy loss of less than 0.5 (as depicted in Fig.5). These hazardous objects were inclusive of fall, electric shock, scaffold, heavy machines, and cranes. While examples of the image evaluation as displayed in Fig.6.

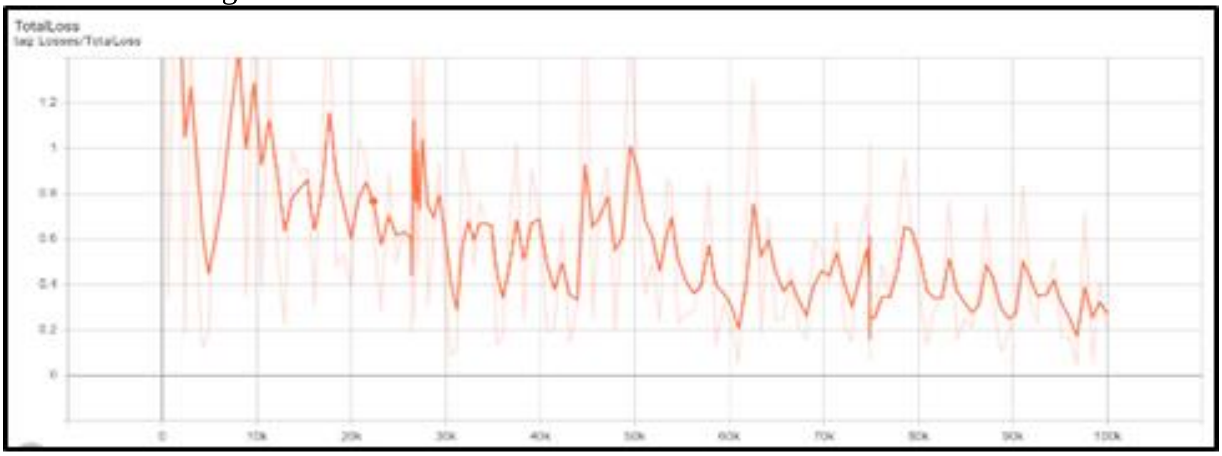

Fig. 5. Total Loss Accuracy Rate

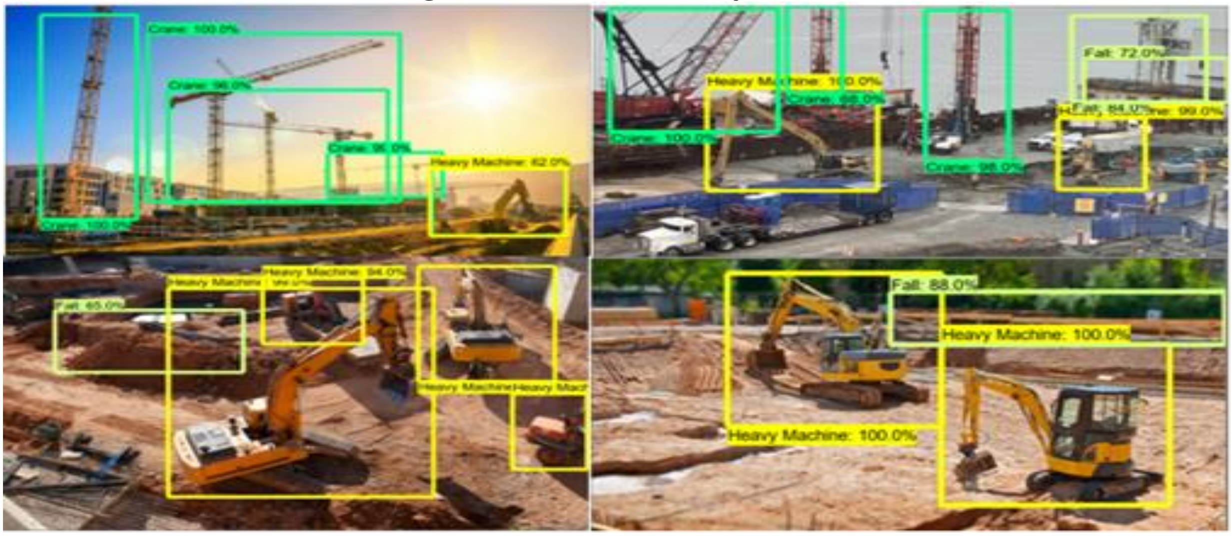

Fig. 6. Examples of the Tested Images

Based on our experiment and analysis, it is very significant to detect these hazardous objects, before deciding either it is a safe or dangerous condition at the construction site. At the moment, we are still lack of image database that can classify scenery correctly. By completing this hazardous object image detection model, we are also contributing to create a new database for a construction site for hazardous objects. Researchers with the same interest can use our database as a benchmark or as guidance in the future.

In terms of the result for our experiment, many factors are affecting the accuracy rate such as threshold value, training dataset, input image resolution, and training configurations including batch size, input image resizes, learning rate, and learning rate decay [20]. Furthermore, factors such as momentum optimizer, image resize, and image sharpness also contributed to the accuracy rate. With an accuracy of 70%, we considered it as a promising result, since it was the real-time detection. The Faster R-CNN helped us for better accuracy based on its owns feature.

CONCLUSION

Many factors need to be considered in image detection at the construction site such as the threshold value assigned during the data configuration settings and the momentum optimizer value. Further refinement is needed in the future. Nonetheless, this paper has successfully developed a new model based on the hazardous object at the construction site. This work is a part of a larger project. In the future, we will develop safety and dangerous condition at the construction site by using a drone. The result of this paper will be used as the input for future work.

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