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Effect of Color Contrast to the Accuracy of SSD-MobileNetV2

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Abstract: Machine vision with deep learning neural network is currently on the rise, specifically with the emergence of Industrial Revolution 4.0. It is further elevated with the advancement in the computational capabilities of modern edge computing to reduce the computational cost. Thus, making such technology economically viable to the general manufacturing industries for industrial application. Visual quality inspection would be among the most relevant process to have such architecture implemented. This paper explores the feasibility of deploying deep learning model, SSD-MobileNetV2 to replace manual visual inspection for holes counting process after drilling on a carbon-reinforced fiber composite component. The drilled holes were set into three (3) different conditions; bare-holes and holes equipped with semi-transparent or red locating pins. We conclude that the contrasting color of the holes with respect to its surrounding plays a pivotal role in their detections. Holes with semi-transparent or red locating pins are with accuracy of 77.14% and 73.33% respectively; while bare-blackened holes are with accuracy of only 45.95%.

Keywords: *Deep learning, industrial application, machine vision, SSD-MobileNetV2, visual inspection*

1. Introduction

A machine vision system can be simply stated as a system that is utilizing either static images and/or videos as the input [1]. A deep machine vision learning uses these inputs as training data in a Deep Neural Network (DNN) algorithm [3], [5]. The input data have to be labelled; then, sent through a set of algorithm named 'Hidden Layers' to generate a specific AI model based on the labelled data. In a simple term, the AI model is a 'generalized' form of the labelled data.

Convolutional Neural Network (CNN) is notably the most popular basis algorithm used in Deep Neural Network (DNN) architecture [6]. It is especially true for machine vision system. For each images, it was constructed by a matrix of 'pixel' with a certain size. Features were then be extracted from this matrix through the convolutional operation layer.

Smart Manufacturing is coined to be the next big thing within the Industrial 4.0 revolution [8] with visual inspection having the highest potential for machine vision deep neural networks application. The input will be provided by the cameras, and be sent to the network for inference. It may be used either for object classification and/or object detection.

[9] had used SSD-MobileNet algorithm to detect typical defects found on a surface of a container. They had used the model to not only classify the type of detected defects, but also to identify the location of such defects had occurred. Single Shot Multibox Detector (SSD) algorithm had been developed by [10] and it predicts the class and the bounding boxes by applying convolutional filters to the extracted feature map.

However, it is to the best of the writer's knowledge that there are no studies conducted for the application of deep learning neural network within the aerospace manufacturing sector, especially for thermosetting carbon fiber composite material.

This paper presents holes detection and counting method based on SSD MobileNetV2 architecture for an aircraft component manufactured from thermoset carbon fiber composites. There were three (3) method of counting used within this study; first, counting the hole in its raw condition after being drilled; second, counting by using semi-transparent locating pin and third, using locating pin in red color.

The current manual counting process employed in the shop floor was the second method; the semi-transparent locating pin. The operator will place the locating pins into each drilled holes and quality inspector will then take those pins out as means of verification while counting the amount of

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pins used. Theoretically, this method would be sufficient to count and counter-count each drilled holes; however, the problem arose when the amount of holes to be inspected reaching more than thousands per day. This study is conducted with the aim to automate the hole counting process, while simultaneously trying to eliminate the use of locating pins.

2. Method

SSD MobileNetV2 was selected as deep learning architecture used within this project due to its lightweight computational properties, while maintaining a high accuracy result. A combination of SSD approach with MobilenetV2 creates an architecture where real-time inference is able to be computed with devices of less computational prowess [12].

A total of 2500 images were labeled and separated into training (80%) and validation (20%) dataset. Additional 20 images were used as testing dataset. The labelling were done using labelImg [14], an open source labelling tool, as shown in Fig. 1

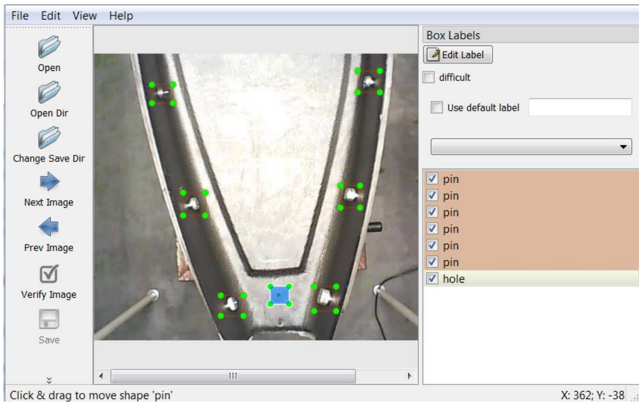

Fig. 1. Sample of labelling activity using labelImg tool

AI model training were constructed and executed using TensorFlow Object Detection Application Programming Interface (API) [15].

3. Results and Discussions

The validations of the AI model were done to a randomly selected images with varying quantity of holes and pins respectively and the result is as tabulated in Table 1. There are a total of 35 pins and 37 holes existed within those10 images and these served as the 'Ground Truth'. However, only 27 pins and 17 holes were detected with accuracy of 77.14% and 45.95% respectively. Fig. 2 shows the sample of the inference result with 11 maximum object detected out of 15 'Ground Truth' objects; 9 being the metal pins and 2 holes.

Table 1. Validation result of 10 images with 'Hole' and 'Pin' labels

Description	'Ground Truth'		Result	
	Pin	Hole	Pin	Hole
Quantity	35	37	27	17
Percentage	-	-	77.14%	45.95%

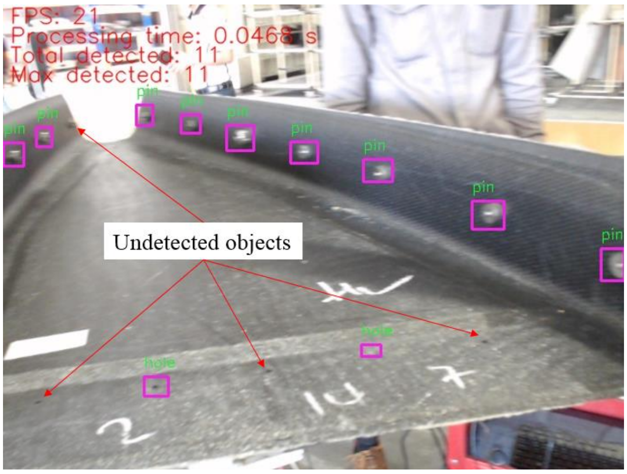

Fig. 2. Sample images with 'Hole' and 'Pin' labels

The inference result with the new labels and dataset was shown in Table 2. The accuracy for the new label "Red Pin" was 73.33% and that was significantly higher in comparison with the old label "Hole" of only 45.95%.

Table 2. Validation result of 10 images with 'Pin' and 'Red Pin' labels

Description	'Ground Truth'		Result	
	Pin	Red Pin	Pin	Red Pin
Quantity	75	60	49	44
Percentage	-	-	65.33%	73.33%

The inference result with the new labels and dataset was shown in Table 2. The accuracy for the new label "Red Pin" was 73.33% and that was significantly higher in comparison with the old label "Hole" of only 45.95%.

MobileNetV2 architecture received its input in a RGB (Red, Green, and Blue) format [16]. A slightly darker hole and the black surface of carbon composite would not have a large color contrast. Thus, this had reduced the ability of the AI model to extract the feature of those holes.

Any features inside the processed image were extracted through convolutional operation. Fig. 3 shows the resultant matrix for convolutional operation performed to an input matrix with the same values. This is to represent an empty background situation with no object within the image.

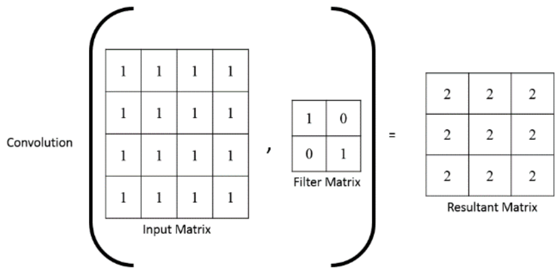

Fig. 3. Sample Convolutional Operation for 'Background' Input Matrix

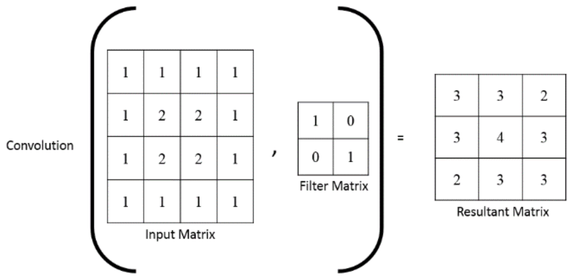

Fig. 4. Sample Convolutional Operation for Image with Low Contrast Object

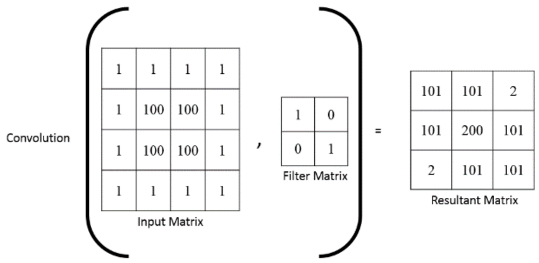

Fig. 5. Sample Convolutional Operation for Image with High Contrast Object

Next, Fig. 4 shows the resultant matrix performed for convolutional operation performed to an image with low contrast object, while Fig. 5 is to high contrast object. The 2x2 matrix located in the middle of the input matrix on both figures are representing the color of the object. The number '2' and '100' each representing the difference in contrast against the background value of '1'.

It could be seen that the extracted features or numbers is higher in Fig. 5, than in Fig. 4. By comparing both of them to the 'background' resultant matrix in Fig. 3, the numbers in resultant matrix of Fig. 5 would have a higher difference than the resultant matrix of Fig. 4. Thus, easier for it to be differentiated from the 'background' and definitely, easier for it to be detected by the algorithm.

4. Conclusions

In general, machine vision architecture has accuracy of less than 50% in detecting the drilled holes. It was found to be contributed by the color of the drilled holes; it was just slightly darker in comparison with its carbon composite panel in the background. Based on discussed results, it can be concluded that an increase in color contrast of intended object to be detected with its surroundings increases the probability of detection.

While it was possible to easily increase the accuracy by introducing additional components to the architecture to increase the color contrast, it was not a sound approach, in both scientific and practical sense. Any additional process made in order to physically increase the contrast may increase the complexity and cycle time of the inspection process; thus, making the transformation less desirable economically.

At its current condition, the industrial application of object detection through deep learning algorithm, namely SSD-MobileNetV2 is still in its infancy. Further study will be made within the machine vision architecture as to find a scientific and mathematical approach to properly tackle the effect to color contrast as to increase the accuracy of the trained AI model.

Conflicts of interest

The authors declare no conflicts of interest.

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