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Method Enhancement of Quality Control in Brake Pads Manufacturing

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Abstract

The disc brake production is coupled with a defect detection process to control quality. The current manufacturing quality is high. However, detection relies on visuals by the operator, posing challenges in terms of accuracy and time. In a high-quality production, using human labor for detection is time-consuming and labor-intensive. This research is aiming at exploring the possibility of applying object recognition using deep learning approach for the in-line defects detection on disc brake pads. Faster R-CNN, Scaled YOLOv4, and YOLOv5s were compared for the detection of two major commonly defective brake pads of brake pad model A. The main criteria for the detection are (a) the detection time must be shorter than residence time of brake pads on the detection station on the conveyor, at 498 milliseconds, and (b) the precision must be higher than 70%. The detection time and precision of YOLOv5s, Scaled YOLOv4, and Faster R-CNN are at 13.9 ms and 83%, 20.0 ms and 83%, and 20.2 ms and 92%, respectively. The detection time of all algorithms investigated in this study is far shorter than the residence time at the checking station with the precision exceeding the criteria. The training time for Faster R-CNN, 220 ms, is five times longer than that of YOLOv5s (49 ms) and Scaled YOLOv4 (41 ms). All three algorithms are capable of real-time detection and yield a consistent result on both splits and poorly consolidated friction material workpieces. Faster R-CNN is chosen because it has the highest precision.

Keywords: Brake pad, Deep learning, Defective brake pad detection, Real-time detection

I. INTRODUCTION

Disc brake pads are a key component of a disc brake system when the driver presses on the brake pedal, the pressure is transmitted through the brake fluid. This pressure pushes the brake caliper, causing the brake pads to clamp onto the brake rotor. This creates a friction force between the brake pads and the rotor, the friction material from the brake pad is transferred to the rotor surface. This transfer of friction material creates a frictional force known as adherent friction. Adherent friction is the frictional force generated when certain layers of the brake lining adhere to the rotor surface. This increased friction force helps to slow down and stop the vehicle. The brake pads are made of a friction material consisting of filler, binder, abrasive, lubricant, and fiber that is designed to be less stiff than the rotor and to wear down over time. These raw materials are blended using a high-speed mixer to create a homogeneous mixture. The mixture is placed in a mold and undergoes curing. Finally, the decoration, where the surface is smoothened, grooves are carved and painted prior to attaching accessories to achieve an attractive appearance.

The quality control and reliability of the brake pads are very important because it means the safety of the driver. Currently, defect detections for brake pads rely on visual inspection by operators, which is time-consuming and low-efficiency. The accuracy is uncertain and dependent on the experience and fatigue of the workers. Additionally, the small size of defects makes them difficult to detect.

The total number of defects in all models was around 2% of total production. They originated from various sources including 0.04% from mixing process, 0.6% from curing process, and 1.3% from decorating process. Brake pads model A were produced during the research period and found defects. In the process of decorating, the number of defects in Model A is relatively low to generate a dataset, but the critical issue with Model A lies in the vulnerability arising from the lack of defects in other brake pad models. Indicates that the production is of high quality whereas the method of detector is labor-intensive and time-consuming, even though the defects are few. This results in labor inefficiency. This led to the selection of Brake Pad Model A for research purposes.

In object detection, convolutional neural networks inside deep learning algorithms have enhanced precision and speed. There are two categories of object detection algorithms: one-stage detectors and two-stage detectors. Input image features are features extracted in the Backbone by the feature extractor and sent to the Neck and Head to detect objects inside the image. Neck aggregate features are blended and combined feature from the Backbone to be ready for detection in the Head. The Head serves to detect objects, detection includes classification and localization for each bounding box. The two-stage detector separates the functionality of feature aggregation, localization, and classification and then combines results later, called Sparse detection. However, single-stage detectors perform all steps simultaneously, referred to as Dense Detection. An example of a two-stage detector is the Faster R-CNN which is high precision, but it is a low speed because of the deep network structure. While one-stage detectors (YOLO) have rapid processing capabilities. Object detection based on deep learning has been applied in many fields such as road surface crack detection using the YOLOv5 [1], detection and classification of plant pathology using the YOLO series and Faster R-CNN [2], finding the landing area of the plane [3], pest detection using old and new versions of the YOLO detector [4], identifying the disc brake pad model, etc.

Figure 1: Research workflow in this study.

This study aims to explore deep learning techniques for detecting defective brake discs composed of splits and poorly Consolidated friction material, using YOLOv5s, Scaled YOLOv4, and Faster R-CNN algorithms. The study refers to the ISO/PAS 22574:2007 standard for referencing the characteristics of defective with the research process as shown in Figure 1.

II. LITERATURE REVIEW

This section explains three algorithms used in this study and applications for defect detection are reviewed.

Faster R-CNN is a 2 stage object detection algorithm [5]. The structure of Faster R-CNN consists of a region proposal network (RPN) and a detection network (Fast R-CNN). The working methodology of Faster R-CNN is shown in Figure 2. The RPN generates a set of region proposals, which are then fed into the detection network to classify and refine the proposals [6]. The processing of the region proposals to output class labels and bounding boxes for each proposal is done by Fast R-CNN network which is part of the detection network in Faster R-CNN.

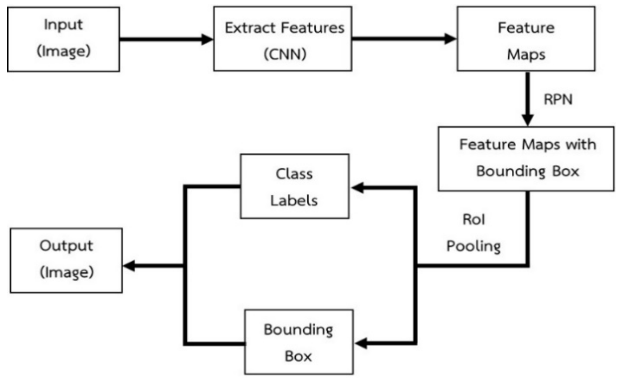

Figure 2: Faster R-CNN structure diagram.

Scaled YOLOv4 is a variant of the YOLOv4 object detection algorithm that has been modified to run on multiple GPUs and to scale to larger input image sizes [7]. Scaled YOLOv4's structure consists of an input layer and feature extraction. The first layer in the network is the input layer, which receives the input image and then forwards it to the feature extraction component. The feature extractor extracts features from the input image, which are then forwarded to the network made up of several convolutional and fully connected layers. The output of the network is a set of bounding boxes and class scores corresponding to the objects present in the image. Although Scaled YOLOv4 is an algorithm modified from an obsolete YOLOv4. Studies have shown that the performance of Scaled YOLOv4 is nearly equal to that of YOLOv5 [8]. Therefore, Scaled YOLOv4 was chosen in this study.

YOLOv5 is a one-stage detector that includes preprocessing and feature extraction. Preprocessing is taken to prepare an input image for processing that includes resizing, normalization, data augmentation, and noise reduction. The feature extraction process consists of several layers of convolutional and pooling operations. The features are extracted from the input image through the application of convolutional layers. The pooling layer reduces the size of the feature map produced by the convolutional layers, improving the model's generalization ability by decreasing the sample size. The Fully connected layer gets extracted features combines the feature maps and makes predictions about the presence and location of objects in the image as shown in Figure 3.

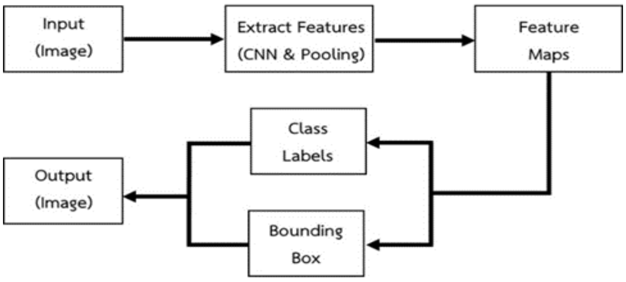

Figure 3: YOLOv5 structure diagram.

The family of YOLOv5 (s, m, l, and x) is designed to trade off accuracy and speed, with larger models tending to be more accurate but slower, and smaller models being less accurate but faster. According to research studies related to the YOLOv5 family. The members' detection accuracy was fairly similar, however, the speed of detection varied greatly [9]. Thus, YOLOv5s was chosen due to its fast detection to be applied to fast-moving brake pads on the conveyor.

YOLOv5 detector has four variants s, m, l, and x to detect defects on particleboard surfaces [10]. The particleboard defects that we aim to detect come in five different types. Training the detector took 300 epochs. YOLOv5s was trained in 9.6 hours while YOLOv5x took 6 days to complete. All four detectors demonstrated a detection precision of over 90%. YOLOv5s had the fastest detection time at only 0.047 seconds, while YOLOv5x had the slowest at 0.069 seconds.

The YOLOv5 was used to identify different types of mold on food surfaces [11]. The dataset was enhanced through data augmentation before training. YOLOv5 was compared to YOLOv3 and YOLOv4 and achieved a precision rate of 98.1%, and had the highest recall rate of 100%.

The YOLO detector was used to detect traffic signs for application in autonomous vehicles [12]. All four versions of YOLOv5 detectors are trained with 50 epochs. The detection precision of the four models is over 80%, YOLOv5x minimum precision is 83% while YOLOv5m and YOLOv5l precision is 87%. The fastest model to detect road marking signs is YOLOv5s, which is only 24.6 FPS. The processing of YOLOv5x is 1.7 FPS which is the slowest among the four detectors.

The YOLOv5 model was compared with Faster R-CNN and YOLOv3 models in detecting spot knots on saw timbers [13]. The training datasets were reduced from 80% to 50% during the training session. As the number of training datasets decreases, the mAP also decreases. YOLOv3 has the largest weight file size, while Faster R-CNN has the longest training time.

YOLOv5 series models, including YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x inspect helmets [14]. The mAP of all YOLOv5s series is over 90%. The YOLOv5s processing peaks at 110 FPS, which is the highest among other series. YOLOv5x is the slowest processing at 21 FPS, but it has a high mAP of 93.6%.

Faster R-CNN detects leaves in complex natural environments to develop smart agriculture [15]. The model was applied to identify sweet potato leaves and the dataset consisted of 8,086 images with varying leaf densities. The model training is set for 50 epochs. In the testing session, the superiority of Faster R-CNN over YOLOv5 is shown in terms of precision and recall.

Faster R-CNN and YOLOv3 were used to detect people wearing face masks during the Coronavirus disease outbreak [16]. The dataset consists of both masked and non-masked people. The mean precision of Faster R-CNN is slightly better than YOLOv3 by only 7%. The processing time of YOLOv3 was almost 3.5 times of Faster R-CNN. In general places, CCTV cameras are used. Therefore, speed is more important, and YOLOv3 is suitable for face mask detection.

The CNN models include YOLOv3, YOLOv4, and YOLOv5. estimate white grape yields [17]. The YOLOv3 and YOLOv4 models require more than 15 hours of training time, whereas the YOLOv5s and YOLOv5x models require 4.6 and 7 hours, respectively, to complete the training process. The models YOLOv4, YOLOv5s, and YOLOv5x have a mAP of over 70%, with YOLOv5s able to process 61 FPS.

YOLOv5s, YOLOv5m, and YOLOv5l are applied to the grasping robot [18]. The dataset contains letter wooden blocks, shape wooden blocks, punctuation wooden blocks, and blank wooden blocks. The test results show that the precision and recall of the three detectors are over 98%. The training time of YOLOv5s is the shortest, only 18 hours, while the longest training time of YOLOv5l is 21 hours. The YOLOv5s processing time is the shortest, only 35 milliseconds. The YOLOv5l's computation time takes the longest to 77 milliseconds.

The YOLOv5 detector family detects the flight of birds [19]. All detector is trained with 20 epochs. The mAP of YOLOv5s, YOLOv5m, and YOLOv5l is above 80%. Except for YOLOv5x, the mAP is 79%. The trend of mAP is like with recall. YOLOv5s, YOLOv5m, and YOLOv5l have a recall rate of over 85%, while YOLOv5x has a recall rate of 83%.

The YOLOv5s and YOLOv3 detectors are used to identify houses damaged by an earthquake [20]. The YOLOv5s take the shortest training time of only 1.4 hours, but YOLOv3 takes up to 5.6 hours. The YOLOv5's average precision is up to 89%, as well as its computing time is up to 100 FPS. The YOLOv3's average precision is only 81% and its processing time is 27 FPS.

The YOLOv5 and Scaled YOLOv4 detectors are used for malaria diagnosis because traditional methods were time-consuming and human error [21]. The YOLOv5 takes 52 minutes to train while the Scaled YOLOv4 takes 206 minutes. The Scaled YOLOv4 archived a mAP of 83% and a recall of 93% while the YOLOv5 had a mAP of 78% and a recall of 79%. YOLOv5 is superior to Scaled YOLOv4 in diagnosing malaria.

III. RESEARCH METHODOLOGY

In this work, three deep learning algorithms for defective brake pads, consisting of YOLOv5s, Scaled YOLOv4, and Faster R-CNN were compared. The algorithm was mainstream during the research period with a wide range of applications and stability. The research process includes a brake pad production study, dataset acquisition, data preparation, experimental environment, and model testing. The process of brake pad production is a one-piece flow process where the defect is detected at the end of the production line before delivering the products to the customers.

The data acquisition involves the process of collecting defective and good brake pads and photographing images to create a dataset. Photographing the brake pad is carried out using the setting shown in Figure 2. The brake pad samples were photographed from different angles. An example of the image photographing angle is shown in Figure 3. Photos were taken with a simple background to maintain a similar environment to the production line. The images were captured using the camera of the iPhone 13 Pro in a studio environment with a black background.

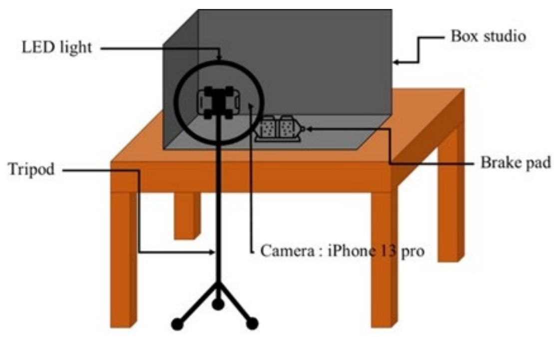

Figure 2: The brake pad photography setting

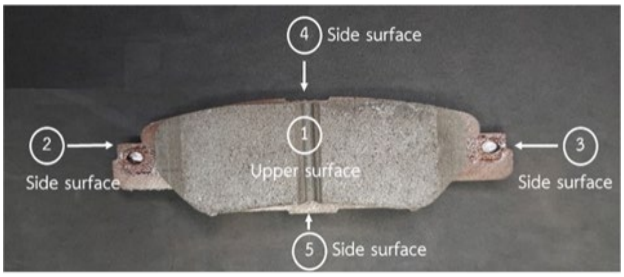

Figure 3: Side of the surface of the brake pad

Data preparation involves 3 steps which are annotation, data augmentation, and split data set. Annotation is a process of labeling the data on images to make algorithms recognize them. In this study, annotation was performed on the Roboflow platform, a software for deep learning tasks established by Joseph Nelson (Iowa, United States). Figure 4 shows an example of data annotation. Three classes of brake pads are selected for this study including split, poorly consolidated friction material, and good brake pads. The classes of defective brake pads are referenced according to the characteristics specified in the ISO/PAS 22574 standard.

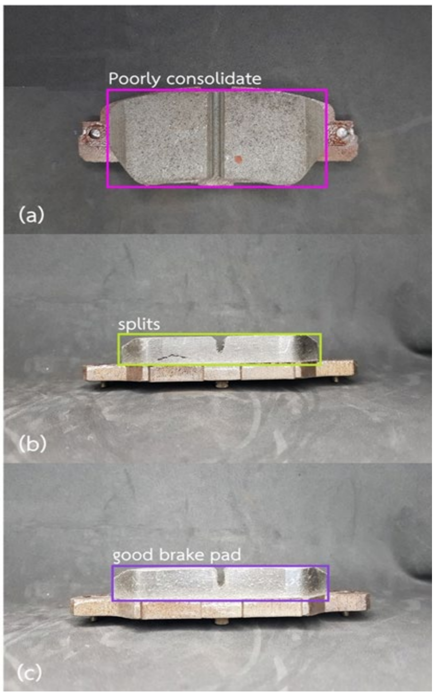

Figure 4: An example of annotations of brake pads on Roboflow: (a) poorly consolidated, (b) splits, and (c) good brake pad

Due to the limited number of raw datasets, data augmentation was performed on the brake pad images after undergoing annotation. The enhancement of brake pads including flip left and right, changes the hue, brightness, saturation, exposure, and grayscale as shown in Figure 5. The annotated images were automatically augmented through the use of the Roboflow platform.

The split dataset is the process of dividing the data to separate into subsets for training and testing purposes. The model training utilizes the training dataset, while the model testing employs the testing dataset. The data splitting process takes place after completing the data preparation.

The experimental environment consists of experiment preparation and algorithm training. Experiment preparation is the process of embedding the object detection framework in the training and testing platform. YOLOv5s, Scaled YOLOv4, and Faster R-CNN were imported from Roboflow and installed on Google Colab. This process runs on a Windows 10 computer with an Intel Core i7-4750HQ CPU at 2.00GHz. Algorithms training is a process of training object detection models which is a learning process of the detector to recognize patterns and make predictions based on the input data provided. The three algorithms train on Google Colab. The training process of three object detection models utilized GPU and the number of epochs was determined by the best precision obtained from three algorithms after training. The next step is model testing.

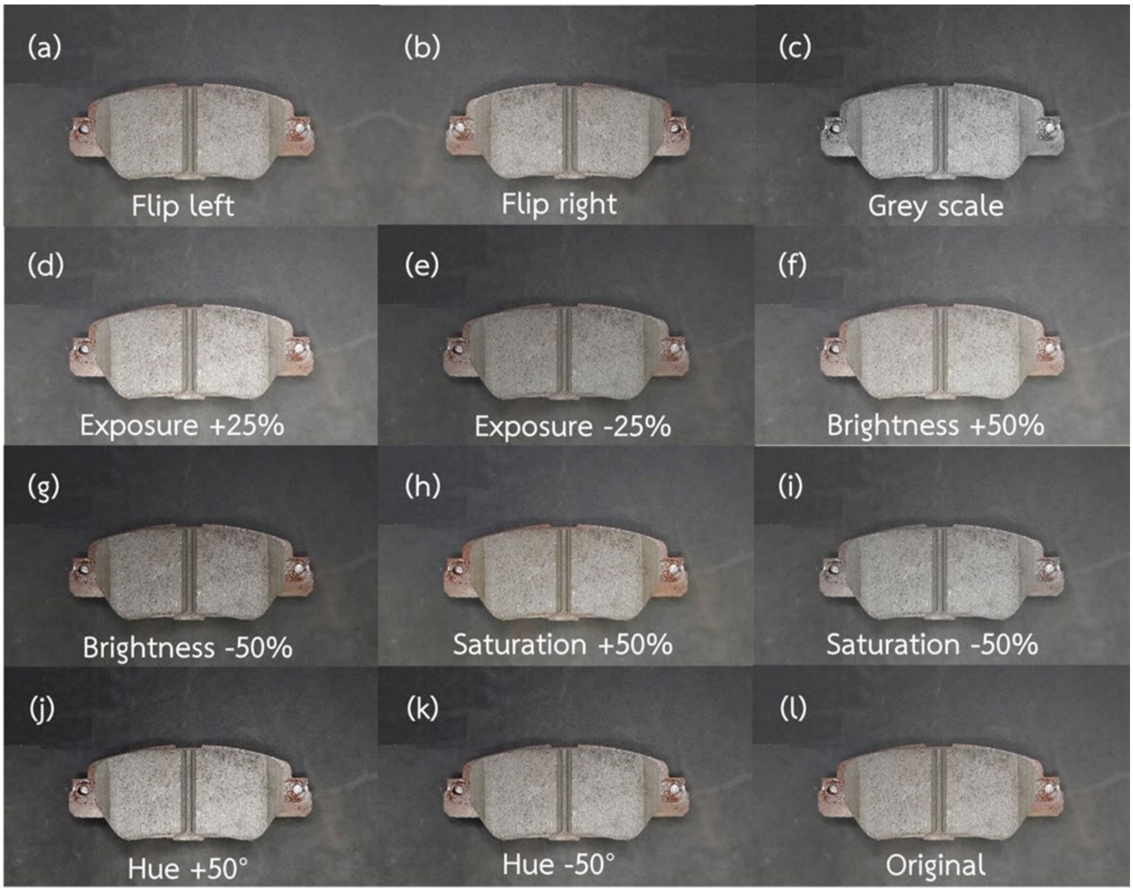

Figure 5: Example of an image using the data augmented technique: (a) flip left, (b) flip right, (c) grey scale, (d) and (e) adjust exposure, (f) and (g) adjust brightness, (h) and (i) adjust saturation, (j) and (k) adjust hue

Model Testing is the process of evaluating the performance and accuracy of a deep learning model on a previously unseen dataset called the testing dataset. The model predictions are compared to the ground truth labels to calculate performance metrics such as precision, recall, F1 score, and detection time. The accuracy in this study is measured by mean average precision (mAP) with the score ranging from 0 to 1. For this study, mAP at an IOU threshold of 0.5 was chosen to measure the accuracy of each class. High mAP indicates that the model can detect and classify different types of defective and good disc brake pads. Recall is the ability of the model to detect objects within an image. The value of recall ranges from 0 to 1. A high recall value indicates that the model is able to detect the objects of interest within the image effectively. The F1 score is a metric used to evaluate the performance of a model by balancing precision and recall rate. The detection time is the time that the model uses for processing.

IV. RESULTS AND DISCUSSION

The defect detection point was chosen to be after the grinding process because defective brake pads found can be recovered for rework. At this step, the conveyor speed is 6.9 meters per second, the area of the conveyor that visualizes the brake pads on all sides is approximately 40 centimeters wide. The brake pads traverse the area in a time frame of 498 to 1790 milliseconds from one edge to the other. Brake pad detectors require less than 498 milliseconds to detect which is set as the main criteria for the brake pad defect detection parameter for this study.

The total number of defects in all models was around 2% of total production. They originated from various sources including 0.04% from mixing process, 0.6% from curing process, and 1.3% from decorating process. The number of defects from model A were the highest in number compared to other models; therefore, it was chosen for this study.

The observed defect for the brake pad from all models was 0.7%. Two major types of defects, “splits” (23% of total defect) and “poorly consolidated (10% of total defect) friction material”, was chosen for this investigation.

The brake pad model A was selected to represent the defect investigation because they were found with the highest number in the brake pads grinding process. The 80 defective samples consist of splits and poorly consolidated friction material.

Both defects represent the most common problems found in disc brake production failures. Splits can cause the brake pad surface disintegration where a small fragment of friction material could fall off quickly, causing noise formation during brake and increasing the braking distance. The cause for brake pads splitting are many parameters such as raw material storage, design, and production [22]. A brake pad with a poorly consolidated friction material can cause noise and uneven wear. Causes for poorly consolidated friction material in brake pad include, foreign matter in chemical mixed, and water dripping into a mixer. The rubber does not dissociate due to clumping in the mixing etc.

Appearance for defect brake pads investigated in this study were shown in Figure 6. Figure 6a shows splits, it has at least one crack with about 1 cm long on the side of the brake pad. Using split brake pads may cause some surface brake pads to slip off and be unable to stop the car. Figure 6b shows poorly consolidated friction material where the presence of foreign material or poor mixing on the upper brake pad surface causes the defect. Figure 6c shows a good brake, the top surface is free of impurities, the edge is not broken, the side surface is smooth.

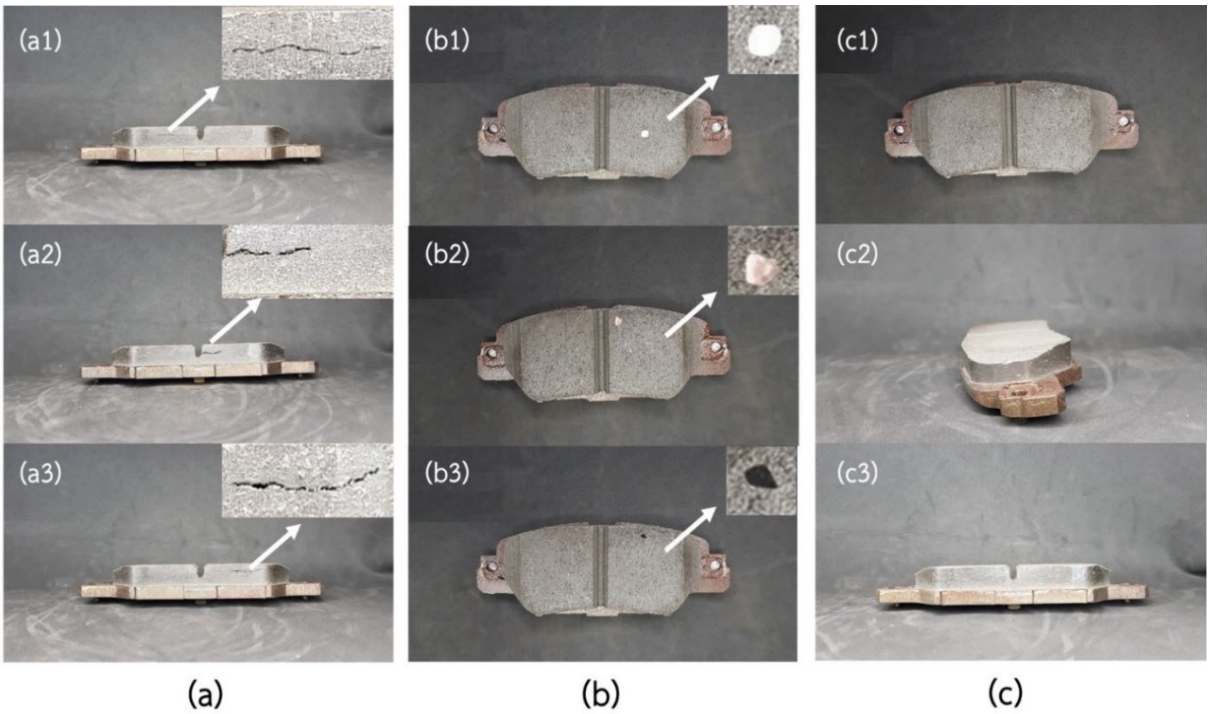

Figure 6: Examples of brake pads in the dataset: (a) splits; (b) poorly consolidate friction material; (c) good brake pad

All 120 images of brake pads were annotated by labeling specific features of the friction material area due to defects appearing on the worn-out area.

Annotated images will undergo augmentation. The image of brake pad that has been annotated and augmentation have been divided into 288 training datasets and 12 testing datasets (ratio 96 to 4) [8]. The detail of datasets is as in Table 1. All characteristics are divided equally, good brake pad calls OK. Datasets were saved as TXT files in YOLO series, XML files in PASCAL VOC for Faster R-CNN.

Table 1: Summary of dataset

Characteristic	Training	Testing
Splits	96	4
Poorly consolidated friction material	96	4
Good brake pad	96	4

A. Result of Model Testing

Table 2 shows the training time of each model. Scaled YOLOv4 has the shortest training time, which is 41 minutes, followed by YOLOv5s (49 minutes), and Faster R-CNN (220 minutes) in that order. Scaled YOLOv4 and YOLOv5s have similar training times as they are both one-stage detectors with strengths in speed. However, YOLOv5s take longer to train than Scaled YOLOv4 due to its high-performance architecture and deeper CNN compared to Scaled YOLOv4. The model with the longest training time is Faster R-CNN, which takes 220 minutes to train, which is significantly longer than the fastest models, which take approximately 5 times less time to train. Faster R-CNN has a complex architecture and a deep CNN, which results in longer training time compared to other models.

B. Performance comparison

The detection of defective and good brake pads by the model includes bounding boxes and labeling. An example of detection is shown in Figure 7.

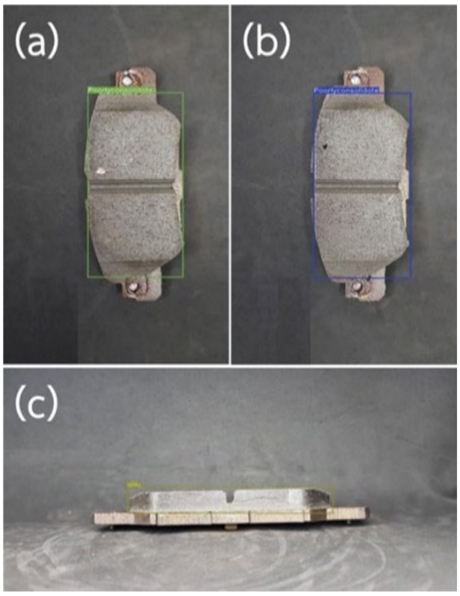

Figure 7: Bounding box and object localization in disk brake detection: (a) and (b) poorly consolidate and (c) splits.

The confusion matrix is shown in Table 3. The results indicate that all models have a similar ability in detecting objects with high proximity. All models can detect defective brake pads that have splits and poorly consolidated friction material, but they still confuse good brake pads with poorly consolidated friction material.

Table 2: Performance of three detector models

Model	Training Time (minute)	mAP	Recall rate	F1 Score	Detection time (ms)
YOLOv5s	49	83.3%	100%	0.91	13.9
Scaled YOLOv4	41	83.3%	100%	0.91	20.0
Faster R-CNN	220	91.7%	100%	0.96	20.2

Table 3: The confusion matrix of YOLOv5s, Scaled YOLOv4, and Faster R-CNN

Predicted / True	Splits	Poorly consolidated friction material	Good brake pad
Splits	1		
Poorly consolidated friction material		1	
Good brake pad		0.5	0.5

The results of brake detection showed that good brake pads were detected as defective brake pads of the poorly consolidated friction material. The misclassified image was compared to the image of a brake pad with poorly consolidated friction material.

Although the disc brake pad with poorly consolidated friction material indicators has a distinct feature that is clearly visible, which is the prominent color spots that differ from the color of the friction material, the color of the friction material surface in other areas is similar to that of the good brake pad. This includes black, gray, and white colors, as well as some parts of the surface texture that are reflective. The images captured from both poorly consolidated friction material and good brake pads are presented above, the light from the studio reflected off the areas with shadows, causing those areas to appear white in the captured images.

Table 2 shows the mAP values for all models in detection brake pads. The mAP indicates the ability to detect objects in an image. Faster R-CNN achieved the highest mAP value of 91.7%. In comparison, other models had an accuracy of 83.3%, indicating that Faster R-CNN has an average ability to detect brake pads with a 91.7% precision rate. YOLOv5s and Scaled YOLOv4 have an average precision of 83.3% in detecting brake pads. The average precision of Faster R-CNN is higher than YOLOv5s and Scaled YOLOv4 because Faster R-CNN performs region proposal before object detection, which helps to reduce false positives and can lead to better precision in terms of mAP. On the other hand, YOLOv5s and Scaled YOLOv4 perform object detection and region proposal simultaneously, which increases the chance of false positives and results in lower precision compared to Faster R-CNN.

The recall rate values of all models are shown in Table 2. All models have a recall rate of 100%, indicating that the models can detect all positive objects. Therefore, all models have high precision in object detection with no False Negatives, meaning the models detect all positive objects. All models can detect all brake pads due to the fact that the brake pads within the image are not complex as it only consists of a single object.

When the recall rate of all models is 100%, it indicates that the F1 scores of all models tend to have a similar trend as the average precision values. The F1 score ranges from 0 to 1, where a value close to 1 indicates high model precision, while a value close to 0 indicates low model precision. Table 2 shows the F1 scores of all Faster R-CNN models, with the highest score being 0.96 for Faster R-CNN and the other models having an accuracy of 0.91, indicating that Faster R-CNN has the highest accuracy.

The detection time of three models for detecting brake pads in the testing dataset is shown in Table 2. YOLOv5s has the lowest detection time at 5 milliseconds, which is the shortest time, while Scaled YOLOv4 has a detection time of 20 milliseconds, and Faster R-CNN has a detection time of 20.17 milliseconds. YOLOv5s has a faster detection time than Scaled YOLOv4 because YOLOv5s is a model developed from the architecture of YOLOv4 with several improvements, such as the use of Feature Pyramid Networks to assist in detecting small objects and SPP-block to reduce the number of parameters, resulting in faster detection. Faster R-CNN has the longest detection time because it uses a region proposal network to locate the regions of interest before performing object detection, which is a complex and time-consuming process. The detection time of YOLOv5s and Scaled YOLOv4 is lower than that of Faster R-CNN because the YOLO detection algorithm is a one-stage detector that does not require the use of a Region Proposal Network, resulting in faster bounding box generation.

V. CONCLUSION

Deep learning principle was applied to brake pads defect detection. Based on a recognition model which included brake pad model A, two defects characteristics and good brake pads. All three object detectors were compared for the performance in terms of training time, mean average precision, and detection time. Scaled YOLOv4 showed the shortest training time at 41 minutes, followed by YOLOv5s (49 minutes), and Faster R-CNN (220 minutes), respectively. Faster R-CNN performs the best in detecting disc brake pads, with a mAP of 91.7%, highest precision. The two detectors have a mAP of 83.3%. Although all detectors have mAP of over 80%, there is still confusion in detecting disc brake pads that needs improvement. All models were able to recognize and detect all disk brake shapes in the images with 100% recall. In terms of object detection speed, YOLOv5s takes only 13.92 milliseconds to detect disc brake pads within an image, followed by Scaled YOLOv4 (20 milliseconds), and Faster R-CNN (20.17 milliseconds). The three algorithms have the potential to detect and process brake pads due to their detection time of less than 498 milliseconds.

The brake pad manufacturing environment comprises high-speed conveyor belts and lighting directions. The essential equipment for implementation consists of five high-speed cameras equipped with vibration reduction systems, lights capable of illuminating the brake pad surface clearly, and a system for eliminating defective brake pads on the conveyor belt. Moreover, the data transmission equipment must be fast to ensure timely processing by the algorithms.

In this research, there are few samples of defects on Brake Pad Model A due to the high-quality production process, resulting in a limited dataset. For comprehensive and effective utilization of deep learning principles in detecting defective brake pads, the dataset must encompass brake pad models from every car model and all types of defects across all models. Furthermore, each car model undergoes constant changes, both major and minor, directly impacting the shape of the brake pads. Therefore, there must be regular updates to the dataset.

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