SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage: https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index

ISSN: 2462-1943

Real-Time Pavement Crack Detection Based on Artificial Intelligence

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ARTICLE INFO

Article history:
Received 15 June 2023
Received in revised form 8 December 2023
Accepted 24 December 2023
Available online 30 January 2024

Keywords:
Crack; pavement; road; damages; Machine Learning

ABSTRACT

Pavement as a structural element is closely related to the road traffic system because it is essentially a support structure for the movement of vehicles. Modern technology has attained significant improvements in road durability, quality, and safety through the use of new materials and construction technology. All civil engineering infrastructures have a specific lifespan. The road surface can be the worst, and repair is more costly if the pavement is not maintained. The objective of this research is to spot the damages over the inspected road and detect cracks in a short time, useful to achieve more comprehensive monitoring and assessment of the condition of road pavement using a smartphone equipped with You Only Look Once (YOLO) to reduce maintenance costs. The method uses advanced image processing techniques and uses YOLO to detect cracked pavement in a short time. More specifically, it is based on the latest generation of Deep Neural Network (DNN) algorithms, such as YOLO V5. YOLO V5 is used as a detector for cracked pavement and image processing as an automated pavement distress detector. The obtained result for longitudinal cracks shows that the area of cracks is 1.1682 m^2, with a threshold value of 0.91, while the result for transversal cracks shows the area of cracks of 1.9627 m^2, with a threshold value of 0.85. Otsu's method works best under conditions such as low noise level, homogeneous lighting, and higher intra-class variance than an inter-class variance. The outcome of this project is improved recognition accuracy compared to the manual recognition currently used.

1. Introduction

Cracking directly affects the quality of the pavement. Road maintenance is an important area of pavement engineering. A flexible pavement structure is typically composed of layers of various materials that increase in strength as users approach the surface [1]. Cracks exist in other artificial or natural objects, such as buildings, bridges, tunnels, etc. Pavement cracks not only affect pavement appearance and driving comfort, but they can also easily expand and cause structural damage to the pavement, decreasing the overall service performance and life of the pavement [2]. Pavement crack images are the most complex of all object images, so image processing and analysis are harder than

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https://doi.org/10.37934/araset.38.2.7182

other crack images [3]. Crack pavement detection systems for detecting cracks in pavements consist of machine learning using You Only Look Once (YOLO) V5 and advanced image processing. The YOLO V5 open-source uses Phyton as its programming language, which uses the Pytorch framework, and the YOLO V5 from Ultralytic can be used in Google Colab or Kaggle. PyTorch is a recent entrant to the league of graph computation tools/programming languages [4]. The benefit of Pytorch is most deep learning frameworks that use computational graphs generate and analyze graphs before runtime [5]. The image recognition-based detection method can analyze road-surface conditions over a large area at a low cost by utilizing a deep neural network. As a result of the advancement of image-recognition technology, this approach has gained popularity in recent years [6]. Machine learning techniques are increasingly applied to road crack detection and segmentation [7]. Feng *et al.,* [8] proposed a method based on a deep convolutional neural network fusion model for pavement crack identification, which combines the advantages of the multi-target single-shot multi-box detector (SSD) convolutional neural network model and the U-Net model. It will give accurate positioning and geometric parameter information and can be used directly for evaluating the pavement condition. The combination of machine learning techniques and pavement crack detection techniques has significantly improved the efficiency and accuracy of pavement crack detection [9].

Performing classification and identification of cracked pavement requires many datasets or scenarios to train machine learning to begin learning and identifying cracked pavements. The crack detector may fail or become less accurate in the circumstances of dataset or scenario changes. YOLO is used in many applications that require object detection. Mandal *et al.,* [10] applied a target detection model YOLOv2 and images from mobile cameras to do automatic pavement distress identification works. Machine learning often requires large datasets for training and testing. Images for pavement crack detection are mainly obtained by devices such as charge-coupled devices (CCD) and ground-penetrating radar (GPR) [3,11]. Another researcher named Hoang and Nguyen [12] came out with an intelligent method for the automatic recognition of pavement crack morphology in the year 2018. This study constructs a machine-learning model for pavement crack classification that includes multiple support vector machines and an artificial swarm optimization algorithm. However, the algorithm is complex and programming has become very difficult.

Cracks are the most common type of stress that occurs on the road surface, mainly due to fatigue of the asphalt pavement layer (upper road layer). They can appear as isolated or as a series of interconnected cracks in the early stages of development, and in later stages, they can be interconnected and appear in a denser pattern. Cracks are roughly classified according to their location. There are three main types of pavement crack stress on road surfaces, i.e., alligator, transversal, and longitudinal cracks, which are the most common tears found on the road these days [1]. One of the deteriorations of roads is the occurrence of residual deformation. This is due to the deformability of the soil, according to the principles of road construction. However, a permanent set is caused by the deformation of the asphalt layer. Apart from that, the causes of this problem are the dynamic load of the road, the deterioration of the material quality of the layers, and the influence of climatic conditions [13]. In 2014, Wang and Wu [14] proposed a pavement crack extraction method based on the valley bottom boundary, it uses a series of image processing algorithms to obtain the crack detection results. However, without the advancement of artificial intelligence, convolutional neural networks (CNN) detection is not quite accurate, making it capable of detecting the crack but time-consuming.

As far as technology evolve, more efficient method and ideology has been conducted. Not far as UAV technology can be used and performs better than the current existing method. UAVs were widely used to ease any bird's eye operation such as mapping, search, and rescue, and building inspection. Therefore, this opportunity should be taken as UAVs can provide a bird's eye view of pavement conditions which is much more convenient than the street view. As UAVs also serve as a part of the low-cost device, the concept can also be the as per method used in smartphones. By applying YOLO application in UAV flight control, image recognition or image detection method can be analyzed, and thus can be used as pavement crack detection devices.

Early warning using smartphones that have been implemented is MyShake Apps which offers another option for turning smartphones into seismometer networks to provide regional EEW [15]. Thus, in this study, the YOLO apps are trained using a custom dataset that includes a large-scale road damage dataset. This dataset comprises 9053 images of road damage obtained with a smartphone. Each image contains an annotated box indicating the location and type of crack [2]. The YOLO apps were trained by Roboflow with a custom dataset that teaches the apps to recognize cracks and classify crack types. In contrast, when a model built using images captured from a smartphone is installed onboard a vehicle, it is simple to apply these images to train the model for real-time situations. Developing custom datasets is preferred by researchers as this enables them to capture the specific requirements of the crack detection algorithm being used. About 30% of researchers used pre-built crack datasets, which contained crack images. These datasets are being used as standards for testing and training crack detection models. Examples of these datasets include Crack500, GAPs384, CrackTree200 and CFD, Aigle-RN. Such datasets are widely used in machine learning models, as they require a large number of images or training, hence, it is deemed more feasible to use standard domain-specific datasets.

Digital image processing primarily concerns signal processing research, including picture contrast adjustment, image coding, image denoising, and filtering. Image analysis differs in that it stresses symbolic representations, analysis, interpretation, and recognition when describing images [16]. Along with the rise of artificial intelligence and deep learning, the sophistication and depth of digital image processing are increasing. People begin their research by replicating human vision to observe, comprehend, and even explain the real-world utilizing picture segmentation, image analysis, and image understanding [17]. Generally, it is utilized to investigate underlying characteristics and superstructures using mathematical models. Image analysis research focuses on face identification, emotion detection, optical character recognition, handwriting recognition, biomedical image analysis, and video object extraction. Image understanding is the process of exploring the properties and relationships of the features and objects to gain a deeper comprehension of the meanings and scenario descriptions. Symbols from description are the objects for image comprehension; the process is comparable to that of the human brain. Video analysis corresponds to image analysis in that it uses computer vision techniques to examine the video frames captured by a security camera. It can also filter backdrop elements such as wind, rain, snow, falling leaves, birds, and flying flags. It is object tracking against a complicated background. Due to variations in illusion, motion, occlusion, color, and backdrop complexity, it is more challenging to develop an object recognition and tracking system [18].

The objective of this research is to spot the presence of various damages over the inspected road, which were useful to achieve more comprehensive monitoring and assessment of the condition of road pavement using a smartphone equipped with You Only Look Once (YOLO), detect cracks in a shortened time, and reduce maintenance costs.

2. Methodology

2.1 Study Area

The study area of this project is in Pasir Gudang, Johor. Pasir Gudang is known as an industrial city that experiences much heavy traffic involving heavy trucks. Thus, damage to the structure of the pavement is inevitable. Microsoft Visual Studio, Pytorch framework, Roboflow, YOLO V5, and Advanced Image Processing in MATLAB are used. The cracks were fed into the YOLO V5 for the classification process.

2.2 Framework of the Project

Figure 1 shows the block diagram of the cracked pavement detection using YOLO and advanced image processing in MATLAB.

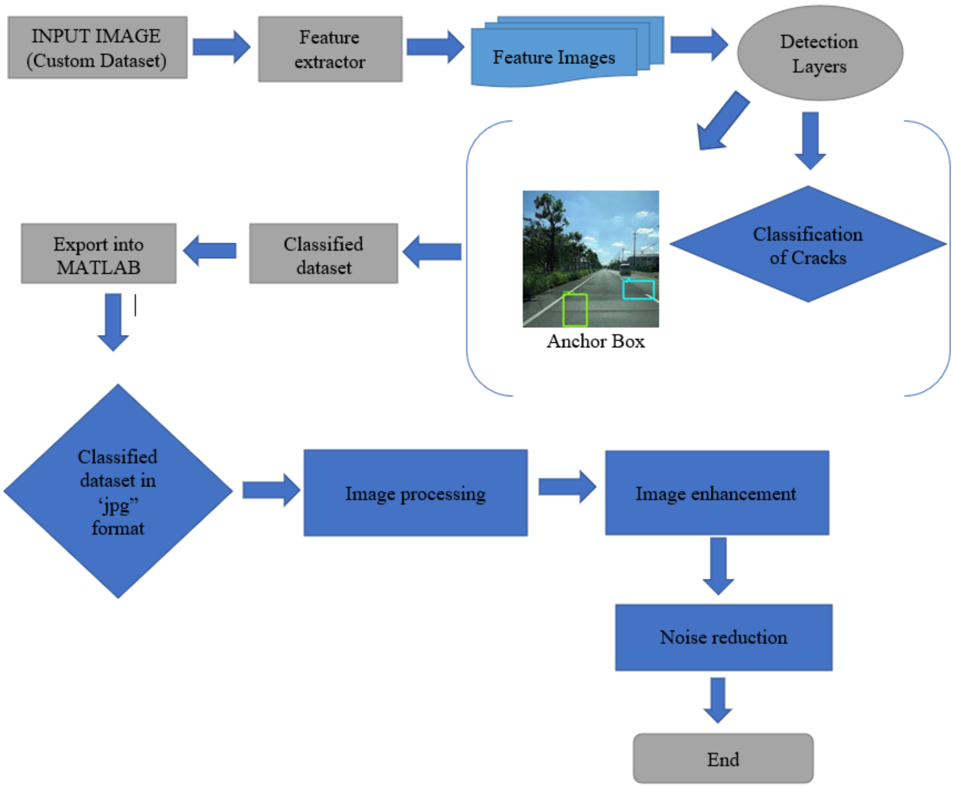


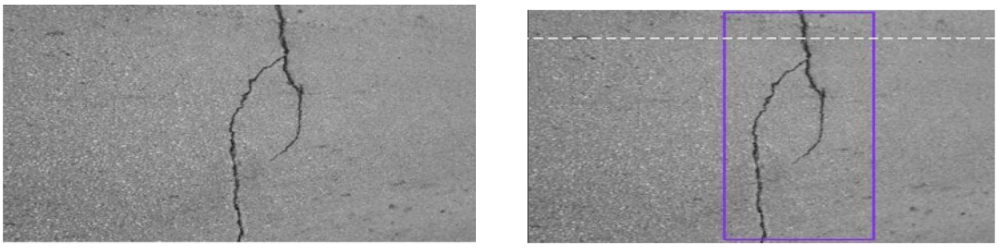
Fig. 1. Block Diagram of The System

2.2.1 Method

i. *Input Image Custom Dataset*

The input images represent the image collected at the site in the study area and are known as the "custom dataset." The custom datasets were imported into Google Colab using API Key in Roboflow to start the training. However, the custom dataset must be trained first for classification. The custom dataset needs to be in "Pytorch YOLO V5" format to train the dataset.

The custom dataset was trained to learn to recognize the cracks and potholes. The trained dataset includes annotation and a bounding box, indicating that it has been trained and is ready for the testing phase, as shown in Figure 2(a) and Figure 2(b). Figure 2(a) shows the non-annotated cracked pavement images that will be marked in Roboflow with a bounding box and annotation before undergoing the development phase. Figure 2(b) shows the result after marking the bounding box in Roboflow. The custom dataset will be marked as an annotated custom dataset with specific types of cracks. The result was imported into advanced image processing, comprising image enhancement, noise removal, and conversion into binary images using a threshold.



(a) (b)

Fig. 2. (a) Non-annotated custom dataset (b) Annotated custom dataset

ii. *Training*

The custom dataset must be converted into ZIP files dueto the huge number of images. The custom dataset also needs tobe converted into the desired framework. The training data has been provided with a boundingbox and annotation in every image. Figure 3 shows that the training data has been augmented in Google Colab, and after training starts, train*.jpg consist of training images, labels, and augmentation effects are obtained.

Fig. 3. The sample of training data

However, if the cracks are unclear, YOLO detection cannot detect cracks such as alligator cracks. Thus, when the cracks are detected, the bounding box is shown in Figure 4.

Retraining of the YOLO model can be used on an ongoing basis to enhance the crack classification system's performance and accuracy. This entails adding recently gathered datasets that were recorded with a smartphone to the current custom dataset. For training and validation purposes, the gathered photos of potentially cracked road surfaces are supplied into the YOLO framework through Roboflow and Google Colab. The YOLO algorithm may then learn and recognize new patterns and variations of road damage when the custom dataset is improved with the fresh data. Iteratively retraining the model makes it better at precisely identifying and categorizing pavement cracks, thereby improving the system's overall performance.

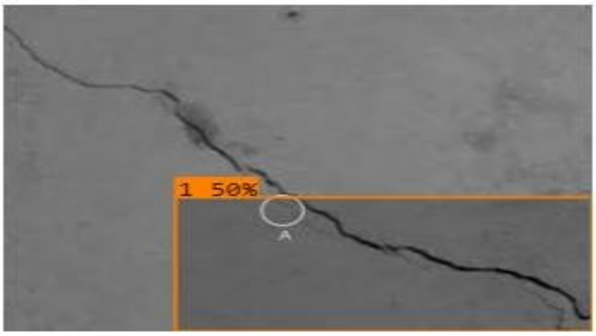


Fig. 4. Bounding box for cracks

iii. *Pre-Processing*

The dataset underwent segmentation,noise removal, and thresholding, which turns the images into binary images. Pre-processing was used to improve the quality of the input image to facilitate the analysis and interpretationat subsequent stages. Important tasks in pre-processing can include filtering for noise removal, deblurring the image, and highlighting specific features, such as cracks on the pavement. Image segmentation is the process of dividing animage into five meaningful regions, such as objects of interest and background. The main parameters concerning pavement management are pattern classification and measurement ofvarious parameters from crack features. Advanced image processing techniques were used to deal with pavement pictures. Although this method can obtain no more pavement parameters than commercial systems, it will reduce the hardware cost. Several methods were used to detect cracks in thepavement image, e.g., enhancement, threshold, dilation, erosion, and connection method. Enhancement improves the contrast for every given image, making the conversion from grayscale to binary image easier through the thresholding method.

The value of 50% is the confidence value for the detection to be recognized well. Furthermore, the training in Roboflow also yielded the mean average precision (mAP) value, as shown in Eq. (1), i.e., the metric unit used to evaluate object detection models such as FastR-CNN, YOLO, and Mask R-CNN. The values of these parameters were calculated over recall values from 0 to 0.1.

$$\mathrm{mAP} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i \tag{1}$$

Mean Average Precision Formula

3. Results and Discussion

3.1 YOLO V5 Training

Advanced image processing and crack detection were tested with various types of cracks. The steps start from Roboflow YOLO V5, where the custom dataset was trained to learn and recognize the cracks with each type of class. Figure 5 shows the interface of crack detection in Roboflow and its training results, including mAP, recall, and precision. The low mAP value is due to the lack of a compatible dataset to run with YOLO V5 since some datasets are not clear at all and render a lack of detection accuracy.

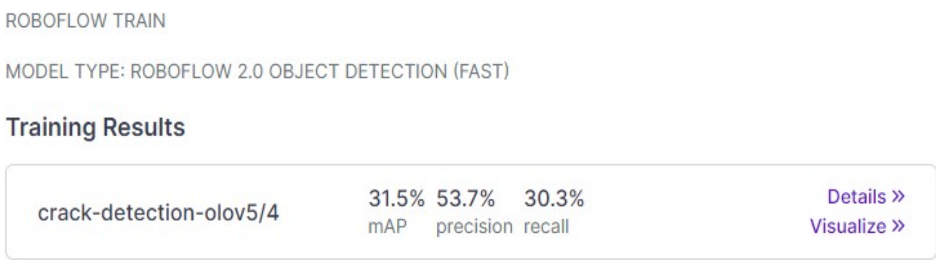


Fig. 5. Result of training in Roboflow

The size of images COCO trains at native resolution of 640, though due to the high amount of small objects in the dataset it can benefit from training at higher resolutions such as 1280. If there are many small objects then custom datasets will benefit from training at native or higher resolution. Best inference results are obtained at the same resolution as the training was run at, such as if train at 1280 then should also test and detect at 1280. The training went well, and the results are shown below, with a transversal crack in Figure 6, annotated as “1,” and potholes in Figure 7 with a bounding box.

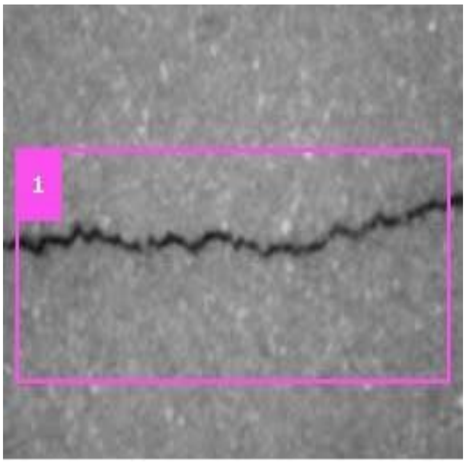


Fig. 6. Bounding box of transversal cracks

Fig. 7. Bounding box of potholes

i. *Transversal Crack*

The transversal crack underwent the same method as transversal and was exported to MATLAB to make an advanced image processing to detect the area of the cracks and reduce the noise for a better image of the cracks. The imported images were converted into greyscale images (Figure 8). An enhancement process was applied to the greyscale image through a 9×9 filter to determine the area of a crack in Figure 9. Meanwhile, Figure 10 shows the result of the conversion from enhanced images into binary images using threshold theory, and Figure 11 depicts the removal of noise from the image. Figure 12 shows the result of image processing complete with the area of crack and annotation in the red line.

A pavement image with three transverse cracks is shown in Figure 8. The image after enhancement is shown in Figure 9. In the following, image fractal thresholding is used.

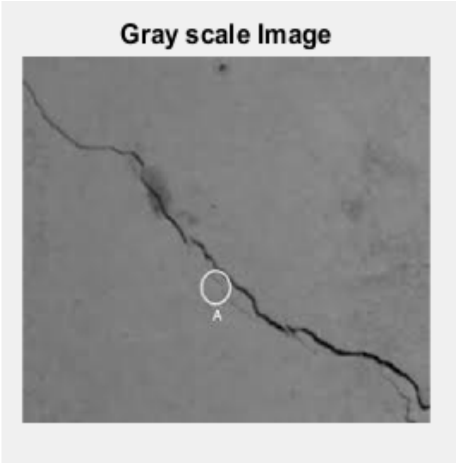


Fig. 8. Image converted into greyscale

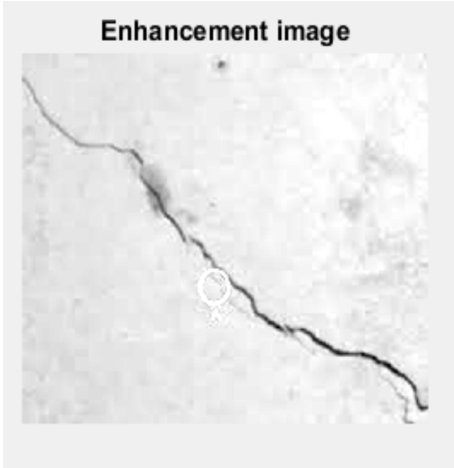


Fig. 9. Greyscale image undergoes image enhancement through a 9 × 9 low pass filter

The binary image contains discontinuities in cracks and noise, as shown in Figure 10. The discontinuities are filled after applying the closing operation. The method explained has a better result than median filtering. Eight gaps on two cracks are connected after applying the connectivity algorithm, as shown in Figure 11.

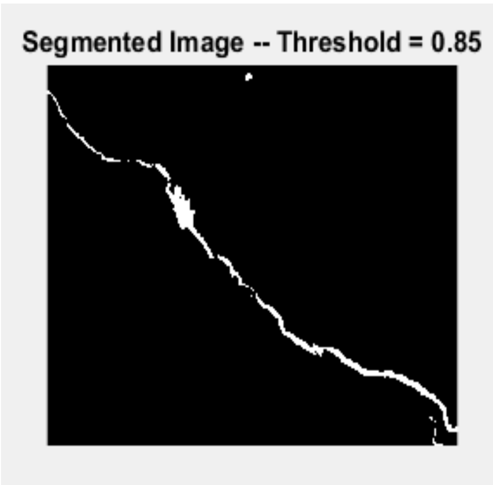


Fig. 10. Greyscale image converted into a binary image using a threshold

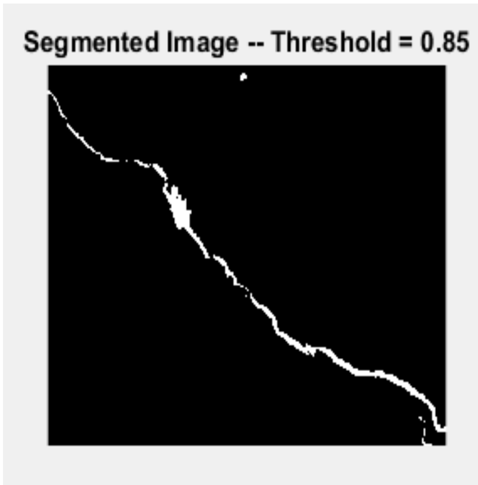


Fig. 11. Binary image undergoes the noise removal process

Figure 12 shows the skeletonization result. The noise points are removed after using the connected component method, except for a large patch of noise because of the connection of cracked pixels. The result in Figure 12 shows the area of transversal cracks of 1.9627 m^2. The result is obtained from the start of detection and exported into advanced image processing, which goes through segmentation, noise removal, and threshold theory.

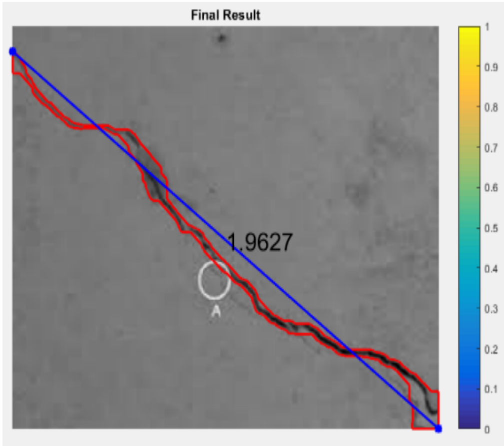


Fig. 12. The result of the image processing towards cracks detection and the area of the cracks itself

ii. *Longitudinal Cracks*

The longitudinal crack underwent the same method as transversal and was exported to MATLAB to make an advanced image processing to detect the area of the cracks and reduce the noise for a better image of the cracks. Figure 13 shows that the imported images were converted into grayscale images. The enhancement process has been applied to the grayscale image through a 9 × 9 filter to determine the area of a crack in Figure 14. Figure 15 shows the result of the conversion from enhanced images into binary images using threshold theory, and Figure 16 shows the removal of noise. Figure 17 is the result of image processing, complete with the area of crack and annotation in the red line. The binary image contains discontinuities in cracks and noise, as shown in Figure 16. The discontinuities are filled after the closing operation, as shown in Figure 16, the image of a noise reduction process. Three gaps on two cracks are connected after applying the connectivity algorithm, as shown in Figure 16.

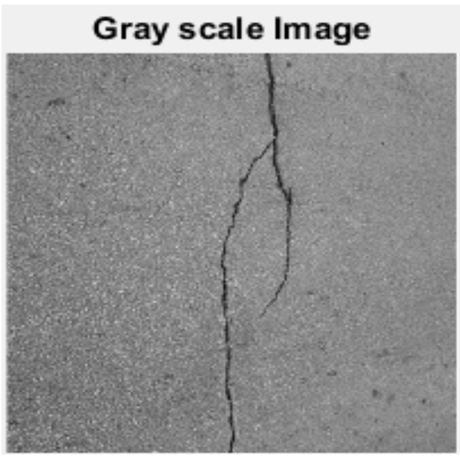


Fig. 13. Image converted into greyscale

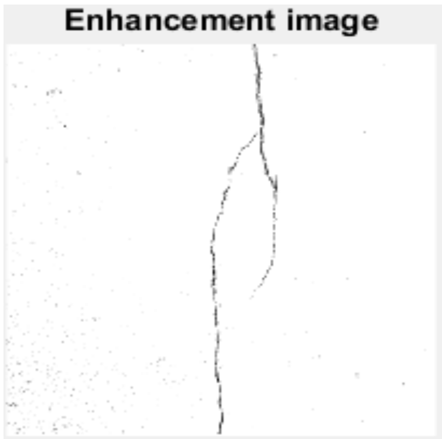


Fig. 14. Greyscale image undergoes image enhancement through a 9 × 9 low pass filter

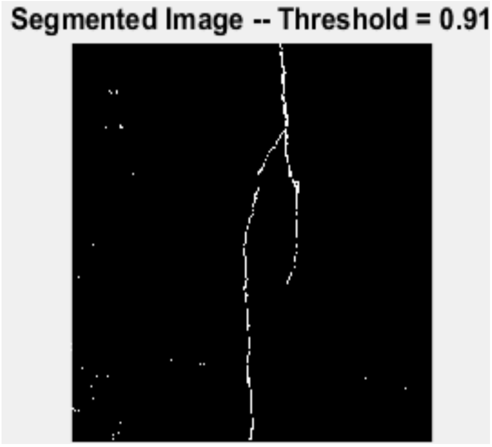


Fig. 15. Greyscale image converted into binary image using threshold theory

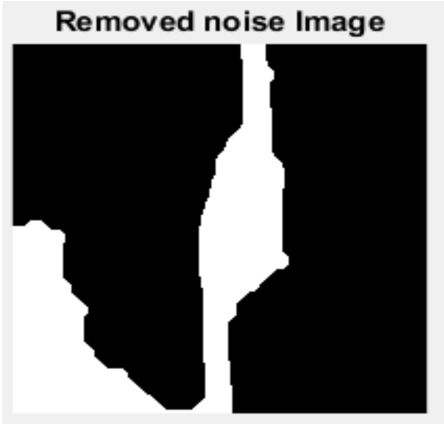


Fig. 16. Binary image undergoes noise removal process

Figure 17 shows the skeletonization result. The noise points are removed after using the connected component method, except for one white patch due to the connection of cracked pixels.

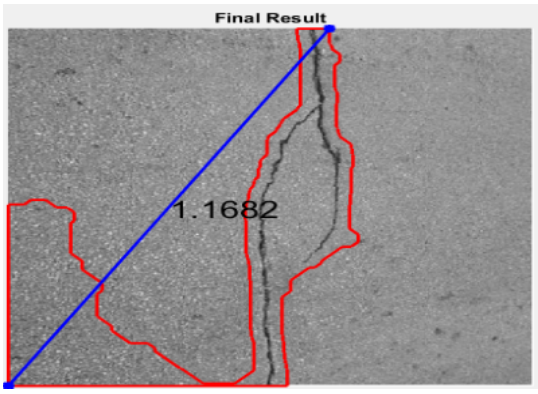


Fig. 17. The result of the image processing towards cracks detection and the area of the cracks itself

3.3 Comparison Threshold Value and Area of Cracks

The threshold of image intensity is set manually at a specific value or automatically set by an application. This advanced image processing uses the automatic thresholding method, which does not require a manual configuration of the threshold value. Meanwhile, for denoising, an image before thresholding contributes a good image to be a candidate for another process, i.e., calculating the area of cracks.

The result for longitudinal cracks shows the area of cracks of 1.1682 m^2, with a threshold value of 0.91. The result was obtained from the start of detection and exported into advanced image processing, which goes through segmentation, noise removal, and fractal method in thresholding.

Thus, the result for transversal cracks shows the area of cracks of 1.9627 m^2, with a threshold value of 0.85 as shown in Table 1. Otsu's method works best under conditions such as low noise level, homogeneous lighting, and higher intra-class variance than an inter-class variance.

Table 1
The threshold value and area of cracks with 2 types of cracks

Types of cracks	Threshold Value	Area of Cracks (m^2)
Transversal	0.85	1.9627
Longitudinal	0.91	1.1682

4. Conclusion

The system has been devised to develop a low-cost system that can detect cracks on pavement and reduce manpower supply by combining image processing and machine learning. The outcomes of this experimental framework outlined the ability to spot the various damages over the inspected road, which were proven useful to achieve more comprehensive health monitoring and assessment of road pavement condition. The information has been successfully gained through advanced image processing using Otsu's Method.

The findings of this study will benefit society, considering that the current IR 4.0 technology can play an important role in providing and ensuring the pavement condition is sustained. The increase of road users every year will justify the need for more effective ways and image processing technology applications to improve the quality and sustain pavement conditions. The manual approach to maintaining the pavement structure is time-consuming and requires manpower. This Real-Time Crack Pavement Detection based on Artificial Intelligence can help reduce the burden of local authorities, and preventative actions can be taken promptly in undesired conditions.

Acknowledgment
The authors would like to express their gratitude to the Research Management Centre (RMC) at Universiti Teknologi MARA, Shah Alam, for funding grant no. 600-IRMI 5/3/LESTARI (035/2019) to publish this paper. The authors also would like to thank the School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, for supporting the conduct of the research.

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