Broken Road Detection Methods Comparison: A Literature Survey

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ABSTRACT

Roads are infrastructure built to facilitate regional development. Good road conditions will certainly provide a sense of comfort for every vehicle that will pass through it. For that, care and attention to road conditions needs to be done. The occurrence of damage to the road will hinder the development process. Currently, detection of damaged roads is still done manually using human resource. It makes the detection process take quite a lot of time to determine how bad the damage is. So there needs a way to help improve time efficiency and accuracy in detecting damaged roads. One of them is by utilizing machine learning technology. In this paper, we will discuss what methodology can be use and their comparisons to be able to use appropriate and effective methodologies to detect cases of damaged roads

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KEYWORDS
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Image Detection
Literature
Machine Learning

1. Introduction

Roads are public facilities that intend for general traffic that supports the mobility and accessibility of road user in the form of convenience to reach a destination [1], [2]. Good roads are so important to support safety, security, comfort and shorten the travel time of road users [3]. So, if the road conditions are inadequate, arrive to the destination will be disrupted. In addition, the high activity of the community will be directly proportional to the high traffic load [4]. High traffic loads will increase the road load, and cause pavement damage. Road pavement damage is damage that occurs on the road surface which results in a decrease in road function [5]. The occurrence of road pavement damage causes many problems and disturbances that occur. Various disturbances both to users and to the government as road organizers. Congestion, safety, repair costs and accident compensation costs are real examples of the impact of road damage that has always been faced so far [6], [7]. One of the activities that must be carried out to determine road conditions is to conduct road surveillance, namely the implementation, observation, utilization of roads and road conditions and observation reports and proposed actions on the results of observations submitted to road organizers or appointed agencies to help determine maintenance and repair actions. What improvements are needed. Manually, road condition checks are carried out by trained survey officers to make direct observations on the road sections to be assessed [8], [9], [10]. On roads that have heavy traffic flow and high vehicle rates, this can endanger the safety of survey officers and disrupt the smooth flow of traffic with the survey activities [11], [12]. In addition, the manual detection and recording process by fully human workers can take up to two weeks for a 1 km road before reaching the repair process [13]. Then a low level of accuracy can also cause the detection process to be carried out again and require time to return [14], [15].One way to overcome the above is by using machine learning technology. Machine learning (ML) is studying how the computer to simulate or to realize the study behavior of human being[16]. Thus, the detection of damaged roads will be carried out and classified by the computer, which is expected to reduce the time to run effectively and increase the accuracy of the detection process. Many methods can be used for machine learning. This paper will discuss these various methodologies and their technical designs to assist the detection process of damaged roads can run better.

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Image classification is one of the implemented techniques using machine learning. This method is also called computer vision that is allowing the computers to have the ability to understand the image and classifying it into corresponding classes. Deep neural networks are subsequent of machine learning that is using neural network for modeling with backpropagation for minimizing a loss function. One of the best deep learning models used for image classification is Convolutional Neural Network (CNN) that is proven to get the highest accuracy possible for image classification. I will compare simple image classification for face recognition with 40 different classes using a dense neural network model with a couple of hidden layers and with a convolutional neural network [17], [18].

The CNN (Convolutional Neural Network) model is one type of deep learning model that uses the concept of convolution. This model is most commonly applied to image analysis in machine learning. When using CNN, there is a layer called conv2d which takes the input of a tensor and specifies the size of 2–dimensional kernels as a parameter [19].

2. 2. Method

2.1. Materials and Tools

Design of Road Asphalt Damage Detection System Through Video Using Fast Fourier Transform This paper explains the concept of how to detect damaged roads by utilizing information from videos using the Fast Fourier Transform calculation method [20].

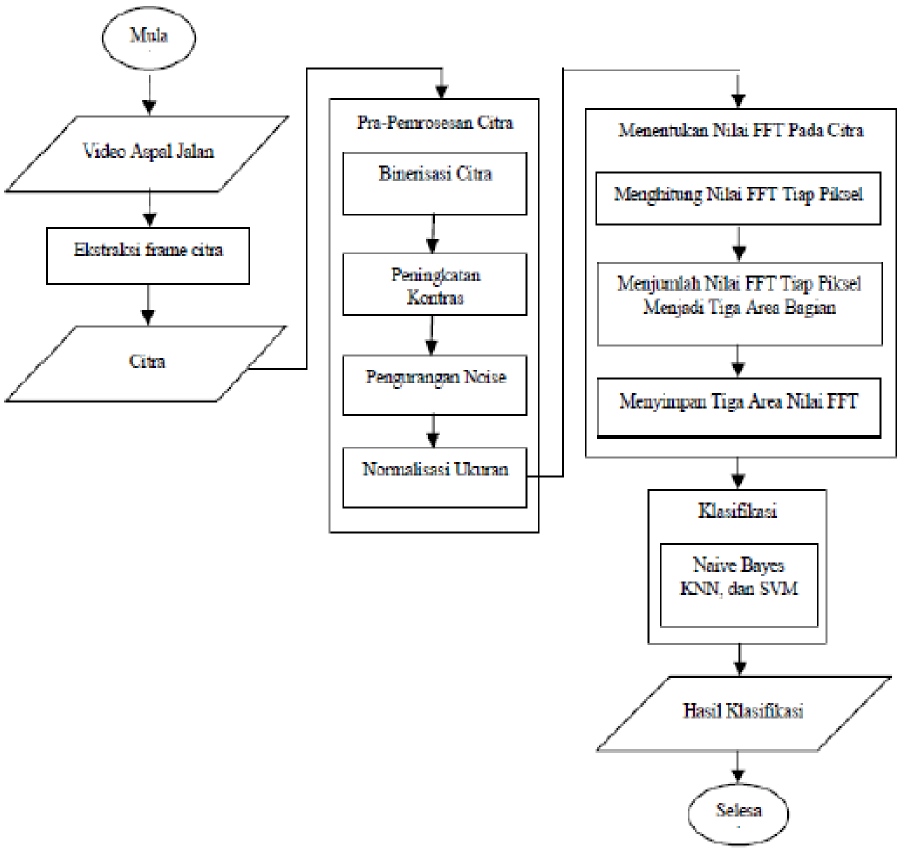


Fig.1. Flowchart

From the diagram above, the process begins with the activity of recording road conditions at a speed of 5km/hour [21]. The goal is to reduce the blur that will affect the processing. Furthermore, at the pre-processing stage, the extraction process is carried out into image frames which will then be converted into grayscale [22]. After that perform image binarization and increase contrast to produce a clearer and more visible area of road damage [23]. In the image binarization process, the method used is the thresholding method.

After the thresholding process produces a clear enough damage area, the next step is the noise reduction process. Noise is an object created from the image processing process that needs to be removed because it will affect the results of the next stage of image processing [24]. In this process, blurring and removal of objects in the area of the resulting image will be carried out. The methods used are median filtering, opening operation, and connected component [25]. The following is the result of the noise removal process carried out.

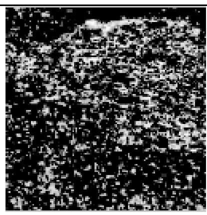
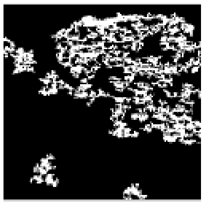
Citra Asli	Citra Biner	Hasil Pengurangan Noise
		

Fig.2. Noise Reduction Results

The next process is the normalization process, where the video resolution adjustment will be made to facilitate the Fast Fourier Transform calculation process [26]. Image pixels are a two-dimensional matrix representation, with the help of Matlab software which provides a function to calculate the FFT value for each pixel of the asphalt road image [27]. After getting the FFT value, the FFT value is calculated in a circular manner starting from the outside of the matrix to the inside of the matrix. So that we get 128 which contains the sum of the FFT values which is termed the area.

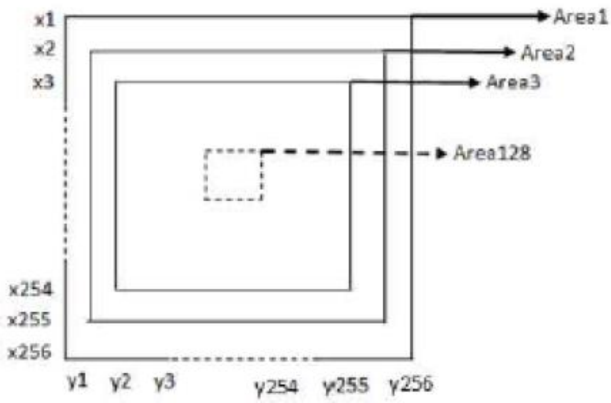


Fig.3. Illustration of the Sum of FFT Nilai Values

The three areas which are the sum of the FFT values are used as features to distinguish between the images extracted from the asphalt road video recordings into good, moderate, lightly damaged, and heavily damaged criteria [28]. After the normalization process, the next process is to classify. This process aims to conclude whether the asphalt road image that has been included in the category of good, moderate, lightly damaged, or damaged based on manual measurements, then with three, five and seven areas the FFT value does have a good classification accuracy. There are 3 classification methods used, namely Nave Bayes, KNN, and SVM with 10 folds cross-validation and 70:30 data comparison.

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Table 1. Result of Training Data Classification

No	Method	Time	Accuracy	
			Correctly Classified Instances	Incorrectly Classified Instances
1	Naïve Bayes	0 Sec	97%	3%
2	KNN	0 Sec	97%	3%
3	SVM	0.23 Sec	97%	2%

The following are the results of the classification process using test data.

Table 2. Classification Results Using The Naïve Bayes Method

Prediction Class					
Actual Class	Condition	Good	Medium	Lightly Damage	Heavily Damage
	Good	25	0	0	0
	Medium	0	25	0	0
	Lightly damaged	0	0	23	2
	Heavily damaged	0	0	1	24

Table 3. Classification Results Using The Naïve Kkn Method

Prediction Class					
Actual Class	Condition	Good	Medium	Lightly Damage	Heavily Damage
	Good	25	0	0	0
	Medium	0	25	0	0
	Lightly damaged	0	0	23	2
	Heavily damaged	0	0	1	24

Table 4. Classification Results Using The Naïve SVM

Prediction Class					
Actual Class	Condition	Good	Medium	Lightly Damage	Heavily Damage
	Good	25	0	0	0
	Medium	0	25	0	0
	Lightly damaged	0	0	23	2
	Heavily damaged	0	0	0	24

The conclusion from the results of this study shows results that are consistent with the FFT calculation to calculate the area before the classification process is carried out with examples using three classification methods, namely naïve Bayes, KNN, and SVM.

3. Data Analysis and Discussion

3.1 Road Crack Detection Using Deep Convolutional Neural Network

This paper discusses the mechanism for detecting damaged roads using the Deep Convolutional Neural Network method. This method allows the detection and classification process to be carried out directly from the RAW images obtained. So with this method, it is expected to have a better level of accuracy.

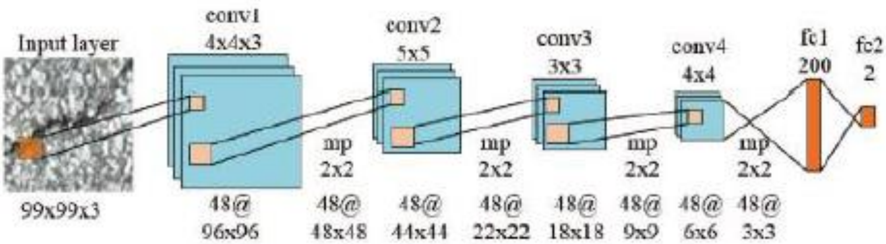

Fig.4. CNN Architecture Illustration

The mechanism of the detection process described in this paper is to collect training data with more than 500 examples of high-resolution images which will be processed starting with a resolution of 99 x 99 pixels[28]. Then the training data using the GPU and perform the detection testing process. Besides using CNN, this paper also describes a comparison with the SVM method with the same technique, but there is misclassification of the SVM method. So the level of accuracy obtained is lower than the Deep CNN method

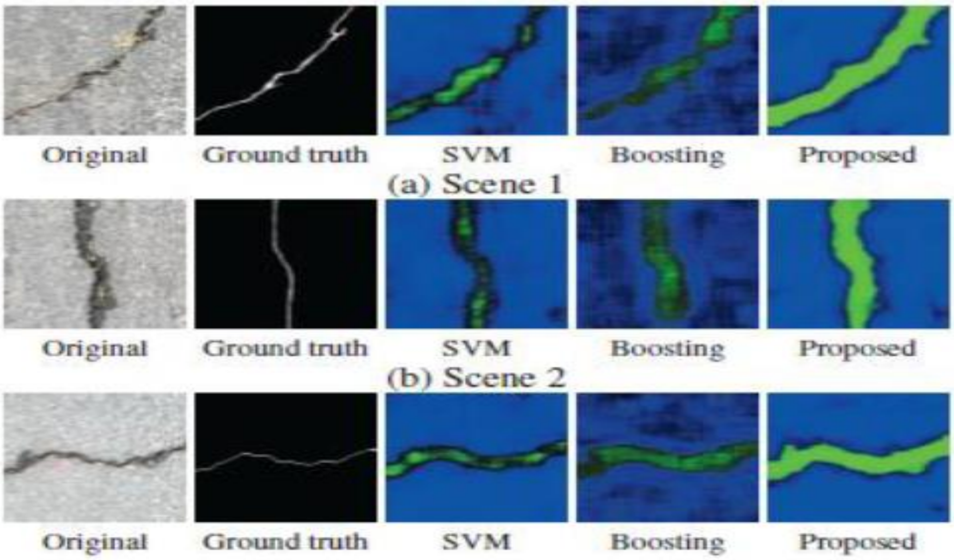

Fig.5. Test Results

3.2 Deep Network For Road Damage Detection

This paper explains how to technically classify damaged roads using the Faster R-CNN method. Faster R-CNN is a development of the R-CNN method. The difference is from the detection mechanism carried out by Faster R-CNN using the Region Proposal Network (RPN) to form objects faster than R-CNN which uses object proposals. So, in terms of performance, Faster R-CNN has a higher detection speed than R-CNN. The following is the method used in this paper.

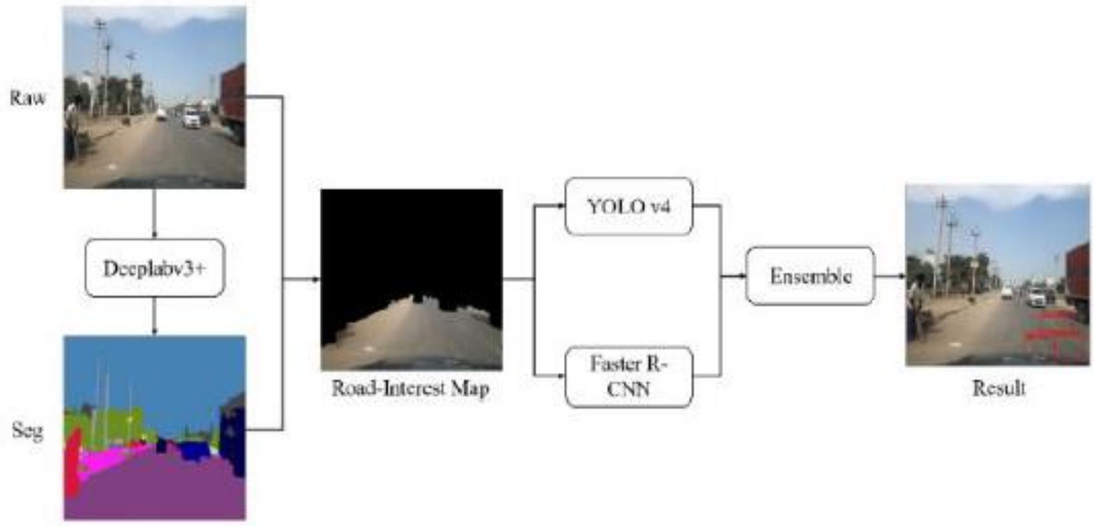

Fig.6. Detection Method with Faster Method R-CNN

The results obtained from this method show that the Faster R-CNN method produces better performance than R-CNN in general.

4. Conclusion

After comparing several methods of classification and detection of damaged roads, it is seen that the Faster R-CNN method has high performance. However, thus the level of accuracy has not been described in detail compared to the classification method combined with FFT calculations. So it requires further research to determine the level of accuracy given by the Faster R-CNN method with FFT calculations. In addition to conducting further research related to increasing the level of accuracy of the Faster R-CNN method, the next stage is the implementation of the method used on IoT devices to detect damaged roads directly (live). Functionally, the hope is that it can assist humans in detecting damaged roads quickly and accurately so that the repair process can be carried out immediately.

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