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Application of neural network method for road crack detection

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ABSTRACT

The study presents a road pavement crack detection system by extracting picture features then classifying them based on image features. The applied feature extraction method is the gray level co-occurrence matrices (GLCM). This method employs two order measurements. The first order utilizes statistical calculations based on the pixel value of the original image alone, such as variance, and does not pay attention to the neighboring pixel relationship. In the second order, the relationship between the two pixel-pairs of the original image is taken into account. Inspired by the recent success in implementing Supervised Learning in computer vision, the applied method for classification is artificial neural network (ANN). Datasets, which are used for evaluation are collected from low-cost smart phones. The results show that feature extraction using GLCM can provide good accuracy that is equal to 90%.

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1. INTRODUCTION

Evaluating road quality is an important task in many countries. For example, in France, national roads are examined every three years to estimate reparations, required construction, and to estimate quality. These aspects can be calculated to estimate crack on road pavement surface based on compliance with regulations, micro texture, macro texture, and surface degradation. In Banjarmasin, Indonesia, the condition of subgrade, which mostly consists of peat is the major origin of road crackings. Considering the vast wetlands of South Kalimantan reaching 382,272 ha is a major problem to be tackled. All road evaluation inspections in Indonesia are done manually, whereas in other countries automatic systems have been performed with non-invasive techniques such as image processing [1-3].

There are several ways to detect road damage including analyzing road conditions based on images taken on the road surface. Research on detection of road surface damage using image processing techniques has been actively carried out, achieving very high detection accuracy. Many studies only focus on detecting the presence or absence of damage. However, in a real-world scenario, when road managers from the management agency need to repair such damage, they need to clearly understand the type of damage to take effective action. In addition, in many previous studies, researchers obtained their own data using different methods. Therefore, there is no uniform road damage dataset available openly, which causes no benchmark for detection of road damage [4, 5].

This research will propose an intelligent system in image processing to detect cracks on road surfaces. To examine road infrastructure efficiently, especially road conditions, several methods using laser technology or image processing have been studied [6-9]. However, the technique of using a laser requires a high cost [10, 11].

Futhermore, at a lower cost, there were several studies using computer vision approach for solving this problem in 11 years [12-17]. In computer vision, it is first necessary to extract features from the dataset to obtain quantitative data from image data, then the next process is to detect road pavement cracks. Research conducted by E. Zalama, G. Jaime, and R. Medina [4] demonstrated that using Bank Gabor filter for feature extraction methods in detecting road pavement cracks, the accuracy obtained is 90%. The Bank Gabor filter method represents the image in a one-angle orientation scale, while the GLCM represents it in 4 angles namely 0^0, 45^0, 90^0, 135^0, so that the extraction of the resulting features will represent the extracted image more.

For the detection stage, monitoring the process is considered as one of the most important tasks in the detection process. Many researchers utilize Supervised Learning in the detection process, especially the ANN method. A road detection strategy using the ANN method for the classifier was introduced by M. Mokhtarzade, H. Ebadi, and M. J. Valadan Zoej, where the dataset was satellite imagery [5]. Researches done by I. Kahraman, M. Kamil Turan, and I. Rakip Karas also apply ANN in detecting road cracks with results that the ANN method is able to detect road cracks with 93.35% success [18]. Referring to those researches, this study proposes ANN method in detecting road crack and also applies GLCM to extract features from images into quantitative data.

2. RESEARCH METHOD

To detect road surface cracks, features of a road cracking are required. The features are shape feature and texture feature, where these features can be used to distinguish road conditions [19, 20]. Figure 1 shows the stages of the road surface crack detection process. Further explanation of Figure 1:

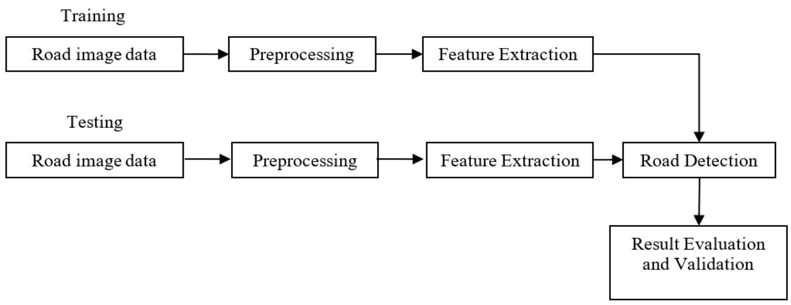


Figure 1. Proposed road surface crack detection stages

a. Road image data

The collected data is labelled as a cracked road image. Road images are taken using low-cost smartphone camera, where the distance between the road surface and the camera is 1 meter in front of the camera. Data is collected from some roadway sections in Banjarmasin, which consists of two types, namely cracked road and non-cracked road images. Figure 2 presents an example data of road surface with cracks.

b. Data pre-processing

In the pre-processing stage, image data is segmented first. Segmentation is the process of separating objects contained in an image, which aims to ease the processing of digital image on each object. Then thresholding, which is the process of changing a grayscale image into a binary or black and white image. The goal of thresholding is to see clearly which areas are included in the object and in the background of an image. Next step is morphology. Morphology is a digital image processing technique which uses shapes as a reference in processing the image. The value of each pixel in a digital image is obtained from the results of a comparison between the corresponding pixels in the digital image and the adjacent pixels. Morphology operations depend on the order of pixels and do not pay attention to the value of pixels; thus, this technique can be used to process binary images and grayscale images.

c. Feature extraction

Feature extraction is applied to retrieve assessment information from the analysis and calculations performed on digital images [21, 22]. The results of this extraction have a significant effect on the results of the classification later. The feature extraction process is carried out using Matlab software, where the GLCM method is applied in the feature extraction of road pavement crack detection. GLCM utilizes texture calculations in the second order. Measurement of textures in the first order assigns statistical calculations based on the pixel value of the original image, such as variance, and does not pay attention to neighboring pixel relationships. In the second order, the relationship between pairs of two original image images is taken into account [23].

For example, f (x, y) is an image of size Nx and Ny that has pixels with the possibility of L levels and $\vec{r}$ is a spatial offset direction vector. $GLCM_{\vec{r}}(i,j)$ is defined as the number of pixels with $j \in 1,..,L$ that occurs in offset $\vec{r}$ to the pixels with values $i \in 1,..,L$, which can be stated in the (1) [24].

$$GLCM_{\vec{r}}(i,j) = \#\{(x_1,y_1),(x_2,y_2) \in (N_x,N_y) \times (N_x,N_y) | f(x_1,y_1) = j^{\vec{r}} = \overrightarrow{(x_2 - x_1, y_2 - y_1)}\} \quad (1)$$

In this case, offset $\vec{r}$ can be an angle and/or distance. For example, the Figure 3 shows the four directions for GLCM.

Figure 2. Road surface cracking image

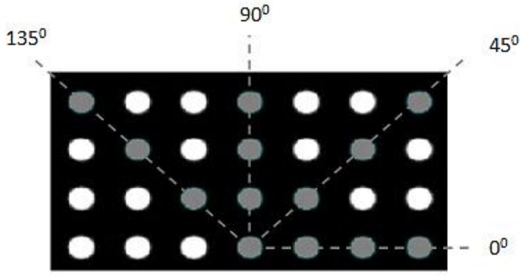


Figure 3. Example directions for GLCM with angles 0^0, 45^0, 90^0, dan 135^0

d. Road detection

Road crack detection can be done after the extraction of road image features. The data will be divided into two parts, namely training data and testing data. After that the classification of crack roads and good roads will be carried out using a machine learning approach which is artificial neural network (ANN) method. ANN is a processor that carries out large-scale distribution, which has a natural tendency to store a recognition that has been experienced, in other words ANN has the ability to be able to do learning and detection of an object [25].

e. Result evaluation and validation

In performance measurement using confusion matrix is used to measure how well the detection performance of the ANN method is to recognize tuples from different classes. TP and TN provide information when the detection results are true, while FP and FN tell when the values are false [4, 26]. Then after the confusion matrix obtained, Accuracy, Precision and Recall value can be calculated. The Accuracy value is obtained by (2). The Precision value is obtained by (3). The Recall value is obtained by (4) [27, 28]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} x100\% \quad (2)$$

$$Precision = \frac{TP}{TP + FP} x100\% \quad (3)$$

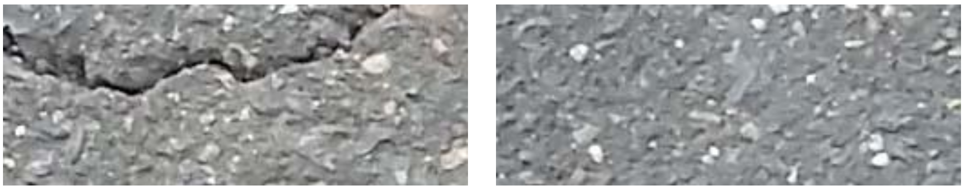
$$Recall = \frac{TP}{TP + FN} x100\% \quad (4)$$

where:
– TP is true positive, which is the amount of positive data that is properly classified by the system.
– TN is true negative, which is the amount of negative data that is properly classified by the system.
– FN is false negative, which is the amount of negative data but classified incorrectly by the system.
– FP is false positive, which is the amount of positive data but is classified incorrectly by the system

3. RESULTS AND ANALYSIS

3.1. Data processing

Image data will be cropped first to uniform all data. The amount of data is 100, which is labeled crack and no_crack. The data to be processed is a dataset of 256x100 pixels. Then feature extraction will be performed to all images. Examples of dataset are depicted in Figure 4.



(a) (b)

Figure 4. Example of dataset with (a) crack and (b) no crack

3.2. Feature extraction

Feature extraction utilizes the gray level co-occurrence matrix (GLCM), which applies five quantities, namely angular second moment (ASM), contrast, inverse different moment (IDM), entropi, and correlation [29-31]. Examples of the results from feature extraction can be seen in Table 1. The values from the feature extraction will be the input parameters in detecting road cracks.

Table 1. Data of feature extraction result

No	Label	ASM	Contrast	IDM	Entropy	Correlation
1	crack	3,37E+11	1,78E+17	0.123868916860676	8.515.177.221.615.980	9,10E+11
2	crack	3,54E+11	1,46E+17	0.148823309991595	8.419.985.894.605.640	9,11E+11
3	no_crack	4,22E+11	1,51E+17	0.133652331513828	8.235.894.329.981.770	0.001376067169563
4	no_crack	8,06E+11	1,25E+17	0.170254651932088	7.773.661.510.499.480	0.001538142413451
5	crack	2,37E+11	4,37E+17	0.084879178580005	8.854.083.850.684.690	7,78E+11

3.4. Result and evaluation

Before training the data, the learning rate is set 0.01 with momentum 0.9. The network architecture model which is obtained from the training dataset produces a network architecture with 5 inputs, namely: ASM, contrast, IDM, entropy, correlation; as well as with 5 hidden layers. The network architecture is shown in Figure 5. As for the weights of hidden layer are shown in Table 2. These weights were generated from the training data results of 500 epoch repetitions. The network architecture model brings about two groups of output, namely crack and no crack. Table 3 shows the resulting weight outputs, meanwhile Table 4 exhibits the assessment results.

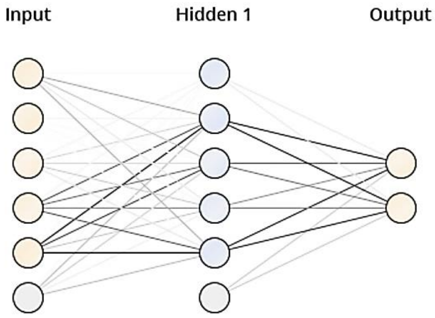


Figure 5. The best network architecture from training datasets

Table 2. The weight of hidden layer

Hidden Layer	Threshold	ASM	Contrast	IDM	Entropy	Correlation
1	-0.088	0.064	0.002	-0.149	-0.139	0.072
2	-0.756	0.132	0.132	-0.470	-1.541	-2.232
3	0.569	-0.638	0.085	0.394	1.307	1.696
4	-0.214	0.289	-0.093	-0.563	-1.011	-0.609
5	0.708	-0.847	0.030	0.298	1.496	2.627

Table 3. The weight output

Output Layer	Node1	Node2	Node3	Node4	Node5	Threshold
Crack	-0.280	-2.177	1.322	-1.056	2.057	-0.602
No_crack	0.274	2.158	-1.299	1.098	-2.072	0.588

Table 4. The Assessment results

Measurement	Results
Accuracy	90.00%
Precision	93.50%
Recall	87.50%

The assessment results in Table 4 demonstrate that ANN Backpropagation method reaches 90% accuracy for the detection of road damage, which can be categorized as high accuracy level. It can also be seen that the precision value is higher than the accuracy value, namely 93.50%. Meanwhile, the recall value has the lowest value, which is 87.50%. The highest accuracy is obtained with a value of 90%. This is because the data is well prepared, and the data used is data from crack and non crack data images (good asphalt). No other road damage data is presented. The value of precision is 93.50% which is higher than the accuracy. This means that the accuracy of the detection area is higher than the accuracy of the detection. The recall result is 87.50%. this result is categorized as good. This result obtained from total correct data detection each class (crack and non crack data) divided by all data classified correctly.

4. CONCLUSION

The proposed approach of road crack detection is able to identify cracks with an accuracy of 90%. The image processing technique applies feature extraction using the GLCM method. This method produces image feature extraction from four angles namely 0^0, 45^0, 90^0, and 135^0. The experimental results demonstrate that a set of 4 angles, consisting of properties derived from projective integrals and crack object properties cooperates to achieve the most accurate prediction. In addition, the inclusion of characteristics of cracked objects such as ASM, contrast, IDM, entropy and correlation has been proven to provide more information for classification. This fact is exhibited through the good experimental results. ANN is a supervised learning approach that has been implemented to study the mapping function between the image input and output features of crack and no crack classifications. Based on the experimental results, ANN can be concluded as a competent classification method. Thus, the application of ANN integrated with GLCM feature extraction method is highly recommended for the detection of road pavement cracks. Future work should also investigate the applications of different algorithms and other feature extraction methods in order to improve prediction accuracy. Last but not least, it is necessary to collect more image datasets to improve the ability of the current road pavement crack detection model.

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