Implementation of Computer Vision in Asphalt Damage Identification on the Trans-Sumatera Road

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Abstract: Roads are infrastructure made to facilitate land transportation in connecting one area to another. In general, roads in Indonesia use asphalt as a material in the road construction process. The cross-Sumatra route is one of the accesses that plays an important role in increasing economic progress in areas that connect areas on the island of Sumatra. The development of computer vision using various image recognition classification methods results in more accurate data accuracy. The Decission Tree and K-Nearest Neighbor methods in image recognition classification of asphalt damage can be a solution in identifying damage and measuring the area of damage through machine learning from images taken from the field. The design and implementation of making applications is continued using the Decission Tree method using python as a programming language. Asphalt damage conditions are divided into three classification categories of asphalt damage, namely mild, moderate and severe. The results of the identification can be used as a report or field survey of the damage conditions that occur on the Sumatra route. The accuracy value of the training is carried out using a dataset of 560 images. The Decission Tree method can get light damage 99.3damage, the accuracy value is 99.3for light damage is 79.12accuracy from Machine learning carried out in this study show the highest accuracy value obtained from the Decission Tree method in identifying road damage.

1 INTRODUCTION

In road inspections it is usually carried out by officers who go into the field by measuring and recording the types of damage that occur in the field and then taking pictures as report material. Road damage caused by various factors causes road conditions to become damaged quickly and is not feasible, thus endangering road users crossing the road.Potholes, cracks and distortions are most commonly found on Sumatran highways. This is caused by several things, namely the condition of the soil structure, asphalt cracks that are left, standing water or flooding and landslides. The trans-Sumatra route has land routes that often experience damage problems. Pruning process Along with the advancement of technology, the use of humans in surveys in the field can be supported by technology that suits the needs in the field, making it easier to make data and reports. With the development of computer vision which is from the development of computer science technology that can work like humans (Dompeipen et al., 2021), the inspection and identification of roads that were previously done manually can be done with digital image processing and digital image processing candetermine the type and measure road damage.

Factors that damage the road that occurs in the field. in Indonesia there are four classes of roads in accordance with Law no. 22 of 2009 concerning road traffic and transportation. Until now, Public Works Department workers and project consultants have not used computer technology. During the process of identifying road damage, it is still done manually to find and determine the type of road damage. The measurement process is carried out manually using a simple measuring device (roll meter) with human assistance. Detecting holes manually requires a lot of effort and time (Aparna et al., 2022).

Research by Agus Irawan, Adi Pratomo, Mey Risa, Heldiansyah (2016) entitled "Design of Road Asphalt Damage Detection System Through Video Using Fast Fourier Transform" In research designing a road asphalt damage detection system (Ouma and Hahn, 2017) via video can make it more cost effec-

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tive, faster and more safe in the implementation of observation and evaluation of the condition of the road. This study uses video footage of road asphalt and then extracts it into image frames. By utilizing several areas the result of the sum of the Fast Fourier Transform values (Ma et al., 2021) in the image is used as a damage feature to classify the image of asphalt roads into good, moderate, slightly damaged and heavily damaged categories.

Computer vision is a science that uses image processing (Oppong et al., 2022) to make decisions based on images obtained from sensors. In other words, computer vision aims to make the system work automatically by "seeing" images/videos (Azhar et al., 2016). Common frameworks that are commonly used in computer vision are: image acquisition, pre-processing, feature extraction, detection/segmentation, high-level processing, and decision making. Seeing the complexity of the acquisition process up to decision making, the research includes two major stages, namely feature extraction for edge detection (Vijayarajeswari et al., 2019) between objects and its application for object recognition, namely to identify the type of damage (Riana et al., 2022) to asphalt roads, such as in the form of potholes, corrugated, cracking and raveling and edge scouring (Ouma and Hahn, 2017).

Asphalt damage image identification from the dataset is divided into three categories of asphalt damage classification, namely mild, moderate and severe. (Chitale et al., 2020) With these three categories, damage to asphalt with potholes, cracks and distortion can be identified and processed through a machine learning digital image recognition system (Feng et al., 2023). Machine learning is a computational model that is currently widely used in various fields.

The Gabor filter is used to analyze the texture (Hendrawan et al., 2019) or obtain features from the images used in the dataset with various types of asphalt damage images to process the images to be tested (Permadi et al., 2021). Then proceed with Discrete Cosine Transform in image compression.

2 RESEARCH METHODS

In this study the authors carried out the research method described in Figure 1 with the initial stages starting from taking image acquisition, then entering the Machine Learning Process starting from Preprocessing, Segmentation, Classification Methods and applications displaying the results and extent of damage.

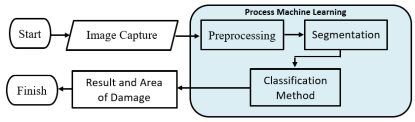

Figure 1: Research Method.

2.1 Data Collection

Asphalt image collection is done by taking pictures directly in the field so as to get various types of damage that occurs on the asphalt. The number of image data tested was 550 data and the training data tested were 300 images. From the results of the inspection carried out, it was found that three types of damage occurred, namely severe, moderate and light. To assess the type of road damage using the SDI (Surface Distress Index) method, the road performance scale is obtained from visual observations (Singh and Gupta, 2019). The images obtained will be continued with the segmentation process and preprocessing will be carried out.

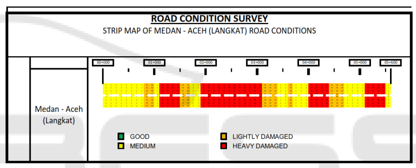

Figure 2: Result Type of Road Damage.

2.2 Preprocessing

The preprocessing stage is the stage of the digital image processing process before the image features are extracted. The process carried out using the GLCM method is one of the methods used for texture feature extraction in images (14,). The features used in GLCM, GLCM features have a total of fourteen features and this study uses ASM features of contrast, difference, homogeneity, correlation, second corner moment (ASM), and energy (Leonardo, 2020). The author uses the ASM feature and uses this entropy feature to detect the type of asphalt damage with the equation used in the ASM feature as follows:

$$ASM = \sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j)^2 \tag{1}$$

$$H = -\sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j) log_2 p(i,j) \tag{2}$$

2.3 Segmentation

Segmentation is performed to divide an image into homogeneous regions based on certain similarity criteria. (Li et al., 2022) The segmentation process uses the Gabor Filter method. Gabor filters can be used to detect asphalt damage. Gabor filter is one of the filters that is able to simulate the characteristics of the human visual system in isolating certain frequencies and orientations from the image (Coulibaly et al., 2022). Gabor filter in extracting local features from images (Waluyo et al., 2023). The Gabor filter equation can be seen from the equation below.

$$G(x,y;f,\theta,\psi,Y) = exp - \frac{x'^2+Y^2y'^2}{2\sigma^2} cos2\pi f x' + \psi \tag{3}$$

Where:
$G(x,y;f,\theta,\psi,Y)$: Gabor filter values at coordinates (x, y).
x' = x cos θ + y sin θ and y' = -x sin θ + y cos θ : Rotation of coordinates with respect to angle θ.
f : The spatial frequency of the Gabor filter.
θ : Gabor filter orientation (in radians).
ψ : Gabor filter phase.
Y : Gabor filter aspect ratio.
σ : Gabor filter Gaussian variance.

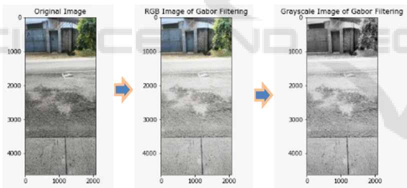

Figure 3: Process Result Changing Image.

2.4 Classification Method

The classification method in this study uses the two Decission Tree methods and the K-Nearest Neighbors Method to find the highest accuracy results. From the results of the accuracy values of the two methods used, the method that produces the highest accuracy value will be used to create an application system that can measure the type of damage and extent of asphalt damage. The K-Nearest Neighbor method is a new data grouping classification method based on the distance of the new data with some of the closest data or called data/neighbors (Coulibaly et al., 2022). The K-Nearest Neighbors method is a method used to classify objects based on training data that have the closest distance to the test data object (Arfani, 2021).

The steps with the KNN method are started by entering: training data, training data labels, k, test data. All testing data must be calculated the distance to each test data with the Euclidian distance formula as in the following equation.

$$d(x,y) = \sum_{i=1}^{n}(x_i - y_i)^2 \tag{4}$$

Where:
x_i = sample data
y_i = test data or training data
i = data variable
d(x,y) = dissimilarity/distance
n = data dimension

The Decision Tree method is a type of classification that represents the shape of a tree structure. Where each node represents the attribute, the branch represents the value of the attribute, and the leaves represent the class.

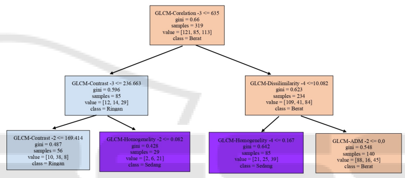
Figure 4: Process Result Changing Image.

Table 1: The results of the accuracy of training and testing of image data carried out produce a comparison of the accuracy values.

Categories	K-NN	Decission Tree
Lightly	97.1%	99.3%
Medium	87.8%	98.6%
Heavy	81.1%	99.3%

3 DATA AND APPLICATION TESTING

On the initial page before starting the application, the user can enter images to measure the extent of damage to asphalt using the built application.

The machine learning process on images can recognize the type of image to then enter the process of classifying the type of damage, asphalt damage category and the system can calculate the area of asphalt damage based on the pixel conversion value in meters area unit.

The highest precision value of the type of groove damage with the heavy damage category and the type

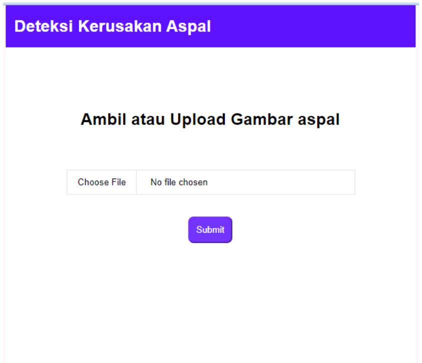

Figure 5: Initial Appearance of the Application.

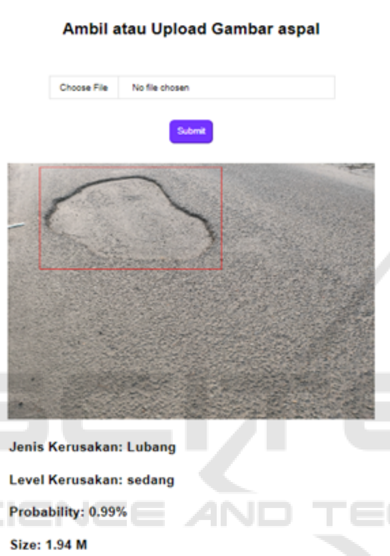

Figure 6: Detection Results and Damage Area.

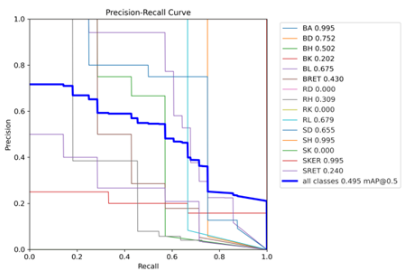

Figure 7: Precission-Recall Curve.

of curly damage with the moderate damage category.

Accuracy shows the accuracy of the results obtained from the closeness of the value obtained with the actual value. Precision is the suitability of the data taken with the required information. Recall is success in getting information back. F1-score is a comparison of the average precision and recall (Qudsi et al., 2020), (Kurniawan and Barokah, 2020). Precission Recall Curve results from the highest class label

Table 2: Precission-Recall Value Results.

No	Damage Type Code	Damage Category Type	Precission Recall
1	BA	Groove Weight	0.995
2	BD	Distortion weight	0.752
3	BH	Severance Weight	0.507
4	BK	Obesity Weight	0.202
5	BL	Hole Weight	0.675
6	RH	Broken Thirst	0.309
7	RL	Light Hole	0.679
8	SD	Moderate Distortion	0.655
9	SH	Being Thirsty	0.995
10	SK	Moderate Obesity	0.000
11	SKER	Medium Curly	0.995
12	Straight	Cracking	0.240

get the type of asphalt damage with heavy grooves, medium wear and medium curly getting the highest value, namely 0.995 while for light damage distortion, light obesity and moderate obesity have a value of 0.000 because the results of the image dataset did not find the type of damage that read by the system.

In taking images in the field, it is necessary to carry out technical training so that the images can be appropriate and produce the best accuracy values, so that the system can produce asphalt damage areas according to the type and category of asphalt damage. The shooting technique can be done by taking a 45 degrees angle towards the image object and can use shooting with a slanted technique. In accordance with the results of the accuracy of the KNN and Decission Tree methods, the researchers decided to use the Decision Tree method as an image classification method because it has better results and can develop according to the type of asphalt damage.

4 CONCLUSIONS

In taking image acquisition, it is necessary to pay attention to the distance of taking, the quality of lighting at the location and the perspective of the direction of shooting because these factors become obstacles that occur when the system conducts data training and tests system results on applications in identifying the type of damage and predicting the extent of the size of the damage that occurs on asphalt. The Decission Tree method and the K-NN method are widely used to carry out image processing classification processes and are applied to machine learning as a classification model. The Decision Tree method is able to provide results in the form of a decision tree which can be used as a reference in observing decisions made based on the category of damage that occurs and is tested by the system. Implementation of the best method for the accuracy of asphalt damage identification results is made into a web-based application that can be run offline or online. Based on the overall accuracy test the results of the decision tree method show an accuracy value of 98.6% and the KNN method gets an overall accuracy value of 74.07%. This result is obtained from the category of heavy damage to asphalt. The types of asphalt damage carried out in the tests were carried out using images of groove damage, distortion, fatness, wear and tear, curl, holes, and cracks. The comparison of classifiers results that the decision tree classifier gives the best accuracy value from KNN.

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