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Road Defect Assessment Algorithm on Flexible Pavement

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Abstract: This study aims to examine the condition of road pavement mechanically which requires large, time-consuming, impractical, and can only identify one type of road damage. The development of digital technology, then identifying the type of damage can be done with an algorithm or method to detect and analyze the type of road damage quickly and accurately. The purpose of the study is to identify the value of road damage with the visual method of Dirgolaksono and Mochtar, create a model of a road damage assessment algorithm based on digital imagery, and apply the digital image method to the road section being reviewed. The research method with the initial step of the algorithm process is taking pictures using a type of digital camera, so that a digital image is produced which is then processed using Matlab R2016a. The results obtained are the classification of road damage and the damage value of the road section obtained by visual road damage and digital imagery accurately. Validation is carried out with a strong correlation between visual and digital damage, which means that there is no difference between the visual damage value and the digital image damage value.

Keywords: Damage value algorithm; Road damage; Road damage value; Visual inspection

Introduction

Road damage is a common problem. Many roads in big cities are damaged or in the process of being damaged. This condition is a problem for almost every big city in Indonesia. Roads with minor damage often do not get attention so that the damage gets worse and reduces road capacity (Albalate & Fageda, 2019). A way is needed to detect road damage before the damage becomes severe. This effort can be done by conducting periodic road condition inspections. Inspection of road pavement conditions using (mechanical) tools is hampered by funding issues, because the price of these tools is quite expensive and for one type of tool it only measures one particular condition, for example the amount of flexibility, surface hardness and others. The visual inspection method is one of the good plans, because it is quite practical, simple and efficient. There are several methods for assessing the level of damage visually that are often used so far, one of which is the D&M method (Dobosz et al., 2025). Wang et al. (2015) stated that a refinement of existing visual road damage assessment methods. The refinement is that the D&M method divides the road section into segments so that the assessment is more precise (Sun et al., 2023).

The level of road damage is grouped into three levels, namely light, moderate and severe damage according to the parameters of each level of damage (Ningrum et al., 2024; Vlašić et al., 2022). It is felt that there are still weaknesses in the visual assessment of road damage. The visual assessment method is very subjective, depending on the assessor. The assessment of one assessor can be very different from the assessment results of others for the same road section (Rodriguez-Segura & Schueler, 2023; Doyle, 2023). Another thing that contributes to the weakness of visual assessment is human eye fatigue so that the assessment of road damage becomes less precise (Du et al., 2023; Sun et al., 2024). Seeing the weaknesses of the visual road damage assessment method, it is necessary to create an algorithm or method to detect and calculate the amount of road damage quickly and accurately. Research that has been done in terms of digital image processing for crack damage (Azouz et al., 2023). Wang et al. (2024) obtained

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crack patterns on the pavement surface, crack patterns from linear tracking devices (LINTRACK) with photos to obtain crack length, percentage and crack area. Deng et al. (2023) used a method with an initial image segmentation algorithm to calculate the area and length of damage or road surface defects.

Kumar et al. (2024) conducted research with image processing techniques to extract features from images. The Neural Networks approach is used to detect image areas with defects. Yuan et al. (2024) performed edge detection in the process for crack identification and classification. Other researchers by Krishna & Nagamani (2022), who use images in terms of conducting more detailed evaluations in detecting road pavement cracks. Kim et al. (2023) conducted an analysis in digital image processing using bilinear interpolation to obtain a corrected image based on the segmentation threshold with statistical analysis. Previous research that has been carried out with digital images is only at the stage of detecting cracks, not at the stage of assessing road damage based on the detected road damage (Putra et al., 2022; Zulfachmi et al., 2024). Based on this, this study aims to conduct a visual road damage assessment based on the Dirgolaksono and Mochtar method and create a road damage assessment algorithm model based on digital imagery and apply the digital image method to the road sections reviewed with the scope of assessment on crack damage, crocodile skin cracks, and holes.

Method

The research method used in this study is a quantitative research type (Kilani & Kobziev, 2016). This study hypothesizes a visual assessment of road damage with digital images. This research hypothesis uses the Dirgolaksono and Mochtar method and creates a road damage assessment algorithm model. There is a strong correlation between the visual damage value and the damage value in Digital Imagery. The correlation coefficient is 0.99 and is significant.

Ho = the population average of visual damage values with digital damage values is not different (identical).
H1 = the population average of visual damage values with digital damage values is different (not identical).

Hypothesis Acceptance Criteria:
If the calculated $t_{value} < t_{table}$, then Ho is accepted.
If the probability value of the calculated $t > 0.05$ then Ho is accepted.

From the table it is known that the t count is 1.38 with a probability value of 0.23, then Ho is accepted, meaning there is no difference between the visual damage value and the digital damage value.

Road Damage Inspection

According to the Road Inspection Manual Number: 03/MN/B/1983 issued by the Directorate General of Highways, damage or defects in flexible pavement can be divided into five major parts, namely: First, cracking. Types of cracks include: Alligator cracks, Edge Cracks, Edge Joint Cracks, Lane Joint Cracks, Reflection Cracks, Widening Cracks. Second, changes in shape (distortion). Changes in the shape of the pavement are the result of a subbase that is lacking or the subgrade is moving. Changes in shape can also be accompanied by cracks, in addition to causing danger to traffic, allowing water to accumulate and often causing the pavement to experience greater damage. Changes in pavement shape include: Channel, corrugation and shoving, grade depression, upheaval and utility cut depression. Third, surface damage (disintegration). Disintegration is the breaking of the pavement layer into loose parts, including the release of aggregate particles. If disintegration is not handled immediately, it will develop into severe damage. Forms of disintegration include: potholes and reveling.

Fourth, slippery surface, Dry surface conditions cause the road to become slippery due to the presence of a thin layer of asphalt on the road surface, wear of the surface layer aggregate and due to a lot of oil, mud and others (Masri et al., 2023). In wet conditions, the surface also becomes slippery, this is due to the presence of a layer of water on the road surface which reduces wheel grip. This type of damage is dangerous for drivers with moderate to high vehicle speeds. Slippery surface includes: bleeding/flushing asphalt, polished aggregate. Fifth, damage due to surface treatment. Differences in work methods in surface handling can cause abnormalities in the results obtained. Surface treatment includes: loss of cover aggregate, longitudinal streaking and transverse streaking.

Determining Visual Assessment of Damage Categories

Visual assessment of road damage categories is carried out by referring to the largest damage factor. This category is divided into five levels. The first category includes types of damage with the highest damage factor, such as potholes or holes in the road, which have a multiplier factor of 6. The second category includes damage in the form of cracks, such as crocodile skin cracks, with a multiplier factor of 2. The third category consists of damage due to road surface deformation, such as grooves or rutting, which has a multiplier factor of 1.5. Furthermore, the fourth category includes minor damage, such as fine cracks or loose gravel, with a multiplier factor of 1. Finally, the fifth category includes surface damage that has a greater impact on aesthetics than on road functionality, with a multiplier factor of 0.5.

Research Stages

The stages of the research method are as illustrated in the flow diagram in Figure 1.

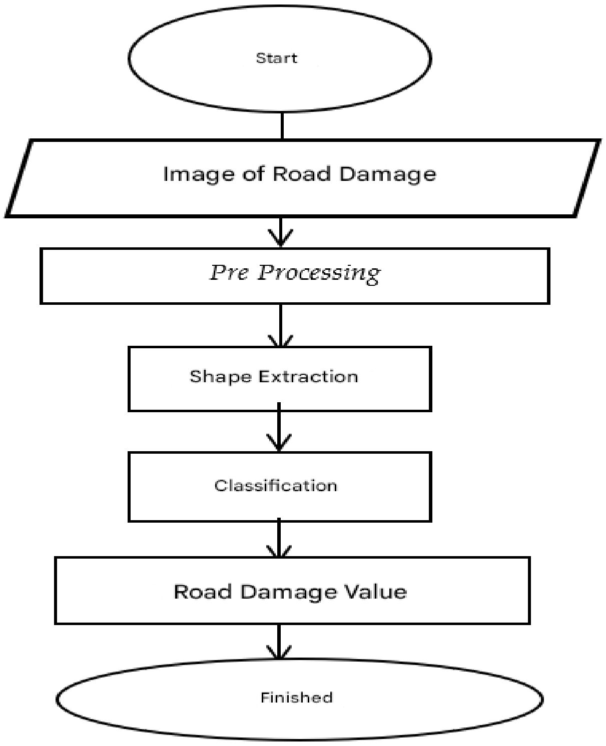

Figure 1. Flowchart of research stages for road damage assessment using digital images

Image Processing

Image processing or often called image processing is a process or effort to change an image into another image that involves several specific techniques. The image itself is a two-dimensional image produced from a two-dimensional analog image that is continuous into a discrete image through a sampling process. The image processing process has input data in the form of images that have been taken using a camera and has output data in the form of other images that have gone through several processes using certain image processing techniques. After the test image is converted into a binary image, the next process is the feature extraction process. The objects in the test image are then extracted for their characteristics, so that each object will have its own characteristics. Image classification is a process that describes and distinguishes data classes that aim to be used to predict the class of objects whose class labels are unknown.

K-Nearest Neighbor (k-NN or KNN)

The K-Nearest Neighbor (k-NN or KNN) algorithm is a method for classifying objects based on learning data that is closest to the object.

Location and Time of Research

The implementation of the research began with data collection in the form of images of road damage on five road sections located in Depok. Using a Canon 550D digital camera and a tripod with a height of 80 cm, with an angle of 60°. The data obtained was then processed by carrying out the process of extracting road damage images, using MATLAB R2016a after the extraction process, a classification process will be carried out to determine the type of road damage. The research time was carried out for 6 months.

Materials and Research Aids

The data used in this study were image data or photos of road damage. The data amounted to 565 (five hundred and sixty-five) photos for the three types of road damage. For the type of damage, cracks, crocodile cracks and holes. The data was obtained by taking pictures using a Canon EOS 550D digital camera and a tripod with a height of 80 cm, with an angle of 60°.

Result and Discussion

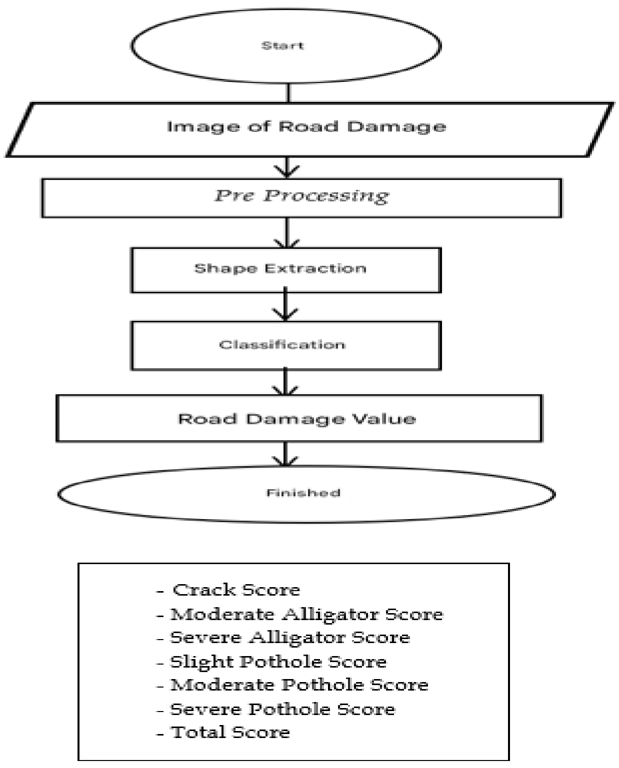

Figure 2. Road damage assessment flowchart

This segment classification program aims to find out what types of damage are found in a segment that is inputted, along with the value of each type of damage, and also the total value of the damage. In the database, a segment is a directory (folder) that contains images of road damage along the segment. The first time it is run, the program will ask for input of the segment directory to be classified. Then the program will ask for input of the percentage of real damage value in the segment (damage percentage). The real damage percentage is the total percentage of the damaged road section of the segment. Furthermore, each image in the segment will be classified one by one using the radial vector algorithm as explained previously. The program will record the classification results of each image for use in the next stage, namely the scoring stage. After each image in the segment has been completely classified, the next stage is calculating the score. The score is calculated separately for each type of damage, so there are 6 types of scores, namely: Crack score, Moderate Alligator Score, Severe Alligator Score, Slight Pothole Score, Moderate Pothole Score and Severe Pothole Score. The six scores are then accumulated based on their weights to produce a total score. The seven scores are then presented as program output. For more details, see Figure 2.

Image Classification Algorithm in Segment Directory

From the segment classification algorithm explained earlier, there is a process of classifying the type of damage for each image in the segment directory. The purpose of this algorithm is to determine the percentage of damage experienced by the segment for each type of damage. The percentage results will later be used to calculate the final score of the damage value for the segment. After the percentage value is input, N iterations will be carried out. N here is the number of images in the segment. First, the image is read by the program and then the radial vector classification algorithm is carried out as explained earlier. This algorithm produces labels, namely cracks, crocodile skin cracks, or holes. If the label is cracked, 1 is added to the crack counter. The counter variable here functions as a counter for the number of images that have experienced damage. For example, in the segment the number of cracked images is 10, then the crack counter will be worth 10.

If the label is crocodile skin crack, then the crocodile skin crack classification algorithm will be run which will be explained in the next section, the result of the crocodile skin crack classification will be buaya_lv1 (moderate alligator) or buaya lv2 (severe alligator). If the label is a hole, then the hole classification algorithm will be run which will be explained in the next section, the result of this hole classification will be Lubang_lv1 (pothole slight), Lubang_lv2 (pothole moderate), or Lubang_lv3 (pothole_severe). After all the images that have been calculated for each type of damage, finally the total number of images that have been damaged can be calculated by adding up all the damage type counters. Then the percentage for each type of damage can be calculated using the formula as shown in the program code above.

Crocodile Skin Crack Type Damage Classification Algorithm

This algorithm is called when the label obtained is crocodile skin crack type damage or alligator has two levels of damage, namely moderate and severe, so an additional algorithm is needed to perform further classification to determine the level of crocodile damage in the image. The following is a flowchart of the classification of crocodile skin crack damage types, as shown in Figure 3.

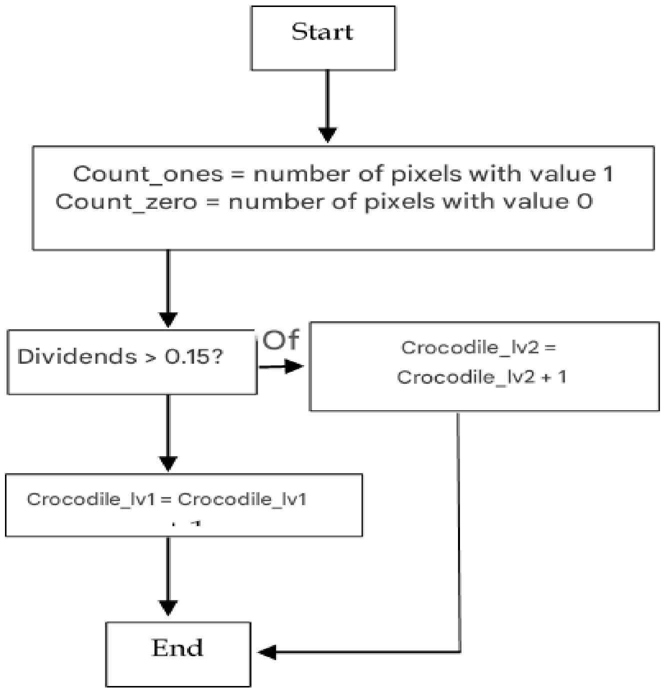

Figure 3. Damage classification flowchart

The first step is to count the number of pixels with a value of 1 (white) in the binary image. Then count the number of pixels with a value of 0 (black). Then divide the number of white by the number of black. If the division result is greater than or equal to 0.15, the damage is severe alligator, and the buaya_lv2 counter is added by 1, if the division result is less than 0.15, the damage is moderate alligator, and the buaya_lv1 counter is added by 1. The idea of this algorithm is that the level of crocodile skin damage is based on the density of the cracks experienced and also based on the number of branches of the cracks (Wu & Fu, 2023; Ghazali et al., 2021; Chen et al., 2024). The more cracks, the more pixels will appear in the image with a value of 1 because the cracks are encoded with a value of 1. Therefore, the greater the ratio between the pixel value and 0, the greater the level of damage. The value of 0.15 is set as the threshold based on the results of trials on several images.

Hole Type Damage Classification Algorithm

This algorithm is called when the label obtained is a hole type of damage or pothole has three levels of damage, namely slight, moderate and severe, so that an additional algorithm is needed to perform further classification to determine the level of hole damage in the image. First, take the object and background from the grayscale image. The object is all the pixels located at the hole location. The background is all the pixels located at locations other than the hole (Yu et al., 2023; Wu et al., 2025). Add up all the pixel values on the object, as well as add up all the pixels on the object, as well as add up all the pixels on the background. Count how many pixels are located on the object and how many pixels are located on the background (Seo et al., 2016; Radoux & Bogaert, 2017; Husein et al., 2019). Calculate the average value of the object, and calculate the average value of the background.

Compare the average value of the object and the average value of the background. If the difference is more than or equal to 25 then it is categorized as severe and the hole_lv3 counter is added by 1. If the difference is between 5 and 25 then it is categorized as moderate and the hole_lv2 counter is added by 1. If the difference is less than 5 then it is categorized as slight and the hole_lv1 counter is added by 1. The idea of this algorithm is that the damage type of hole is distinguished by the depth of the hole, the deeper the hole, the higher the level of damage (Liu et al., 2024; Mardanirad et al., 2021). In an image, the deeper a hole, the more different the pixel intensity between the hole and the background will be (contrast) because of the formation of shadows in the hole, so it will tend to be darker than the background. Therefore, this algorithm compares the intensity of the object and the background, the further the difference, the greater the level of damage (Li et al., 2022; Rusek et al., 2025). The values 25 and 5 are used based on the results of trials on several images.

Road Damage Value Calculation Results

After calculating the visual road damage value based on the Dirgolaksono and Mochtar method and calculating the road damage value using digital images on the same 5 road sections, the results were obtained as in Table 1. It can be seen that the magnitude of the damage value visually and digitally is almost the same. The average value of damage visually is 110.40 while the average value of damage using digital images is 107.13. There is a strong correlation between the visual damage value and the digital image damage value. The correlation coefficient is 0.876 and is significant. This means that the visual damage value and the digital image damage value are not different (identical).

Table 1. Visual and digital image road damage values

Name of road section	Road damage assessment based on visuals	Road damage assessment based on digital imagery
Jl. Arif Rahman	54.00	41.28
Jl. Meruyung Raya	182.00	162.24
Jl. Jambore	38.00	42.56
Jl. Cilodong raya	308.00	236.16
Jl. Raya Sawangan	70.00	53.44

Based on the description above, it shows that there is a significant agreement between the calculation of road damage values visually and through digital images. Of the five road sections analyzed, the average visual damage value of 110.4 and the digital image of 107.1369 shows a very small difference. These data strengthen the reliability of the digital image method in evaluating road damage conditions, approaching the results of visual observations. In addition, the significant correlation coefficient of 0.87 indicates a very strong relationship between the two measurement methods, which implies that the digital approach can be used as an alternative or complement in assessing road damage. When reviewed based on individual road sections, it can be seen that some road sections, such as Jl. Meruyung Raya and Jl. Cilodong Raya, have higher damage values than other sections.

This is consistent in both visual and digital image measurements. For example, the damage value of Jl. Cilodong Raya was recorded at 308 visually and 236.16 in digital images, indicating a significant level of damage compared to other road sections. Meanwhile, the difference in results between the visual and digital image methods, such as on Jl. Arif Rahman and Jl. Jambore, may be caused by certain factors, such as digital image quality, lighting, or the level of damage complexity that is difficult to record digitally (Ercetin et al., 2024; Ding & Liang, 2024). Overall, these results indicate that the digital image method has great potential to be applied in road damage analysis because it produces accurate data that is identical to the visual method (Zhang et al., 2022; Liu et al., 2022). The use of the digital image method also has advantages in terms of time efficiency and data processing, making it very relevant to support more modern and technology-based road infrastructure management (Talaghat et al., 2024; Ivanova et al., 2023; Nowell et al., 2017). However, it is important to pay attention to technical factors that affect the accuracy of the results, such as image resolution and environmental conditions when taking pictures, to ensure optimal results.

Conclusion

From the results of research related to the algorithm for calculating the value of road damage, trials have been conducted on five road sections, namely Jl. Arif Rahman, Jl. Meruyung Raya, Jl. Jambore, Jl. Cilodong Raya, and Jl. Raya Sawangan. The results of the analysis show that the value of road damage obtained through the digital image method is almost identical to the value obtained through visual observation. The average value of road damage visually recorded at 110.4, while the average value calculated through digital imagery is 107.1369. The very small difference between the two methods indicates that the digital image-based approach is able to replicate the results of visual observations with a high level of accuracy. In addition, the correlation between the two measurement methods has a coefficient of 0.876, which indicates a very strong and statistically significant relationship. This indicates that the digital image method can be a reliable and efficient alternative in analyzing road damage conditions. With these results, it can be concluded that the damage value produced through the digital image-based algorithm is practically no different or identical to the results of visual observations. This study proves that the digital image method has great potential to be applied in road infrastructure analysis. The advantages of this method include time efficiency and ease of data processing, making it an innovative solution in infrastructure management. However, further application needs to consider technical factors to maintain the accuracy of the results.

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Author Contributions
Conceptualization, methodology, investigation, resources, data curation, visualization, I.A.A.A. and D.; validation, formal analysis, original draft writing, I.A.A.A.; review and editing, D. All authors have read and approved the published version of the manuscript.

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Conflicts of Interest
This research was conducted on the mandate of the institution to improve the competence and capacity of lecturers. It is expected that the findings of this study can provide a significant positive impact on the development of human resources, especially in the academic environment, as well as support the creation of innovation and progress in the world of education.

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