

# Comparison of Road Damage Classification Accuracy Based On Grayscale Bit Depth Using GLCM Feature Extraction and Backpropagation Neural Network

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## Abstract

Road surface damage such as cracks, potholes, and patches can reduce driving comfort and threaten road user safety. Manual road inspection is time-consuming and inefficient, especially for large urban areas. This study proposes an image-based approach to classify road damage types using Gray Level Co-occurrence Matrix (GLCM) feature extraction and a backpropagation artificial neural network. Road images were captured directly in Palembang City using a smartphone camera and converted into grayscale images with five different bit depths: 4-bit, 5-bit, 6-bit, 7-bit, and 8-bit. Texture features including contrast, correlation, energy, and homogeneity were extracted using GLCM and used as inputs to the neural network classifier. Experimental results show that higher grayscale bit depth produces better classification accuracy, with 8-bit grayscale achieving the highest performance compared to lower bit depths. The results confirm that grayscale resolution significantly affects texture representation and classification accuracy. This approach can support automated and efficient road damage detection systems.

**Keywords:** artificial neural network; GLCM; grayscale bit depth; image processing; road damage detection

## 1. Introduction

Road infrastructure plays a crucial role in supporting economic activities and daily transportation. However, road surfaces often experience degradation due to traffic load, weather conditions, and aging materials. Common road damage types include cracks, potholes, and patches, which may compromise safety if not handled promptly. Traditional road condition inspections rely on manual surveys that require significant time, labor, and cost, making them inefficient for large-scale monitoring.

Advances in digital image processing and pattern recognition enable automated road damage detection using visual data. Texture-based analysis is particularly suitable for road surface inspection because different damage types exhibit distinct texture characteristics. Gray Level Co-occurrence Matrix (GLCM) is a widely used statistical method for texture feature extraction due to its simplicity and effectiveness. After feature extraction, classification techniques such as artificial neural networks can be applied to identify damage categories.

Grayscale representation is an important preprocessing step in image analysis. Different grayscale bit depths affect the number of intensity levels and consequently influence texture information. Despite many studies on road damage detection, limited research specifically investigates the effect of grayscale bit depth on classification accuracy. Therefore, this study focuses on comparing road damage recognition accuracy across multiple grayscale bit depths using GLCM and a backpropagation neural network.

## 2. Literature

### 2.1. Data acquisition

Road damage images were collected directly from several road segments in Palembang City, Indonesia, using a smartphone camera with a resolution of 108 MP. The dataset consists of three common road damage types, namely cracks, potholes, and patches. Image acquisition was performed under natural lighting conditions to reflect real-world scenarios. All captured images were manually selected to ensure clarity and relevance to the research objectives.



Fig. 1: (a) crack, (b) pothole, (c) patch.

### 2.2 Image preprocessing and grayscale bit depth conversion

The collected RGB images were preprocessed by cropping the region of interest containing road damage and resizing all images to 256×256 pixels. The images were then converted into grayscale format. To analyze the effect of grayscale resolution, each grayscale image was transformed into five different bit depths: 4-bit, 5-bit, 6-bit, 7-bit, and 8-bit. These variations represent different numbers of gray intensity levels and significantly influence texture information.

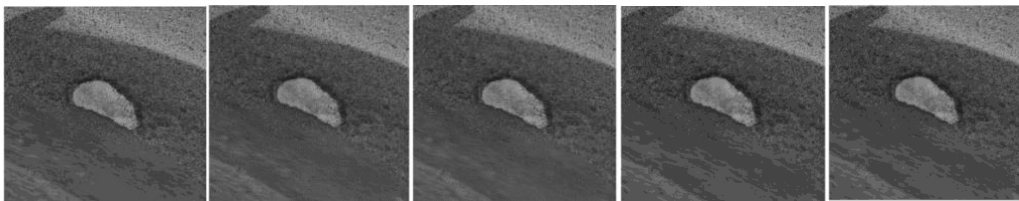


Fig. 2 Comparison of grayscale images with different bit depths.

### 2.3 GLCM feature extraction

Texture feature extraction was performed using the Gray Level Co-occurrence Matrix (GLCM) method. GLCM analyzes the spatial relationship between pixel intensity values at a specific distance and orientation. In this study, GLCM features were computed using predefined directions and distances. Four statistical texture features were extracted from each image, namely contrast, correlation, energy, and homogeneity, which were then used as input parameters for classification.

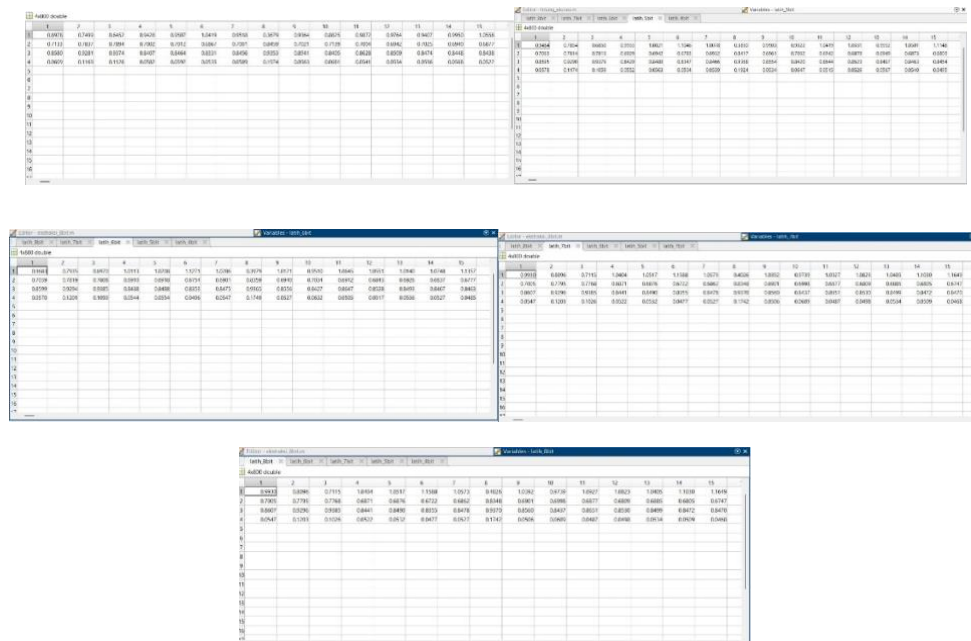


Fig. 3 Classification accuracy comparison across different grayscale bit depths.

### 2.4 Classification using backpropagation neural network

The extracted GLCM features were classified using a backpropagation artificial neural network. The network architecture consists of an input layer corresponding to the extracted texture features, one hidden layer, and an output layer representing the three road damage classes. The network training process utilized supervised learning, where labeled data were used to adjust network weights to minimize classification error.

### 2.5 Performance evaluation and analysis

The performance of the classification system was evaluated using accuracy as the primary metric. Experiments were conducted separately for each grayscale bit depth to analyze its impact on classification performance. The results show that increasing grayscale bit depth leads to higher classification accuracy. The 8-bit grayscale configuration achieved the best performance, while lower bit depths exhibited reduced accuracy due to limited intensity representation and loss of texture details

### 3. Results and discussion

This section presents and discusses the experimental results obtained from the road damage classification system. The comparison of classification accuracy across different grayscale bit depths demonstrates a clear trend: higher grayscale resolutions yield better performance. This improvement occurs because higher bit depths preserve more detailed texture variations, which are effectively captured by GLCM features such as contrast and homogeneity. The experimental findings indicate that 4-bit and 5-bit grayscale images suffer from significant information loss, leading to reduced classification accuracy. In contrast, 7-bit and 8-bit grayscale images provide richer intensity levels that enhance the discriminative power of texture features. The backpropagation neural network is able to learn more representative patterns from these features, resulting in improved classification accuracy. These results are consistent with previous studies that emphasize the importance of image resolution and texture quality in computer vision-based road.

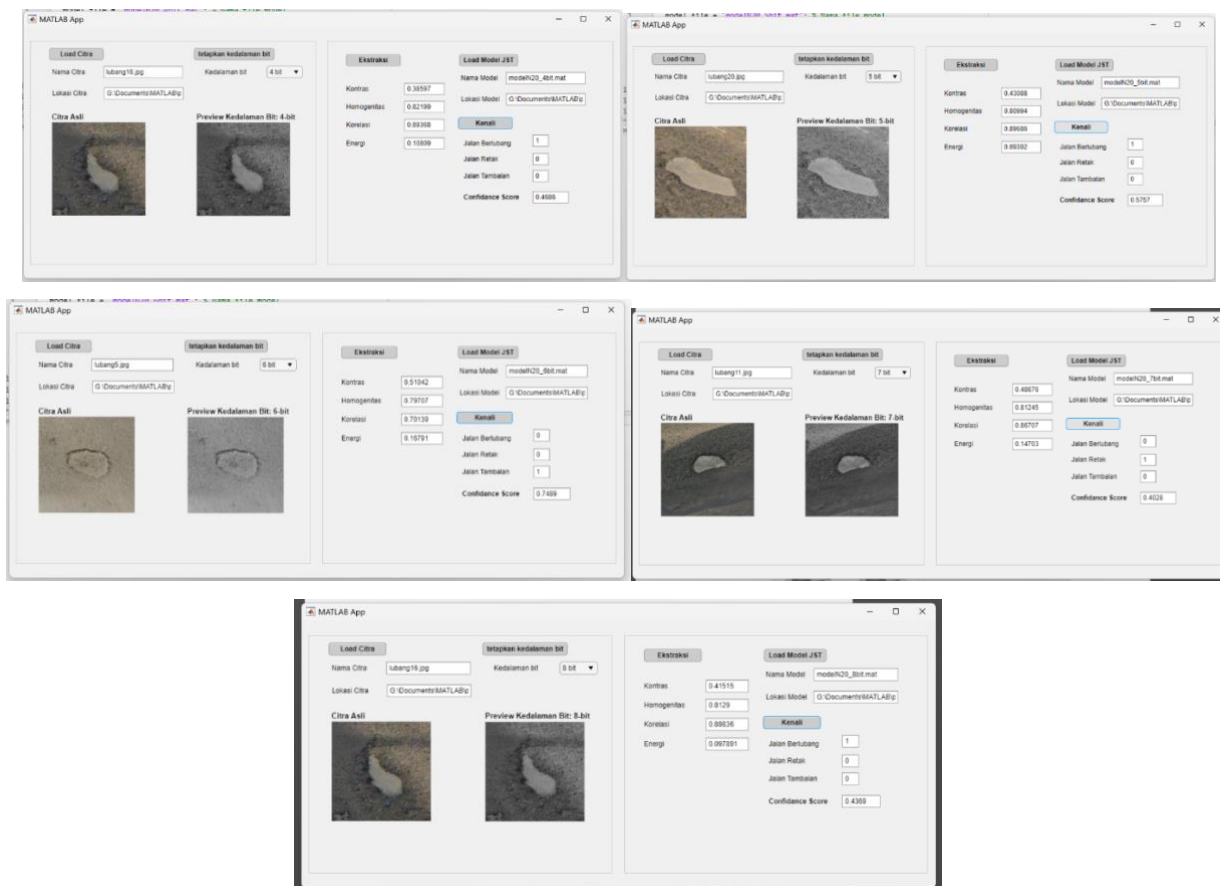


Fig. 4 Pothole testing with gray scale levels of 4,5,6,7,8 bit

### 4. Conclusion

This study concludes that grayscale bit depth has a substantial impact on road damage classification accuracy using GLCM feature extraction and a backpropagation neural network. Higher grayscale resolutions provide more detailed texture information, leading to improved classification performance. Among the evaluated configurations, 8-bit grayscale achieved the highest accuracy in identifying cracks, potholes, and patches, demonstrating its suitability for texture-based road damage recognition systems.

### 5. Suggestion

Based on the results of this research, several suggestions can be proposed for future work. The incorporation of additional texture features or hybrid feature extraction methods may further enhance classification accuracy. Expanding the dataset with more diverse road conditions,

lighting variations, and damage types is also recommended to improve system robustness. Furthermore, future studies may explore deep learning-based approaches and real-time implementation to support large-scale and automated road condition monitoring systems.

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