JESICA: Journal of Enhanced Studies in Informatics and Computer Applications
Journal homepage: jesica.itsk-soepraoen.ac.id
e-ISSN: 3046-6938 p-ISSN: 3046-6997
Vol. 3, No. 2, July 2026, Pp. 80-87

Comparative Analysis of Texture Feature Extraction-Based Machine Learning Algorithms for Road Surface Condition Classification

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Keywords:
GLCM, ML, Road Surface Condition, Texture Feature Extraction

Abstract
Road surface conditions play a crucial role in ensuring transportation comfort and safety. Conventional road inspection methods that rely on manual observation are often time-consuming, expensive, and prone to subjectivity. This study proposes an automated approach to classify road surface conditions using texture-based feature extraction and machine learning algorithms. A total of 802 road images were independently collected, representing three classes: good, fair, and damaged. The images were preprocessed through resizing, grayscale conversion, Contrast Limited Adaptive Histogram Equalization (CLAHE), and pixel normalization to improve image quality. Texture features were then extracted using Gray Level Co-occurrence Matrix (GLCM), including contrast, homogeneity, energy, and correlation. The extracted features were used as input to four classification algorithms: Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Random Forest, and Naive Bayes. Experimental results show that KNN achieved the best performance with 96.27% accuracy, followed by SVM and Random Forest with comparable results. Naive Bayes performed the lowest due to its detrimental assumption of feature independence. These findings demonstrate that texture-based features combined with appropriate machine learning algorithms can effectively classify road surface conditions. This approach has strong potential for implementation in automated, real-time road monitoring systems, especially on devices with limited computing resources, contributing to more efficient and objective infrastructure management.

1. Introduction

Road infrastructure is a major pillar of global mobility, contributing to economic growth, social connectivity, and the smooth operation of national logistics systems. Road surface conditions not only affect driving comfort but are also key factors in traffic safety, fuel efficiency, and vehicle durability. As the number of vehicles and the resulting load on roads increase annually, damage to road pavement structures becomes a challenge that governments and transportation authorities struggle to avoid [1]. This damage generally begins on a small scale and, if not promptly detected, can develop into serious damage, such as potholes and cracks, which require much higher repair costs.

To date, road condition evaluations are still largely conducted through manual inspections by technicians or surveyors in the field. This conventional method relies on direct visual observation to identify the type and extent of road damage. However, this approach has several limitations, including the need for large human resources, high operational costs, safety risks in heavy traffic areas, and a high degree of subjectivity [2]. Differences in experience and perception between surveyors often lead to inconsistent assessment results. Thus, a more modern way is necessary, that is, a system that can automatically, objectively, and measurably assess using digital image processing technology and machine learning.

The use of computer vision in road condition monitoring offers a more efficient solution through the ability to collect and analyze data continuously without direct human intervention [3]. With the help of a camera device, images of road conditions can be recorded to determine their condition classification. Visual information, especially road surface texture, contains statistical characteristics that can represent the condition of the pavement material. Roads in good condition generally have a uniform texture, while roads that are damaged show a rougher, irregular texture and have a high intensity contrast [4].

Several previous studies have shown that machine learning has significant potential in detecting and classifying road damage. Several studies have used texture feature extraction methods, such as GLCM, combined with classification algorithms such as k-NN [5] and SVM [6] to differentiate road surface conditions. The results of these studies generally show a high level of accuracy in identifying damage patterns based on image texture characteristics. On the other hand, recent developments also point to the use of deep learning approaches, such as CNN, which are capable of automatic feature extraction and provide superior performance, especially on large-scale datasets [7]. Nevertheless, feature-based methods such as GLCM remain relevant because they are computationally lighter and suitable for implementation on devices with limited resources [8],[9].

Although various studies have demonstrated that the combination of GLCM and machine learning algorithms is capable of effectively classifying road surface conditions, several research gaps remain. Most studies only evaluate a single classification algorithm or use a binary classification (good and damaged), thus failing to provide a comprehensive comparison of the performance of various algorithms in classifying a wider range of road conditions. Furthermore, computational efficiency for implementation in road monitoring systems is also limited. Based on these gaps, this study offers a novelty by utilizing GLCM as a texture feature extraction method and comparing several machine learning classification algorithms to classify road conditions into three categories: good, bad, and damaged. This approach is expected to produce a model with optimal performance and efficiency to support the implementation of an automated road condition monitoring system. Furthermore, this study also compares the performance of several classification algorithms to determine the most optimal model for real-world implementation.

This research is expected to contribute to the development of a faster, more accurate, and more objective road condition monitoring system, thereby supporting data-driven decision-making for the government and relevant agencies. Furthermore, the results are expected to improve efficiency in road infrastructure maintenance planning, minimize repair costs through early damage detection, and improve overall road user safety. Furthermore, this research can serve as a reference for the future development of similar technologies in intelligent transportation.

2. Research Method

machine learning for road condition classification, as shown in Figure 1. The first stage is data collection, which is carried out independently by researchers through photographs of road surface conditions taken at various representative locations. Data collection is carried out using a camera device by considering variations in road conditions, such as good, poor, and damaged roads, so that the obtained dataset can represent real conditions in the field. The details of the road condition images for each class are presented in Table 1. Providing these details aims to provide a clear picture of the visual characteristics of each class.

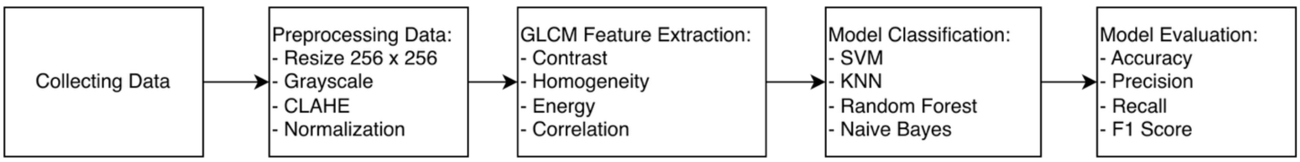

Figure 1. Research methodology

Table 1. Detailed visual description of road conditions

Road condition category	Visual and texture description	Maintenance objectives
Good Road	Smooth surface, high homogeneity, free from cracks or holes.	Routine preventive maintenance to maintain integrity.
Bad Road	The appearance of fine cracks, texture wear, or minor discontinuities.	Minor repairs to prevent structural damage.
Damaged road	There are holes, alligator cracking, and severe deformation.	Emergency repairs or total reconstruction of the road surface.

The next stage is data preprocessing, which aims to improve image quality before further analysis. This process includes resizing the image to 256 × 256 pixels to standardize the input dimensions, converting the image to grayscale to simplify color information, applying the Contrast Limited Adaptive Histogram Equalization (CLAHE) method to increase image contrast, and pixel normalization to adjust the range of intensity values.

The next step is the feature extraction stage using GLCM method. In this stage, image texture features are extracted based on several statistical parameters, namely contrast, homogeneity, energy, and correlation. These four features form a feature vector that serves as input for the classification algorithm.

Contrast to measure local contrast intensity [10]. High contrast values indicate large intensity differences between neighbouring pixels [11], which directly correlate with the level of road surface roughness due to cracks or potholes. Equation 1 is used to measure contrast [12].

$$Contrast = \sum_{i}\sum_{j}(i-j)^2 * P(i,j)$$

Homogeneity to measure the uniformity of intensity distribution in an image [10]. A smooth and well-maintained road surface will have a high homogeneity value due to the very smooth asphalt color transition [13]. Equation 2 is used to measure homogeneity [12].

$$Homogeneity = \sum_i \sum_j \frac{P\ (i,j)}{1 +\ (i-j)^2}$$

Energy to measure the regularity of texture patterns [10]. Images with repetitive and uniform textures will have high energy values [14][15], which indicate the condition of the road surface that is still original and has not experienced damage. Equation 3 is used to measure energy [12].

$$Energy = \sum_i \sum_j P(i-j)^2$$

Correlation is used to measure the linear dependence of a pixel's gray value on its neighbors [10]. This feature reflects the structural relationship between pixels that helps distinguish between longitudinal cracks and solid surface areas. Equation 4 is used to measure correlation [12].

$$Correlation = \frac{\sum_i \sum_j [ij * P(i,j)] -\ \mu_x * \mu_y}{\sigma_x *\ \sigma_y}$$

The next stage is model classification, where the extracted features are used as input for several classification algorithms, namely SVM, KNN, Random Forest, and Naive Bayes. The use of these algorithms aims to compare the performance of each model in classifying road conditions. The configurations used in each algorithm are presented in Table 2.

Table 2. Algorithm configuration

Algorithm	**Configuration**
SVM	Kernel = RBF, C = 10, Gamma = scale
KNN	K = 5
Random Forest	N_estimator = 100
Naïve Bayes	Gaussian Naive Bayes

The final stage is model evaluation, which measures the performance of the classification model. The evaluation uses accuracy, precision, recall, and F1-score metrics to determine the model's accuracy and reliability in objectively classifying road conditions. The model with the highest performance based on the evaluation results is declared the best algorithm in this study's comparison of machine learning methods.

3. Results and Discussion

3.1. Data Collection Results

Road condition image data were collected from October to December 2025. The images were collected based on the detailed visual description of road conditions shown in Table 1. An example of a visual representation of road surface conditions successfully collected in this study is presented in Figure 2. There are visual differences between the three classes. In the class, there are a total of 802 images successfully collected. Good Road has 250 images. In the Bad Road class, there are 250 images. While in the Damaged Road class.

The distribution graph of each class can be seen in Figure 3. The data distribution between classes is kept relatively balanced, which is a fundamental step to prevent model bias towards a particular class during the training phase. A balanced distribution allows the algorithm to learn the unique features of each class with equal weight, thus increasing overall accuracy on previously unseen data [16].

Figure 2. Road conditions (a) good, (b) poor, (c) damaged

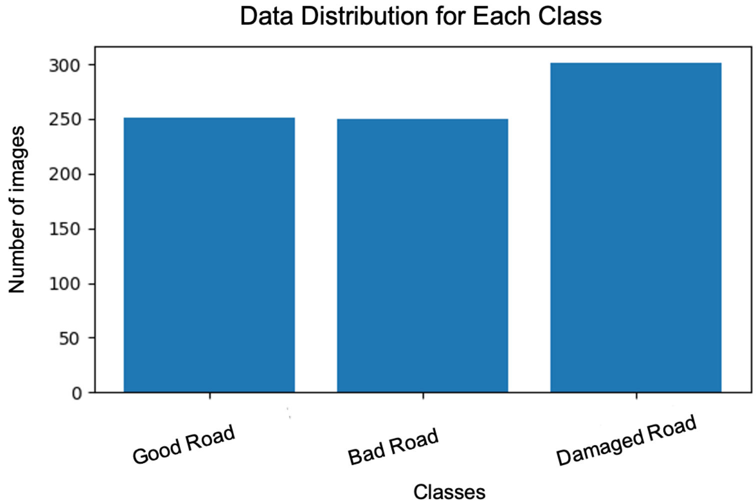

Figure 3. Data distribution for each class.

3.2. Data Preprocessing Results

The preprocessing stage is carried out to improve image quality so that it is more optimal in the feature extraction process [17]. Based on the image presented in Figure 4, it can be seen that the original image still contains diverse color information and lighting variations that can affect texture analysis. Therefore, a conversion to grayscale is carried out to simplify the image information by removing color components and maintaining intensity, so that the road surface texture pattern becomes clearer and more focused.

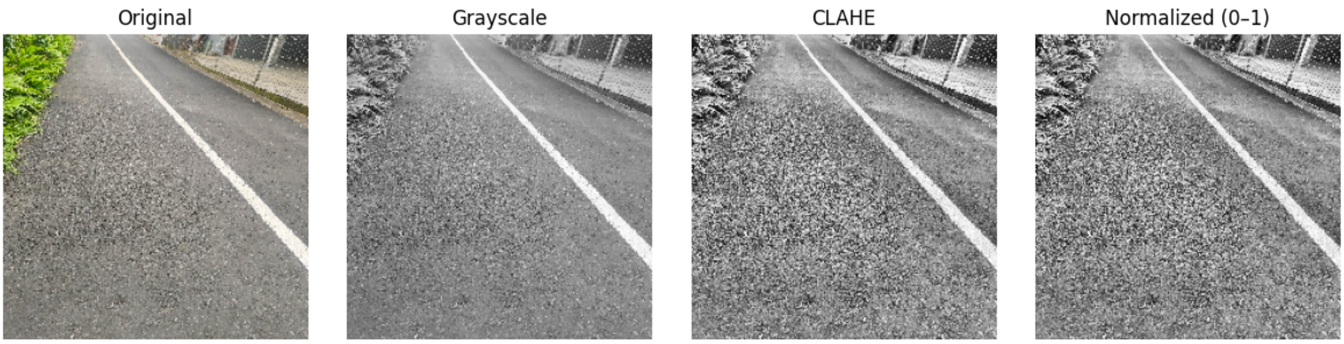

Figure 4. Image of data preprocessing results

Next, CLAHE was applied to enhance local contrast in the image. The results show that road surface texture details, such as aggregate grains and surface irregularities, are sharper and more easily distinguished compared to the previous grayscale image. This improvement is important for strengthening the texture characteristics that will be used in the feature extraction stage.

The final stage in preprocessing is normalizing pixel values to a range of 0–1. This process does not significantly alter the visual structure of the image, but plays a role in adjusting the intensity scale to make it more stable and uniform during subsequent processing by the algorithm. Thus, all preprocessing stages performed have been proven to gradually improve image quality, both in terms of information simplification, contrast enhancement, and pixel value consistency, thus supporting the process of texture feature extraction and more accurate classification of road conditions.

3.2. GLCM Feature Extraction Results

In the feature extraction stage, this study used the GLCM method to obtain the texture characteristics of each road surface image. Based on the process that has been carried out, the entire dataset of 802 images was successfully extracted into 802 rows of data, where each row represents one image. The resulting features consist of four main parameters, namely contrast, homogeneity, energy, and correlation, and are equipped with label and class_name columns as markers of road condition classes, as shown in Table 3.

Table 3. Texture feature extraction using GLCM

Contrast	Homogeneity	Energy	Correlation	Label	Class_name
842.619072	0.082438	0.021177	0.744541	0	Good Road
1285.727942	0.071307	0.018196	0.676548	0	Good Road
2143.863752	0.052834	0.012225	0.545791	1	Bad Road
2914.116712	0.034289	0.007854	0.348954	2	Damaged Road
3220.321283	0.033436	0.007591	0.320292	2	Damaged Road

Conceptually, the contrast feature represents the degree of intensity difference between pixels in an image, so high values generally indicate a rough or irregular texture, such as a damaged road. Conversely, homogeneity measures the degree of uniformity of the pixel intensity distribution, with high values indicating a smoother and more uniform surface, such as a road in good condition. The energy feature describes the degree of texture regularity, while correlation indicates a linear relationship between pixels in the image.

The extraction results show that the four features can capture the differences in texture characteristics between road condition classes representatively. Road images in good condition tend to have higher homogeneity and energy values and lower contrast, while damaged road images show the opposite pattern, namely high contrast values and lower homogeneity. Thus, the features generated by the GLCM method are proven to be relevant and discriminative for use as input in the road condition classification process in the next stage.

3.2. Comparative Analysis of Model Performance

Based on the results of comparative testing of the four classification algorithms, a significant difference in performance was obtained for each model, as shown in Table 4. The KNN algorithm showed the best performance with an accuracy value of 0.9627, precision 0.9607, recall 0.9624, and F1-score 0.9613. These results indicate that KNN has excellent capabilities in recognizing proximity patterns between data based on the resulting texture features, so it can classify road conditions with a high level of accuracy.

Table 4. Comparison of classification algorithm performance

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.9378	0.9351	0.9357	0.9347
KNN	0.9627	0.9607	0.9624	0.9613
Random Forest	0.9378	0.9378	0.9350	0.9350
Naïve Bayes	0.8322	0.8328	0.8260	0.8277

Meanwhile, SVM and Random Forest showed relatively balanced performance, with an accuracy value of 0.9378 each. SVM had a precision of 0.9351, a recall of 0.9357, and an F1-score of 0.9347, while Random Forest recorded a precision of 0.937888, a recall of 0.9350, and an F1-score of 0.9350. Both algorithms can be said to have stable and reliable performance in classifying data, although they are still below KNN in terms of overall accuracy.

On the other hand, Naïve Bayes showed the lowest performance compared to other algorithms, with an accuracy value of 0.8322, precision of 0.8328, recall of 0.8260, and F1-score of 0.8277. The low performance of Naïve Bayes is thought to be caused by the assumption of independence between features, which is less in accordance with the characteristics of GLCM texture features that tend to decrease. Based on the results of the confusion matrix on each algorithm presented in Figure 5, a more in-depth analysis can be carried out on the ability model in classifying each class, namely Good (B), Poor (KB), and Damaged (R).

The SVM algorithm shows that most of the data were correctly classified, particularly in the Damaged (R) class, with 59 correct predictions and no misclassifications to other classes. However, there were still some errors in the Poor (KB) class, where 6 data were misclassified as Good (B), and 2 data from the Good class were predicted as Poor. This indicates that the SVM is quite good at recognizing damaged road patterns but still experiences confusion between the Good and Poor classes, which have relatively similar texture characteristics.

The KNN algorithm's classification performance appears to be more optimal than that of other algorithms. This is demonstrated by the high number of correct predictions across all classes: 49 for Good, 47 for Poor, and 59 for Damaged. Classification errors are relatively small, occurring only in a few instances of data being swapped between the Good and Poor classes. There were no errors in the Damaged class relative to other classes, indicating that KNN is highly effective in consistently distinguishing damaged road textures.

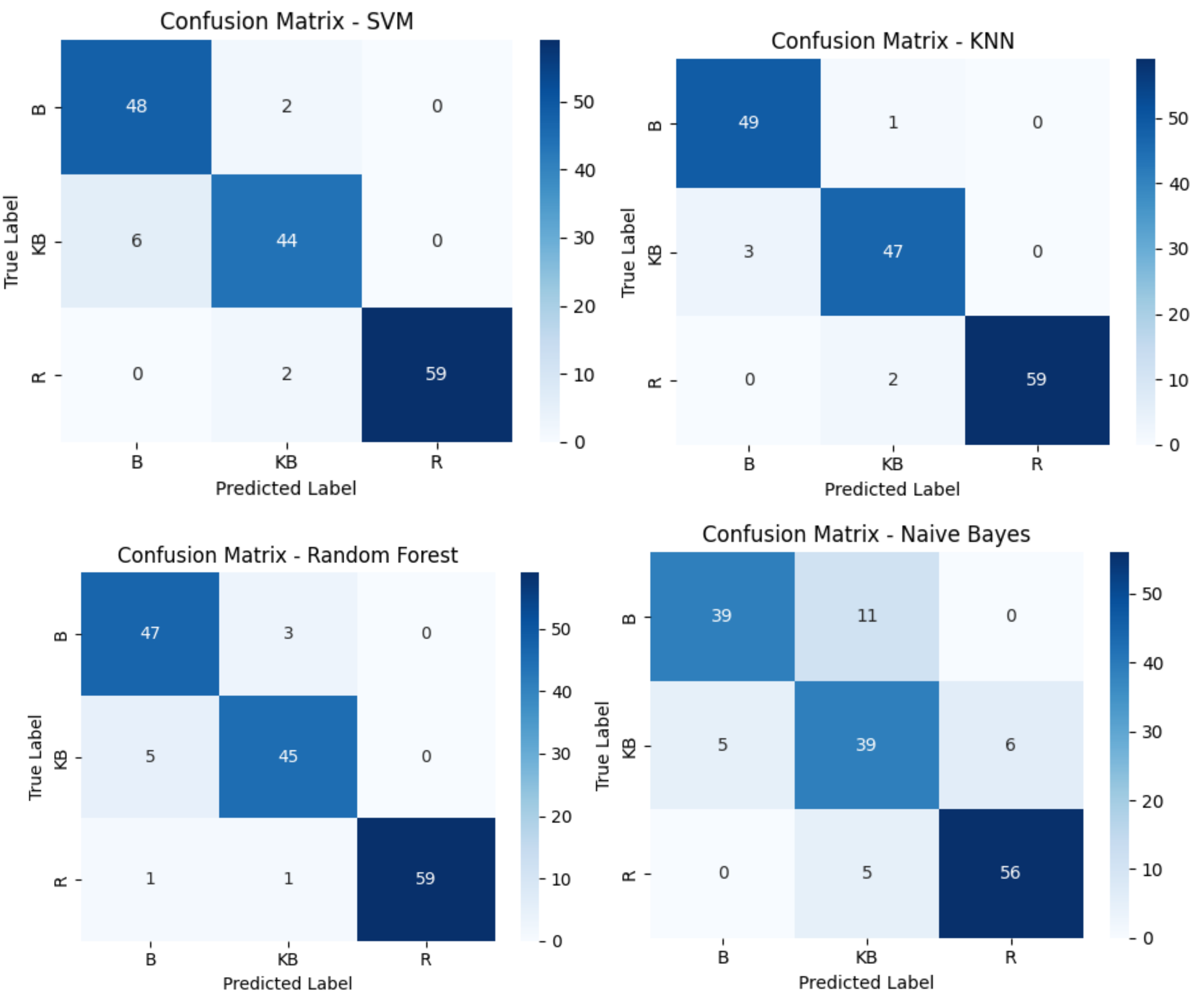

Figure 5. Confusion matrix of each algorithm

For the Random Forest algorithm, the confusion matrix results show stable performance and are close to SVM. Correct predictions for the Good class are 47, Poor 45, and Damaged 59. Classification errors still occur, especially between the Good and Poor classes, and there is a small error in the Damaged class, which is predicted to be Good and Poor, each with 1 data. This indicates that although Random Forest is quite powerful, there are still limitations in distinguishing classes with adjacent texture characteristics.

Meanwhile, the Naïve Bayes algorithm showed the highest error rate compared to other models. In the Good class, there were 11 data points misclassified as Poor. Furthermore, in the Poor class, the error was quite significant, with 5 data points predicted as Good and 6 as Damaged. In the Damaged class, there were 5 data points misclassified as

Poor. This error pattern indicates that Naïve Bayes has difficulty modelling the relationships between interdependent texture features, resulting in less accurate predictions.

Overall, this confusion matrix analysis confirms the results of the previous evaluation, where KNN was the best-performing algorithm, as it was able to minimize classification errors across almost all classes. Furthermore, it can be concluded that the main challenge in this classification lies in distinguishing between the Good and Poor classes, which have relatively similar texture characteristics compared to the more easily recognized Damaged class.

The results of this comparison indicate that the choice of classification algorithm significantly influences the performance of the road condition classification system. Furthermore, this study also demonstrates that the quality of the image preprocessing stage plays a crucial role in producing more representative texture features. The resizing, greyscale conversion, contrast enhancement using CLAHE, and pixel normalization stages have been shown to improve the quality of the input data, thus supporting the overall performance of the classification algorithm. As shown in Figure 4, it can be observed that the preprocessing process significantly improved the quality of the road surface image. This visual quality enhancement plays a crucial role in strengthening the texture characteristics of the image, thus making the features generated during the feature extraction stage more representative and improving the performance of the road condition classification process. Overall, the combination of the GLCM feature extraction method and the KNN algorithm provided the most optimal results in this study. This approach has great potential for application in an efficient, objective, and feasible automated road condition monitoring system on devices with limited hardware specifications.

4. Conclusion

This study shows that a texture-based pattern recognition approach using GLCM is effective in classifying road surface conditions. Based on comparative testing results, the KNN algorithm provides the best performance with an accuracy rate of 96.27%, followed by SVM and Random Forest, which also show stable and high performance. Meanwhile, the Naive Bayes algorithm has a relatively lower performance, which is suspected to be caused by the assumption of independence between features that is less suitable for the characteristics of texture features that tend to be correlated with each other.

The results of this study also confirm that the image preprocessing stage plays a very important role in improving the quality of the resulting features. Processes such as image size standardization, conversion to grayscale, contrast enhancement using CLAHE, and pixel value normalization have been proven to be able to produce more representative and discriminative texture features. The success of this approach opens opportunities for the development of an automatic road condition monitoring system that can be implemented on devices with limited resources, thus potentially becoming an efficient and economical solution in road infrastructure management.

However, this study still has limitations because it uses a single texture feature extraction method and a dataset with limited environmental conditions, so the model's generalization ability to variations in lighting, weather, and different road pavement types has not been thoroughly evaluated. Therefore, future research can explore combining GLCM with other feature extraction methods or deep learning approaches, using more diverse datasets, and testing the model's implementation in a real-time road monitoring system to improve its robustness and applicability in real-world environments.

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