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Research Article

Implementation of Adaptive Thresholding Method for Road Surface Damage Detection in Digital Images

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Abstract: Road surface damage, such as cracks and potholes, can reduce driving comfort, increase maintenance costs, and pose significant safety risks to road users. Therefore, an automatic and efficient road damage detection system is required to support road condition monitoring and maintenance. This study aims to implement the Adaptive Thresholding method for road surface damage detection in digital images. The proposed approach consists of grayscale conversion, Gaussian Blur filtering, Adaptive Thresholding, Contour Detection, and Hough Line Transform for image preprocessing and segmentation. Subsequently, Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and image intensity histograms are employed for feature extraction, while the Support Vector Machine (SVM) algorithm is used to classify road surface conditions into three categories: smooth road, cracked road, and pothole. The experimental dataset consists of 802 digital images of road surfaces, which were divided into 640 training images (80%) and 162 testing images (20%). Experimental results demonstrate that the proposed method correctly classified all testing images, achieving 100% classification accuracy on the testing dataset. These findings indicate that the proposed approach provides an effective and lightweight solution for automatic road surface damage detection in digital images.

Keywords: Digital Image Processing, Adaptive Thresholding, Contour Detection, Road Damage, Support Vector Machine

1. Introduction

Road infrastructure is one of the essential components supporting economic activities, transportation, and community mobility. The quality of road conditions directly affects driving comfort, travel efficiency, and traffic safety. However, road surface damage, such as cracks and potholes, frequently occurs due to heavy traffic loads, environmental factors, weather conditions, and pavement aging. If road damage is not identified and repaired promptly, it can continue to deteriorate, increase maintenance costs, and potentially cause traffic accidents. Therefore, an effective and efficient approach is required to support the identification of road surface damage at an early stage (Hasibuan et al., 2025).

Digital image processing has become one of the most widely used technologies for object identification and classification. This field focuses on acquiring, processing, and interpreting information from digital images, where each object is represented by pixels with different intensity values. These intensity variations can be analyzed to extract visual characteristics that distinguish one object from another. The application of digital image processing has expanded into many areas, including medical imaging, industrial inspection, agriculture, transportation, and infrastructure monitoring. In this study, digital image processing is applied to analyze road surface conditions using images captured by a smartphone camera (Gonzalez & Woods, 2021).

Although various image processing methods have been applied for road surface damage detection, their performance is often affected by uneven illumination, shadows, road textures, and environmental conditions. Many previous studies also focused on a single segmentation technique or required relatively complex computational approaches. Therefore, a lightweight and robust segmentation method is still required to improve road damage detection under varying lighting conditions (Indriani & Habibie, 2025).

Among various image segmentation methods, Adaptive Thresholding has been widely recognized as an effective approach for handling non-uniform lighting conditions. Unlike global thresholding, Adaptive Thresholding calculates threshold values based on the local intensity distribution of each image region, allowing more accurate segmentation under varying illumination. This characteristic makes the method particularly suitable for road surface images captured in outdoor environments where lighting conditions are inconsistent (Utami, 2021).

Based on these considerations, this study aims to implement the Adaptive Thresholding method for detecting road surface damage using digital images captured by a smartphone camera. The proposed system is expected to identify road damage automatically and classify road conditions into three categories: smooth road, cracked road, and pothole. Furthermore, the implementation of this method is expected to provide a practical, objective, and efficient solution for supporting road condition monitoring and facilitating faster infrastructure maintenance.

The contributions of this study are summarized as follows: 1) This study implements the Adaptive Thresholding method to improve the segmentation of road surface damage in digital images under varying illumination conditions; 2) This study integrates Adaptive Thresholding with Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and the Support Vector Machine (SVM) algorithm to classify road surface conditions into three categories: smooth road, cracked road, and pothole: and 3) This study proposes a lightweight road surface damage detection framework by combining conventional image processing techniques and machine learning, providing an effective and practical approach for automatic road condition assessment using digital images.

2. Research Method

2.1 Dataset

The dataset used in this study consists of 802 digital images of road surfaces captured using a smartphone camera. The dataset includes three categories of road conditions: smooth roads**,** cracked roads**,** and potholes**.** These categories were selected because they represent the most common types of road surface conditions encountered in daily transportation and serve as the target classes for the classification process.

The road surface images were collected under various environmental conditions to represent different lighting intensities, road textures, and object appearances. This variation was intended to improve the robustness of the proposed model when detecting road surface damage under real-world conditions. Before the classification process, all images underwent preprocessing, including grayscale conversion, Gaussian Blur filtering, Adaptive Thresholding segmentation, Contour Detection, and feature extraction.

To evaluate the classification performance objectively, the dataset was divided into training and testing subsets using an 80:20 ratio. A total of 640 images were used for training the Support Vector Machine (SVM) classifier, while the remaining 162 images were used for testing. This data separation ensures that the performance evaluation reflects the classifier's ability to recognize previously unseen road surface images.

Table 1. Dataset Penelitian

No	Road Condition	Number of Images	Function
1	Smooth Road	251	Training and Testing Data
2	Cracked Road	250	Training and Testing Data
3	Pothole	301	Training and Testing Data
Total		**802**	

The dataset consists of 251 smooth road images, 250 cracked road images, and 301 pothole images, all of which were utilized during the training and testing stages of the proposed road surface damage detection system.

2.2 Proposed Model

The proposed model consists of an integrated road surface damage detection framework that combines digital image processing techniques with machine learning for automatic road condition classification. The framework is designed to classify road surface conditions into three categories, namely smooth road, cracked road, and pothole, by integrating image preprocessing, segmentation, feature extraction, and classification.

The workflow begins with the acquisition of road surface images using a smartphone camera. The captured RGB images are used as the input to the system and processed sequentially through several stages. Each stage is designed to improve image quality, extract representative features, and enhance the classification performance of the proposed framework.

The first stage is image preprocessing, which consists of grayscale conversion and Gaussian Blur filtering. Grayscale conversion transforms RGB images into single-channel grayscale images to reduce computational complexity while preserving structural information. Gaussian Blur filtering is then applied to suppress image noise and smooth pixel intensity variations before image segmentation.

Following preprocessing, Adaptive Thresholding is employed to segment damaged regions from the road surface. Unlike global thresholding, Adaptive Thresholding determines threshold values based on the local intensity distribution of each image region, enabling more robust segmentation under varying illumination conditions. The segmented images are subsequently processed using Contour Detection and Hough Line Transform to identify structural characteristics associated with cracks and potholes.

Feature extraction is performed using Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and image intensity histograms. HOG extracts edge orientation information, while LBP captures local texture characteristics of the road surface. These complementary descriptors generate representative feature vectors that improve the discrimination between smooth roads, cracked roads, and potholes.

Finally, the extracted feature vectors are classified using the Support Vector Machine (SVM) algorithm. The trained SVM classifier determines the road surface category based on the extracted features**.** Figure 1 illustrates the overall workflow of the proposed model, from image acquisition through preprocessing, segmentation, feature extraction, and classification. The integration of conventional image processing techniques with machine learning provides an effective and computationally efficient framework for automatic road surface damage detection..

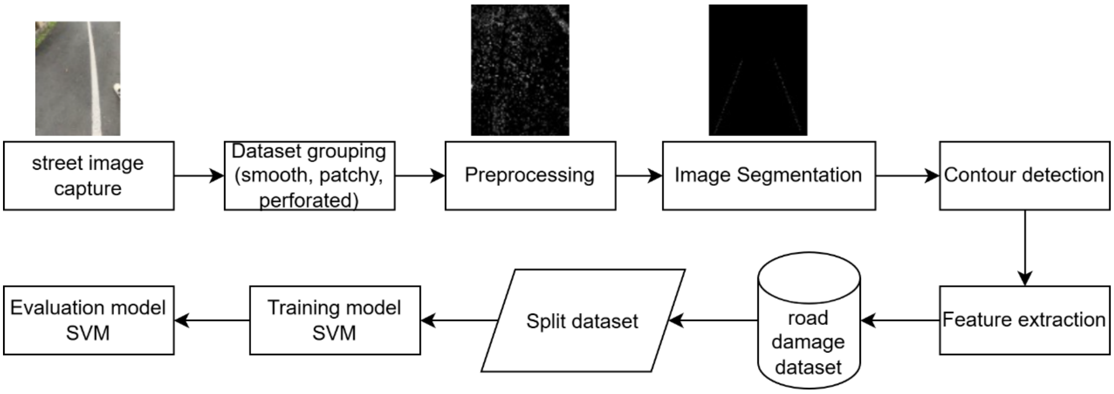

Figure 1. Research Stage Flowchart

2.3 Image Preprocessing

Image preprocessing was performed to improve image quality before the segmentation stage. This stage consists of grayscale conversion and Gaussian Blur filtering, which reduce image complexity and suppress noise while preserving the structural characteristics of road surface damage. The resulting preprocessed image serves as the input for the Adaptive Thresholding stage.

The RGB image is first converted into a grayscale image using Equation (1):

$$\mathrm{Gray} = 0.299\mathrm{R} + 0.587\mathrm{G} + 0.114\mathrm{B} \tag{1}$$

Where R**,** G, and B represent the red, green, and blue color components of the input image. After grayscale conversion, Gaussian Blur filtering is applied to smooth the image and reduce high-frequency noise that may affect segmentation accuracy. The Gaussian function is expressed in Equation (2):

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

Where **x** and **y** denote the pixel coordinates, and **σ** represents the standard deviation controlling the degree of smoothing. The resulting preprocessed image is subsequently forwarded to the Adaptive Thresholding stage for road surface segmentation.

2.4 Data Collection

The data collection process was carried out by acquiring road surface images using a smartphone camera. Image acquisition was conducted at several road locations to capture various road surface conditions, including smooth roads, cracked roads, and potholes. To improve the robustness of the proposed system, the images were collected under different environmental conditions, including variations in lighting intensity, viewing angles, and road textures.

After the image acquisition stage, each image was manually inspected and assigned to one of three predefined classes: Smooth Road**,** Cracked Road, or Pothole**.** The labeling process was performed based on the visible characteristics of the road surface to ensure that each image accurately represented its corresponding category. The labeled dataset was subsequently organized and prepared for the image preprocessing, feature extraction, classification, and performance evaluation stages.

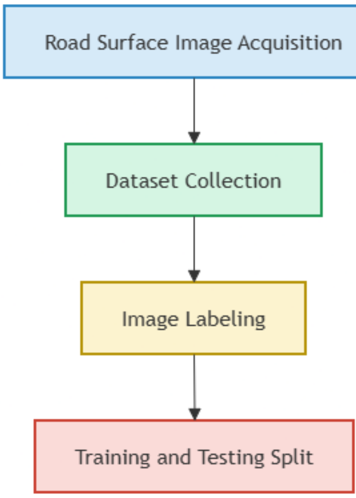

Figure 4. Data Collection Process

Figure 4 illustrates the overall data collection process used in this study. The process begins with the acquisition of road surface images using a smartphone camera to obtain representative images of smooth roads, cracked roads, and potholes. The acquired images are then organized into a structured dataset according to their respective road condition categories. Subsequently, each image is manually labeled as Smooth Road**,** Cracked Road**,** or Pothole to provide reliable ground truth data for the classification process. Finally, the labeled dataset is divided into training and testing subsets. The training dataset is used to train the Support Vector Machine (SVM) classifier, whereas the testing dataset is employed to evaluate the classification performance of the proposed road surface damage detection method.

2.5 Data Preprocessing

The data preprocessing stage was performed to improve the quality of the input images before the segmentation process. The acquired road surface images were affected by variations in illumination, image noise, and irrelevant background objects that could reduce segmentation accuracy. Therefore, preprocessing was applied to enhance image quality while preserving the structural characteristics of road surface damage.

The preprocessing process consisted of three sequential stages: Region of Interest (ROI) extraction**,** grayscale conversion**,** and Gaussian Blur filtering. ROI extraction was performed to focus the analysis only on the road surface area, thereby eliminating unnecessary background information. Subsequently, the RGB images were converted into grayscale images to reduce computational complexity while preserving the intensity information required for image analysis. Gaussian Blur filtering was then applied to suppress image noise and smooth pixel intensity variations before the segmentation stage. The grayscale conversion and Gaussian Blur operations are represented by Equations (1**)** and (2)**,** respectively.

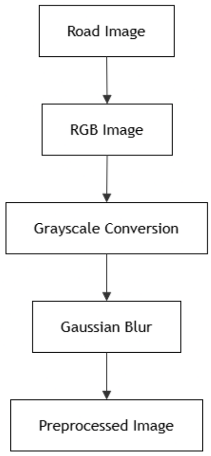

Figure 2. Image Preprocessing Workflow

Illustrates the image preprocessing workflow used in this study. The workflow begins with the acquisition of an RGB road surface image, followed by ROI extraction to isolate the road region. The extracted ROI is then converted into a grayscale image, after which Gaussian Blur filtering is applied to reduce image noise and improve image quality before segmentation.

The resulting preprocessed image was subsequently used as the input for the Adaptive Thresholding process to separate damaged and undamaged road surface regions under varying illumination conditions. The segmented images were then processed using Contour Detection and Hough Line Transform before feature extraction was performed using Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP). Finally, the extracted feature vectors were classified using the Support Vector Machine (SVM) algorithm to determine the road surface category.

2.6 Data Labeling

After the image preprocessing stage, each road surface image was manually assigned a label according to its actual road condition. The labeling process was performed through visual inspection based on the visible characteristics of road surface damage to ensure that each image accurately represented its corresponding category. The labeled dataset served as the ground truth for training and evaluating the Support Vector Machine (SVM) classification model.

The road surface images were categorized into three predefined classes: Smooth Road**,** Cracked Road**,** and Pothole**.** The Smooth Road class represents road surfaces without visible damage, the Cracked Road class represents road surfaces containing crack patterns, and the Pothole class represents road surfaces containing potholes or severe surface deterioration. These labels were used to distinguish the road condition categories during the classification process.

Table 2. Road Surface Image Labels

Road Condition	**Description**
Smooth Road	Road surface without visible damage
Cracked Road	Road surface containing crack patterns
Pothole	Road surface containing potholes or severe damage

The labeled dataset was subsequently used in the feature extraction and classification stages. The manually assigned labels provided reliable reference data for training the classifier and evaluating the classification performance of the proposed road surface damage detection system.

2.7 Feature Extraction and Classification

Following the image segmentation stage, feature extraction was performed to obtain representative characteristics of the road surface images. This study employed Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and image intensity histograms to extract structural and texture information from the segmented images. These complementary feature descriptors were selected because they effectively represent edge orientation, local texture patterns, and pixel intensity distributions associated with different types of road surface damage.

Histogram of Oriented Gradients (HOG) was applied to capture edge orientation and gradient information from the segmented road surface images. HOG represents the distribution of local intensity gradients, making it suitable for identifying crack patterns and the boundaries of potholes. In addition, Local Binary Pattern (LBP) was employed to extract local texture information by comparing the intensity of neighboring pixels with the center pixel. The image intensity histogram was also computed to represent the distribution of grayscale pixel values within each segmented image.

The feature vectors obtained from HOG, LBP, and image intensity histograms were combined into a single feature representation. This combined feature vector provides complementary information describing the structural and texture characteristics of each road surface image, thereby improving the discriminative capability of the classification model.

The combined feature vectors were subsequently classified using the Support Vector Machine (SVM) algorithm. During the training stage, the SVM classifier learned the characteristics of each road surface category from the labeled training dataset. During the testing stage, the trained classifier predicted the class of previously unseen road surface images as Smooth Road, Cracked Road, or Pothole based on the extracted feature vectors.

The classification results obtained from the SVM classifier were then used to evaluate the effectiveness of the proposed road surface damage detection framework. The evaluation was performed using the testing dataset, and the classification performance was analyzed using standard evaluation metrics presented in the subsequent section.

2.8 Performance Evaluation

The performance of the proposed road surface damage detection system was evaluated using a confusion matrix, which summarizes the number of correctly and incorrectly classified images for each road surface category. Based on the confusion matrix, four evaluation metrics, namely accuracy, precision, recall, and F1-score, were calculated to assess the classification performance of the proposed method. Accuracy, precision, recall and f1 score measures the overall proportion of correctly classified samples and is calculated using Equation (3) – (6).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$recall = \frac{TP}{TP+FN} \tag{5}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

In these equations, TP (True Positive) represents correctly classified positive samples, TN (True Negative) represents correctly classified negative samples, FP (False Positive) represents incorrectly classified positive samples, and FN (False Negative) represents incorrectly classified negative samples.

The calculated evaluation metrics were analyzed to assess the capability of the proposed Adaptive Thresholding, Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and Support Vector Machine (SVM) framework in classifying road surface conditions into Smooth Road, Cracked Road, and Pothole categories. These metrics provide a comprehensive evaluation of the effectiveness and reliability of the proposed road surface damage detection system.

3. Results and Discussion

3.1 Preprocessing Results

The preprocessing stage was conducted to improve the quality of the road surface images before segmentation and classification. This stage consisted of grayscale conversion, Gaussian Blur filtering, and Adaptive Thresholding. These preprocessing techniques successfully reduced image noise, minimized illumination variations, and enhanced the visibility of road surface damage, thereby improving the quality of the input images for subsequent processing.

Figure 5 illustrates the preprocessing results obtained from the proposed method. The original RGB image was first converted into a grayscale image to simplify image representation while preserving the intensity information required for further analysis. Gaussian Blur filtering was then applied to suppress image noise and smooth pixel intensity variations. Finally, Adaptive Thresholding segmented the road surface by separating damaged and undamaged regions based on the local intensity distribution, producing clearer damage boundaries under varying lighting conditions.

Table 3. Road Surface Damage Categories

Class	Description
Smooth Road	Images of road surfaces without visible damage
Cracked Road	Images of road surfaces containing crack patterns
Pothole	Images of road surfaces containing potholes

The preprocessing results demonstrate that grayscale conversion successfully reduced image complexity while preserving the structural information of the road surface. Gaussian Blur effectively suppressed image noise and smoothed intensity variations before segmentation. Adaptive Thresholding successfully separated damaged and undamaged regions under varying illumination conditions, resulting in clearer crack and pothole boundaries for subsequent feature extraction.

3.2 Data Distribution

The road surface image dataset used in this study consists of 802 digital images collected using a smartphone camera. Each image was manually verified and categorized into one of three predefined classes: Smooth Road, Cracked Road, or Pothole. The dataset distribution was analyzed to ensure that each class was adequately represented during the training and testing stages of the proposed classification model.

Table 4. Dataset Distribution

Class	Number of Images	Percentage (%)
Smooth Road	251	31.30
Cracked Road	250	31.17
Pothole	301	37.53
Total	**802**	**100.00**

As presented in Table 4, the Pothole class contains the largest number of images, with 301 images (37.53%), followed by the Smooth Road class with 251 images (31.30%) and the Cracked Road class with 250 images (31.17%). Although the dataset is not perfectly balanced, the distribution of images across the three classes remains relatively proportional, allowing the classifier to learn representative features from each road condition category.

The dataset was subsequently divided into 640 training images (80%) and 162 testing images (20%). The training dataset was used to train the Support Vector Machine (SVM) classifier, whereas the testing dataset was employed to evaluate the classification performance of the proposed method. This data distribution provides sufficient representation for each class and enables an objective evaluation of the proposed road surface damage detection system.

3.3 Classification Results

The classification performance of the proposed road surface damage detection system was evaluated using the testing dataset consisting of 162 road surface images. The trained Support Vector Machine (SVM) classifier categorized each testing image into one of three predefined classes: Smooth Road, Cracked Road, or Pothole. The classification results were analyzed using a confusion matrix to determine the effectiveness of the proposed framework.

Table 5. System Testing Results

No	Road Category	Test Images	Correct Predictions	Incorrect Predictions
1	Smooth Road	51	51	0
2	Cracked Road	50	50	0
3	Pothole	61	61	0
Total		**162**	**162**	**0**

As presented in Table 5, all 162 testing images were correctly classified by the proposed classification system. The Smooth Road category achieved 51 correct classifications, the Cracked Road category achieved 50 correct classifications, and the Pothole category achieved 61 correct classifications, with no misclassified images observed during the testing process.

These results demonstrate that the proposed road surface damage detection framework successfully distinguished the three road surface categories in the testing dataset. The integration of Adaptive Thresholding, Contour Detection, Hough Line Transform, Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and the Support Vector Machine (SVM) classifier produced representative feature vectors, enabling accurate discrimination between smooth roads, cracked roads, and potholes.

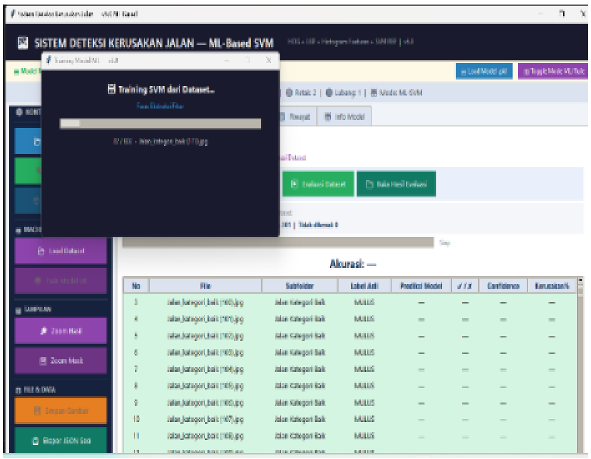

Figure 6. SVM Training and Road Surface Classification Results

The classification interface confirms that the proposed system can automatically predict the road condition category together with the corresponding confidence score. The prediction results indicate that the extracted HOG and LBP features provide sufficient discriminative information for the SVM classifier to distinguish the three predefined road surface categories.

3.4 Discussion

The experimental results demonstrate that the proposed road surface damage detection framework achieved excellent classification performance for the three predefined road condition categories, namely Smooth Road**,** Cracked Road, and Pothole**.** The classification results indicate that the combination of conventional image processing techniques and machine learning provides an effective approach for distinguishing different road surface conditions using smartphone-acquired images.

The high classification performance can be attributed to the effectiveness of the image preprocessing and feature extraction stages. Adaptive Thresholding successfully segmented damaged regions under varying illumination conditions, while Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) extracted complementary structural and texture features from the segmented images. These representative features enabled the Support Vector Machine (SVM) classifier to accurately distinguish the characteristics of each road surface category.

The testing results showed that all 162 testing images were correctly classified, resulting in 162 correct predictions and no misclassified images. These results indicate that the proposed framework effectively learned the characteristics of the three road surface categories within the testing dataset. Furthermore, the integration of conventional image processing techniques with the SVM classifier provides a computationally efficient solution that is suitable for practical road surface damage detection using digital images.

Compared with previous studies that employed only thresholding or conventional image segmentation techniques, the proposed framework combines Adaptive Thresholding with HOG, LBP, and SVM to improve the discrimination of different road surface conditions. This integration enables the system to utilize both structural and texture information, resulting in a lightweight yet effective classification framework suitable for smartphone-acquired images.

Overall, the proposed framework demonstrates that the integration of Adaptive Thresholding, Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and Support Vector Machine

(SVM) provides an effective and lightweight approach for automatic road surface damage classification. The developed system has the potential to support faster, more objective, and more efficient road condition assessment, thereby reducing the need for manual inspection and supporting road maintenance activitie.

One limitation of this study is that the experimental evaluation was conducted using a dataset collected under limited environmental conditions and only three road surface categories. Consequently, further investigation using larger datasets with more diverse weather conditions, road textures, and image acquisition devices is required to improve the robustness and generalization capability of the proposed framework.

4. Conclusion

This study successfully developed a road surface damage detection system using digital images captured by a smartphone camera. The proposed framework was able to classify road surface conditions into three categories, namely Smooth Road**,** Cracked Road, and Pothole, through the integration of image preprocessing, feature extraction, and machine learning techniques.

The experimental evaluation demonstrated that the proposed framework achieved excellent classification performance on the testing dataset. A total of 162 testing images were evaluated, and all images were correctly classified, indicating that the proposed approach effectively distinguished different road surface conditions within the collected dataset. These results demonstrate that the integration of Adaptive Thresholding, Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and the Support Vector Machine (SVM) classifier provides an accurate and computationally efficient solution for automatic road surface damage detection.

The developed system has the potential to support faster and more objective road condition assessment than conventional manual inspection. Future research should focus on expanding the dataset with more diverse road conditions, incorporating additional damage categories, and evaluating the proposed framework under different environmental conditions and image acquisition devices to improve its robustness and generalization capability.

The proposed framework can therefore serve as an alternative lightweight solution for practical road surface monitoring using low-cost smartphone devices.

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