
AI-Driven Road Safety Monitoring and Civic Issue Reporting System Using Computer Vision

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Abstract.

The deterioration of road infrastructure affects traffic safety, vehicle maintenance, and transportation efficiency. Timely identification of potholes and estimation of their severity can support road maintenance and prioritization. Although deep learning methods can achieve high detection accuracy, they generally require large labeled datasets and substantial computational resources, which can limit their use in real-time and resource-constrained environments. This paper proposes a lightweight machine-learning pipeline for classifying pothole severity into Low, Medium, and High classes. Road images are resized and preprocessed, after which structural and surface characteristics are represented using Canny edge density and RGB color histograms. The resulting features are evaluated with Random Forest, Support Vector Machine (SVM), and XGBoost classifiers. On a dataset of 665 pothole images, Random Forest achieves the best performance, with 92.6% accuracy, 92.8% precision, 92.6% recall, and 92.5% F1-score. The results indicate that handcrafted image features combined with supervised learning can provide a practical alternative for lightweight road-condition monitoring and intelligent transportation applications.

Keywords. Road damage detection; pothole classification; machine learning; feature extraction; Random Forest.

1. INTRODUCTION

Urbanisation and increasing traffic cause road damage, creating safety risks, vehicle damage, and maintenance costs. Manual inspection is time-consuming and error-prone, motivating automated vision-based monitoring [1,2]. Although deep learning provides effective detection, its computational demands limit low-cost deployment [3–6]. This study uses Canny edge density and RGB histograms with Random Forest, SVM, and XGBoost to classify pothole severity for lightweight, real-time monitoring [7–9].

2. RELATED WORK

Early road-damage studies used image processing techniques such as enhancement, segmentation, edge detection, color, and texture features. Canny edge detection is widely used for effective edge localization [8], while image-processing and color-histogram methods support feature extraction [9,10]. However, illumination, shadows, and noise remain challenges [7].

Machine-learning methods such as SVM and Random Forest improve classification using handcrafted features [2]. CNN and transfer-learning approaches offer higher accuracy but require greater computational resources [3,4,6,11]. Therefore, this work proposes a compact feature-based pipeline for pothole severity classification.

3. DATASET AND PROPOSED METHOD

3.1. Dataset

The dataset contains 665 road images depicting potholes under varied road, lighting, and back-ground conditions. Potholes are represented by bounding-box annotations in Pascal VOC XML format. The dataset contains one damage category (pothole), while severity is assigned to three levels: Low, Medium, and High. Because the original data do not provide predefined severity labels, samples were manually categorized using pothole size, depth, and surface irregularity with consistent labeling criteria. Images are resized to 64×64 pixels and represented in RGB format. An 80:20 stratified train-test split is used so that the severity distribution is maintained across both sets.

3.2. System Overview

The proposed pipeline consists of image acquisition, preprocessing, feature extraction, super-vised classification, and severity prediction. The design intentionally uses lightweight operations so that inference can be performed on standard CPU-based systems.

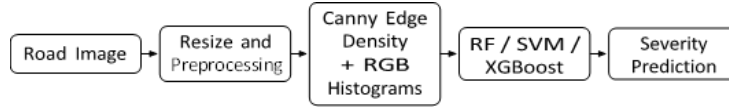


Figure 3.1.1: Lightweight road-damage severity classification pipeline.

3.3. Image Preprocessing

All images are resized to 64×64 pixels to reduce computational cost and provide a consistent input size. Grayscale images are used for edge-based processing, while the original RGB channels are retained for color analysis. Pixel values are normalized to reduce the influence of illumination differences. Canny edge detection is then applied to highlight structural discontinuities caused by potholes and other surface irregularities. The detector uses lower and upper thresholds of 50 and 150, respectively. Edge density is calculated as the ratio of edge pixels to total image pixels, producing a compact feature that represents the amount of structural variation in the road surface [8].

3.4. RGB Color Histogram Features

Structural information alone may not fully describe a damaged road surface. Therefore, RGB color information is incorporated through histogram analysis. Each RGB channel is quantized into eight bins, producing $8 \times 8 \times 8 = 512$ color combinations. The resulting histogram represents the distribution of surface colors and can capture changes associated with asphalt wear, material degradation, water accumulation, and illumination [10]. The color features are combined with edge density to form the final feature vector.

3.5. Machine Learning Classification

The extracted features are evaluated using three supervised classifiers. Random Forest is an ensemble of decision trees and is used for its robustness and ability to model nonlinear relationships. A linear SVM is included as a margin-based classifier suitable for high-dimensional feature spaces. XGBoost is used as a gradient-boosted decision-tree method that can provide strong predictive performance with appropriate regularization. These models represent different learning strategies and provide a compact comparison of severity classification performance.

The classifiers are trained on the hand-labeled dataset. Random Forest uses 150 decision trees. Performance is measured using accuracy, precision, recall, and weighted F1-score. During inference, the same preprocessing and feature-extraction steps are applied to an unseen image before the trained model predicts its severity class.

4. EXPERIMENTAL RESULTS

4.1. Experimental Setup

The experiments were implemented in Python. OpenCV was used for image preprocessing and feature extraction, while scikit-learn and XGBoost were used for model training and evaluation. Experiments were performed on a standard CPU-based system without specialized GPU hardware. The three severity classes were Low, Medium, and High, and the dataset was divided using an 80:20 stratified split.

Table 1: Performance comparison of machine-learning models.

Model	Accuracy	Precision	Recall	F1-score
SVM (Linear)	88.4	88.7	88.4	88.2
XGBoost	90.9	91.1	90.9	90.7
Random Forest	92.6	92.8	92.6	92.5

The results in Table 1 show that Random Forest provides the best overall performance among the evaluated classifiers. It achieves 92.6% accuracy and maintains closely matched precision, recall, and F1-score values. XGBoost follows with 90.9% accuracy, while linear SVM achieves 88.4%. The results suggest that the nonlinear ensemble representation of Random Forest is well suited to the combined edge and color features used in this work.

5. DISCUSSION

The proposed Canny edge density and RGB histogram features provide effective, low-cost pothole severity classification. Random Forest performed best, while the method remains suitable for CPU and edge devices. Limitations include environmental variations and the small 665-image dataset.

6. CONCLUSION

The framework achieved 92.6% accuracy, 92.8% precision, 92.6% recall, and 92.5% F1-score using Random Forest. It offers a lightweight solution for real-time pothole severity monitoring.

7. REFERENCES

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Biographies



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