A Smartphone Sensor-Based Pavement Roughness Grading Method for Non-Motorized Lanes

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Abstract: To address the lack of low-cost and routine methods for pavement roughness monitoring on non-motorized lane, this paper proposes a pavement roughness sensing and grading method based on smartphone sensors. Taking shared electric bicycles as the data collection platform, acceleration, gravity, and magnetic field signals are acquired using built-in smartphone sensors, and the vertical acceleration is obtained through coordinate transformation. To reduce low-frequency interference in the raw signals, a zero-phase high-pass filtering and adaptive preprocessing method is applied. The root mean square of vertical acceleration (RMSVA) is used as the main indicator of pavement roughness. In addition, several vibration statistical features are combined to form a multi-dimensional feature set. A support vector machine (SVM) classifier is then used to achieve five-level pavement roughness grading. Experimental results show that the proposed preprocessing method improves the correlation between vibration features and pavement conditions. The SVM classification results show a 93.75% agreement with the RMSVA-based grading results. Field tests on real roads further confirm the stability and effectiveness of the proposed method under different pavement types. The proposed approach is low-cost, easy to deploy, and suitable for large-scale applications. It can provide technical support for the refined maintenance and management of urban non-motorized road networks.

Keywords: Pavement Roughness; Smartphone Sensors; RMSVA; Support Vector Machine; Non-Motorized Lanes

1. Introduction

With the rapid development of urbanization and the promotion of green transportation, electric-assisted bicycles and other non-motorized vehicles have become important modes of short-distance travel. However, compared with motorized lanes, non-motorized lanes often lack systematic monitoring and maintenance, resulting in varying pavement roughness conditions that may affect riding comfort and safety. With the widespread availability of embedded sensors in smartphones, acceleration data collected from mobile devices have been widely utilized for pavement roughness estimation, providing a low-cost and scalable alternative [1]. Traditional pavement roughness evaluation methods rely on professional inertial measurement systems and vehicle-mounted equipment, which provide reliable results but require high costs and specialized operation [2]. In recent years, machine learning techniques have been increasingly introduced into pavement condition assessment. Neural network approaches have been applied to analyze crowdsourced smartphone data for road roughness prediction, improving modeling capability and robustness [3]. Two-stage machine learning frameworks have also been developed for pavement health monitoring systems, enhancing classification performance through hierarchical modeling strategies [4]. Abnormal pavement condition detection considering vehicle posture and speed variations has further improved robustness under dynamic riding conditions [5]. Moreover, smartphone-based assessment methods have been extended to bicycle and low-speed vehicle scenarios, demonstrating their applicability in non-motorized pavement evaluation [6]. Despite these advances, most existing research focuses on general road environments rather than specifically addressing non-motorized lanes. Therefore, this study proposes a smartphone-based pavement roughness grading framework integrating RMSVA indicators and Support Vector Machine (SVM) classification to achieve stable and interpretable evaluation under electric-assisted bicycle operating conditions.

2. Methodology

2.1 Data Acquisition and Coordinate System Transformation

The overall architecture of the proposed pavement roughness sensing and grading system is illustrated in Figure 1. In this study, the built-in triaxial accelerometer, gravity sensor, and magnetometer of a smartphone are used to collect motion data during cycling, and vehicle vibration signals are recorded at the highest available sampling rate. At the same time, the Amap (Gaode) API is used to obtain positioning information and riding speed, which are applied to road segment labelling and time alignment of multi-source data.

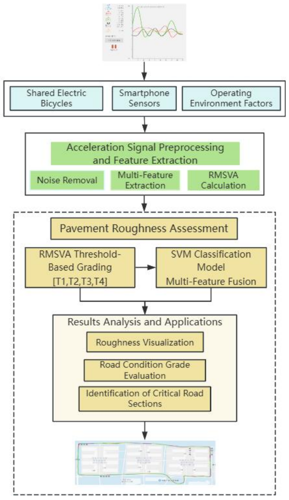


Figure 1. Overall System Architecture

The sensor outputs of a smartphone are expressed in the device coordinate system, while pavement roughness analysis requires the vertical acceleration in the world coordinate system. Therefore, a coordinate transformation is applied to the raw acceleration data. As shown in Figure 2, the device coordinate system is defined by the orientation of the smartphone: the X- and Y-axes lie in the plane of the screen, and the Z-axis is perpendicular to the screen. The world coordinate system follows a fixed ENU (East–North–Up) frame, where the X-axis points east, the Y-axis points north, and the Z-axis points upward.

Figure 2. Illustration of the Device Coordinate System and the World Coordinate System (ENU)

In this study, the SensorManager class in the Android system is used to compute the rotation matrix from the device coordinate system to the world coordinate system by fusing the gravity sensor and geomagnetic sensor data, thereby enabling coordinate transformation of the acceleration measurements. The relationship can be expressed as:

$$\begin{bmatrix} a_{\text{world},x} \\ a_{\text{world},y} \\ a_{\text{world},z} \end{bmatrix} = \mathbf{R} \begin{bmatrix} a_{\text{device},x} \\ a_{\text{device},y} \\ a_{\text{device},z} \end{bmatrix} \quad (1)$$

where $\mathbf{R}$ is the 3×3 rotation matrix computed from the gravity sensor and geomagnetic sensor measurements.

After transforming to the world coordinate system, the vertical acceleration component contains both the gravitational acceleration and the vehicle's motion-induced acceleration, which can be expressed as:

$$a_{\text{world},z} = a_{\text{motion},z} + g \quad (2)$$

By subtracting the local gravitational acceleration g, the pure vertical motion acceleration of the vehicle can be obtained as:

$$a_{\text{motion},z} = a_{\text{world},z} - g \quad (3)$$

To obtain the local gravitational acceleration g, the smartphone is placed horizontally in a stationary state for calibration.

2.2 Pavement Roughness Index Calculation

The vertical vibration generated during bicycle riding can directly reflect the surface roughness condition of the pavement. In this study, a smartphone is rigidly mounted on the vehicle structure to collect the vertical acceleration signal during riding. To suppress the influence of residual gravitational components and low-frequency attitude variations, the vertical acceleration signal is first processed by high-pass filtering to retain the vibration components mainly induced by pavement irregularities.

On this basis, the root mean square of vertical acceleration (RMSVA) is adopted as a quantitative indicator for pavement roughness evaluation, which is defined as:

$$R_A = \sqrt{\frac{1}{N}\sum_{i=1}^{N} A_i^2} \quad (4)$$

where R_A denotes the RMSVA, N is the number of sampling points, and A_i is the filtered vertical acceleration value at the i-th sampling point.

Under constant-speed riding conditions, the RMSVA computed within a fixed time window is used as the pavement roughness index. Experimental results show that when the riding speed is controlled at approximately 4 m/s, the system operates in a relatively stable state, which effectively reduces the influence of human operation factors on the measurement results.

2.3 Data Processing and Pavement Roughness Classification

2.3.1 Data preprocessing strategy

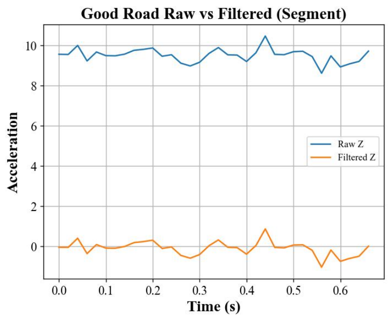
In pavement roughness evaluation based on inertial sensors, the raw acceleration signal is inevitably affected by gravitational components, attitude variations, road longitudinal slope, and differences in sensor installation conditions [7]. Such interferences are mainly concentrated in the low-frequency band. If not effectively suppressed, they will weaken the capability of vibration features to represent pavement conditions. Therefore, systematic preprocessing and filtering of the raw signal are necessary before feature extraction [8].

Let the acquired discrete vertical acceleration sequence be denoted as $x[n]$, with a sampling frequency of $f_s = 50$ Hz. To remove low-frequency interference while preserving the effective vibration responses induced by pavement irregularities, a fourth-order Butterworth high-pass filter is applied, with a cutoff frequency of $f_c = 0.5$ Hz. Considering that conventional one-directional filtering introduces phase delay, a forward–backward filtering strategy is adopted to achieve zero-phase filtering, thereby preserving the amplitude characteristics of the signal without introducing temporal shifts.

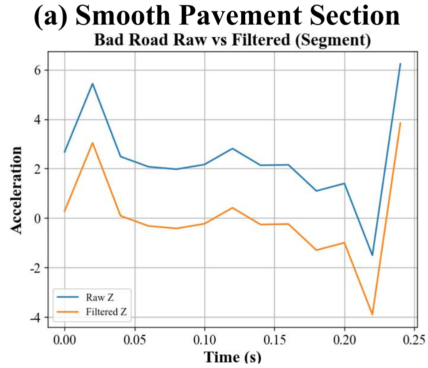
For short time-series data with a limited number of sampling points, an adaptive processing strategy is adopted in this study. When the sample length is insufficient to support stable filtering, only mean removal is applied to the signal to eliminate the DC component. When the sample length meets the required condition, full zero-phase high-pass filtering is performed. This strategy effectively avoids boundary effects and numerical instability that may occur during the filtering of short signal sequences.

In addition, necessary data cleaning and validity constraints are applied to the raw data, including removing records that cannot be parsed or lack key fields, excluding obvious outliers, and discarding samples whose lengths are insufficient to support stable feature computation. In this way, a dataset with reliable quality is constructed.

To verify the effectiveness of the proposed preprocessing method, a comparative experiment is conducted on feature performance before and after filtering. The results show that after zero-phase high-pass filtering, the correlation between the RMSVA feature and pavement grades is significantly enhanced, and the SVM-based classification accuracy increases from 78.2% to 92.5%. Meanwhile, the systematic errors caused by different devices and installation conditions are substantially suppressed. Figure 3 presents the time-domain waveforms of smooth and rough road segments before and after filtering. It can be observed that the low-frequency trend components are effectively suppressed, while the vibration components induced by pavement irregularities are preserved, which verifies the effectiveness of the proposed preprocessing method.



(a) Smooth Pavement Section



(b) Uneven Pavement Section

Figure 3. Comparison of Signals before and after Filtering

2.3.2 Construction of multi-dimensional vibration features and physical consistency analysis

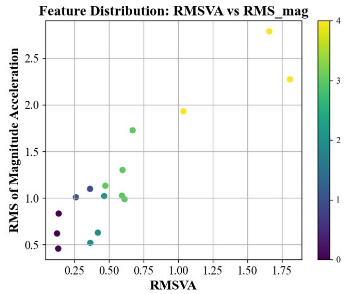
After the preprocessing of acceleration signals, it is necessary to construct feature representations that can stably characterize pavement roughness and enable automatic pavement roughness grading [9]. Although the root mean square of vertical acceleration (RMSVA) can effectively describe pavement excitation intensity from an energy perspective, the robustness of a single feature is still limited under different device installation conditions and riding scenarios. To enhance the adaptability of the model to complex operating conditions, this study constructs a multidimensional vibration feature fusion representation based on RMSVA and adopts a support vector machine (SVM) for supervised classification [10].

For the tri-axial acceleration signals processed by zero-phase high-pass filtering, statistical features are extracted separately from the vertical (z-axis) and horizontal (x- and y-axis) directions and then fused. The feature set includes the root mean square (RMSVA), standard deviation, peak-to-peak value, and maximum absolute value of the vertical acceleration; the root mean square, standard deviation, and peak-to-peak value of the acceleration in the x- and y-directions; as well as the root mean square of the resultant tri-axial acceleration RMS_{mag} and the proportion of vertical vibration energy r_v. Accordingly, each sample is represented as

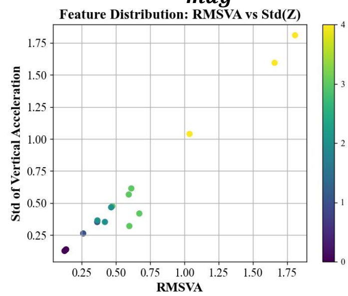
$$\mathbf{x}_i = [RMSVA, \sigma_z, PP_z, A_z^{max}, RMS_x, \sigma_x, PP_x, RMS_y, \sigma_y, PP_y, RMS_{mag}, r_v]^T \quad (5)$$

Here, RMSVA is used as the core indicator to characterise the excitation intensity caused by pavement roughness. The remaining features describe the vibration response in terms of dispersion, impulsiveness, and spatial distribution. In this way, the discriminative ability for complex pavement conditions is improved while physical interpretability is preserved.

To examine the physical rationality of the constructed multidimensional features, the correlations between RMSVA and other representative features are analysed. As shown in Figure 4(a), RMSVA exhibits a pronounced monotonic increasing relationship with the resultant vibration intensity RMS_{mag}, and samples of different grades present a clearly stratified distribution in the feature space. As shown in Figure 4(b), RMSVA shows an approximately linear positive correlation with the standard deviation of vertical acceleration σ_z, with limited overlap between samples of different grades. These results indicate that the multidimensional features are physically consistent with RMSVA and provide complementary descriptions of the same vibration process from different perspectives.



(a) Relationship between RMSVA and RMS_{mag}



(b) Relationship between RMSVA and the Standard Deviation of Vertical Acceleration

Figure 4. Correlation between RMSVA and Representative Features

2.3.3 Roughness grading rules and SVM classification model

Let the vertical acceleration sequence after zero-phase high-pass filtering be denoted as $y[n]$. The RMSVA is defined as:

$$\text{RMSVA} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} y^2[n]} \quad (6)$$

This metric provides a stable energy-based characterization of vertical vibration intensity. It exhibits certain robustness to instantaneous outliers while maintaining good sensitivity to persistent road unevenness.

To establish a unified and stable evaluation criterion, a fixed-threshold method based on RMSVA is adopted to assign samples into five roughness levels, ranked from best to worst as Excellent, Good, Fair, Poor, and Very Poor. The corresponding threshold values are defined as:

$$[T_1, T_2, T_3, T_4] = [0.163, 0.366, 0.472, 0.966] \quad (7)$$

The threshold-based classification results are illustrated in Figure 5. The proposed grading rule demonstrates good stability across multiple experimental datasets.

After constructing the multidimensional vibration feature representation and assigning roughness labels to the samples, a Support Vector Machine (SVM) was further introduced to build a multi-class classification model. It should be emphasized that the purpose of introducing the SVM in this study is not to replace the RMSVA indicator itself, but rather to verify whether the decision structure learned in the multidimensional feature space is consistent with the physical grading rule based on RMSVA.

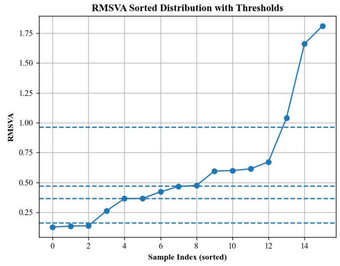


Figure 5. Distribution of RMSVA Values and Threshold-Based Classification Boundaries

The experimental data were collected from multiple continuous riding segments under seven typical road surface conditions. Each road segment was divided into samples using a fixed-length time window. Each sample was represented by a 12-dimensional statistical vibration feature vector and labeled into one of five roughness grades (“Excellent”, “Good”, “Fair”, “Poor”, and “Very Poor”) according to the fixed RMSVA threshold rule.

In the modelling procedure, ten samples were first selected to train the initial SVM model. Six independent samples that were not used in training were then introduced in two batches for consistency validation. The newly added samples in each batch were used only for model prediction and comparison, and were not included in parameter re-training. This design was used to examine the stability and consistency between the SVM predictions and the physical grading rule.

As this task involves a small sample size, multiple features, and a nonlinearly separable classification problem, the radial basis function (RBF) was chosen as the kernel of the SVM, defined as

$$K(x_i, x_j) = \exp\left(-\gamma \parallel x_i - x_j \parallel^2\right) \qquad (8)$$

The one-versus-one (OvO) strategy was adopted to implement the five-class classification. For model selection, the penalty parameter C and the kernel parameter γ were jointly optimised on the training data using a grid search. The final parameter values were set to $C = 1$ and $\gamma = 0.01$. After model training, the six previously unseen samples were fed into the trained SVM in two batches for prediction, and the predicted labels were compared with the physical grading results obtained from the RMSVA threshold rule. The confusion matrix between the two methods is shown in Figure 6.

The results indicate that the SVM predictions are highly consistent with the RMSVA-based grading results for the majority of samples, with an overall agreement rate of approximately 93%. The grades “Excellent”, “Good”, “Poor”, and “Very Poor” achieve complete agreement, while only a few samples in the “Fair” category near the grade boundaries are classified into adjacent levels.

Further analysis shows that the discrepancies mainly occur around the RMSVA threshold boundaries, indicating that when the vibration intensity is close to the grading limits, the combined effect of different statistical features in the multidimensional feature space may slightly influence the decision boundary. Overall, the decision structure learned by the SVM in the multidimensional feature space remains highly consistent with the physical grading rule based on RMSVA, which verifies the structural consistency and rationality of the proposed feature representation and grading scheme. The pavement roughness classification is presented in Table 1.

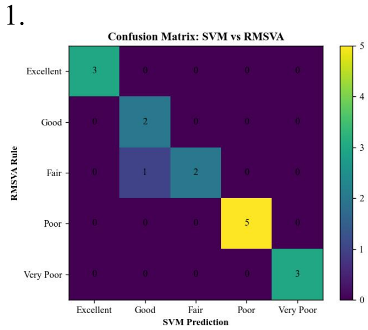


Figure 6. Confusion Matrix Comparing RMSVA-Based Grading and SVM Classification Results

Table 1. Road Surface Roughness Classification Criteria

Smoothness Level	RMS Acceleration (m/s²)	Description of Pavement Condition
Level 1 (Excellent)	[0, 0.163)	Very smooth surface with good continuity; negligible vibration during riding.
Level 2 (Good)	[0.163,0.366)	Slight surface irregularities; minor vibration with no noticeable impact on riding comfort.
Level 3 (Fair)	[0.366, 0.472)	Moderate roughness with localized irregularities; continuous riding remains acceptable.

Level 4 (Poor)	[0.472, 0.966)	Obvious roughness with visible defects or depressions; reduced riding comfort.
Level 5 (Very Poor)	≥0.966	Severe surface deterioration with strong and sustained vibrations, posing potential safety risks.

3. Experimental Analysis

3.1 Software and Hardware Environment

The software is developed on the Android platform and consists of three main user interfaces: a measurement interface, a map interface, and a data management interface. The measurement interface is used to collect road surface smoothness data. The map interface provides map browsing and visualisation of smoothness results, and also supports measurement functions. The data management interface allows users to view and manage local measurement records. The Android data acquisition interface is shown in Figure 7.

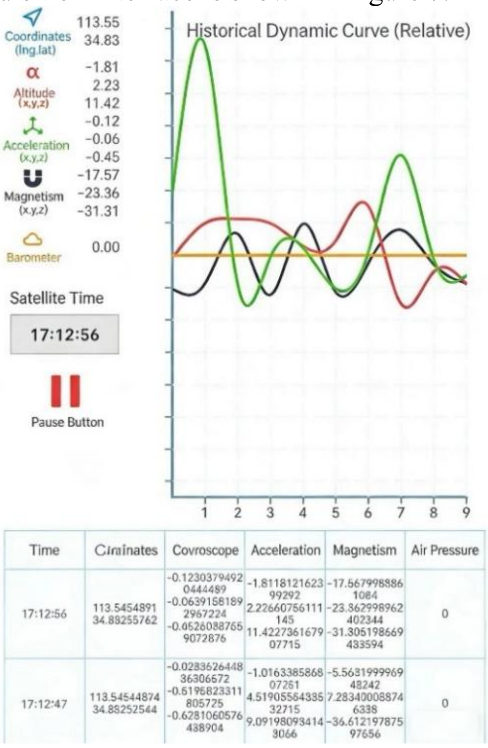


Figure 7. Software Platform

The test vehicle is a relatively new and well-performing electric-assisted bicycle. A phone holder is mounted on the left handlebar, and the smartphone is secured in the holder so that its body remains level, with the longest side parallel to the vehicle. This setup ensures that the Z-axis of the phone points vertically upward, and the Y-axis is parallel to the vehicle and oriented toward the front, guaranteeing accurate sensor data acquisition. The measurement setup is shown in Figure 8.

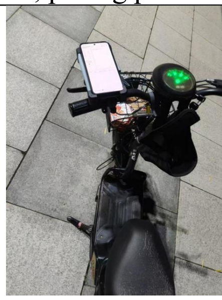


Figure 8. Measurement Equipment

3.2 Test Road Sections

Field measurements were conducted on multiple representative road sections within and around the Lianhua Street Campus of Henan University of Technology, resulting in a total of 12 riding experiments. The raw data were consolidated and organized according to pavement materials and structural characteristics, and the samples were ultimately categorized into seven typical pavement types: asphalt pavement, marble pavement, concrete pavement, uneven brick pavement, small square brick pavement, composite pavement, and manhole cover areas. The test road sections were relatively concentrated spatially, and data collection experiments were carried out independently for each section.

During testing, the electric-assisted bicycle maintained an approximately constant speed, while a custom-developed data acquisition application recorded the smartphone's three-axis acceleration signals in real time. To enhance data stability and reliability, each pavement type was measured 1–2 times. All experimental data were stored in CSV format, containing key information such as timestamps, three-axis acceleration, and the computed smoothness index (RMSVA).

3.3 Experimental Results and Analysis

3.3.1 Data processing indicators

In this study, the root mean square of vertical acceleration (RMSVA) was selected as the core feature for evaluating road surface smoothness, and the road surface classification was achieved in combination with the output of a support vector machine (SVM) model. The RMSVA quantifies the intensity of vertical vibration, with higher values indicating more severe vehicle vibrations and poorer pavement smoothness. The construction of this indicator refers to the evaluation principles of the International Roughness Index (IRI), ensuring that the classification system is both physically meaningful and engineering-interpretable.

3.3.2 Comparison between single-feature and multi-feature fusion models

To evaluate the effectiveness of the multidimensional vibration features in characterizing road surface smoothness, a comparative experiment was designed, in which a model using only the RMSVA as a single feature was compared with an SVM model incorporating multidimensional vibration statistical features. Both models were trained and tested on the same dataset with identical classification labels. The single-feature model used RMSVA as the sole input, whereas the multi-feature model employed the 12-dimensional vibration statistical feature vector constructed previously. Both models shared the same SVM architecture and parameter settings to ensure a fair comparison.

Considering the limited sample size, five-fold cross-validation was used to assess model performance, and the mean classification accuracy over multiple repeated experiments was taken as the evaluation metric. The results indicate that the single-feature model achieved an average classification accuracy of 61.67%, while the introduction of multidimensional features increased the accuracy to 70.00%. These findings demonstrate that the multidimensional feature representation provides superior sample discriminability compared with the single RMSVA feature, as shown in Figure 9.

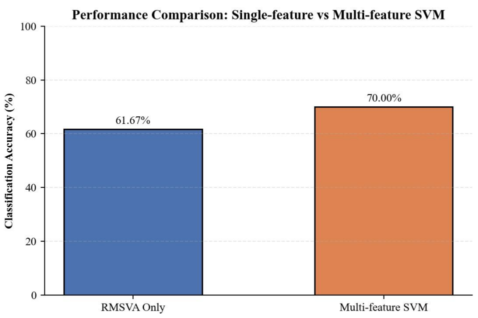


Figure 9. Comparison of Classification Accuracy between Single-Feature RMSVA Model and Multi-Feature Fusion SVM Model

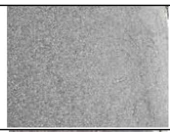
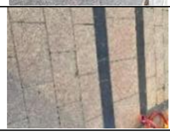
It should be noted that the purpose of this comparative experiment is to validate the effectiveness of multidimensional features in information representation, rather than to optimize classification accuracy. The results suggest that the constructed feature system maintains physical consistency while providing a more discriminative basis for subsequent classification.

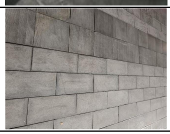
3.3.3 Comparison of pavement roughness among different road types

To ensure comparability among different pavement samples, continuous data collection was performed for each pavement type during the field riding tests. The duration of a single collection ranged from approximately 25 to 625 seconds, corresponding to a riding distance of no less than 200 m. The acquired continuous acceleration signals were segmented using fixed time windows, and a set of feature parameters was calculated for each window. As a result, 6 to 136 feature samples were generated for each pavement type. The overall sample sizes for different pavement types were of the same order of magnitude, sufficient to support subsequent statistical analysis and classification modeling. The collection durations and sample counts for each pavement type are summarized in Table 2.

Based on this analysis, Figure 10 presents seven typical pavement samples sorted in ascending order of RMSVA values, with the corresponding SVM-predicted pavement levels indicated using different colours. As RMSVA increases, the classified pavement levels generally evolve from “Excellent” to “Poor”. A high degree of consistency is observed between the RMSVA ranking and the SVM classification results, with only minor discrepancies occurring near classification boundaries. This indicates that the SVM model yields discriminative results in the multidimensional feature space that are well aligned with the physically meaningful RMSVA scale.

Table 2. Collection Durations and Sample Counts for Different Pavement Types

Pavement Section / Road Section Sample	Collection Duration (s)	Sample Image
Off-campus asphalt pavement	625	
Uneven on-campus asphalt pavement	218	
Campus composite pavement	196	

Uneven brick pavement 1	157	
On-campus asphalt pavement	152	
Marble pavement 1	126	
Asphalt pavement	51	
Uneven concrete pavement	49	
Small square brick pavement	47	
Uneven brick pavement 2	39	
Manhole cover area	37	
Marble pavement 2	25	

Although a five-level smoothness grading standard is defined in Table 1, the pavement samples exhibit clear clustering characteristics and can be broadly grouped into three vibration intensity ranges. This aggregation behavior explains the partial overlap between adjacent grades and confirms the stability of the proposed classification framework under complex pavement conditions.

From a pavement engineering perspective, surface smoothness is mainly influenced by material properties, construction quality, and in-service damage and maintenance conditions [11]. By integrating RMSVA with SVM-based multi-feature classification, the proposed method preserves the physical interpretability of vibration-based indicators while enhancing the ability to distinguish pavements with different deterioration levels. Overall, the smartphone-based pavement roughness evaluation approach demonstrates strong engineering applicability and offers a low-cost, scalable solution for routine monitoring and refined management of non-motorized road networks, which can provide technical support for pavement smoothness improvement and maintenance optimization [12].

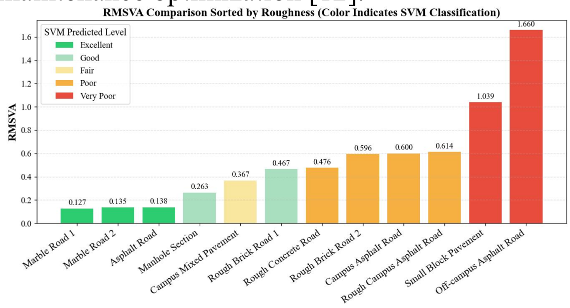


Figure 10. Correspondence between RMSVA Value Ranking and SVM Pavement Smoothness Levels

4. Conclusions

This study proposes a method for detecting and classifying non-motorized road surface smoothness based on smartphone sensors and a multi-feature fusion SVM model. Low-frequency interferences, such as gravity and attitude variations, were suppressed through coordinate transformation and zero-phase high-pass filtering. By integrating multidimensional vibration features with RMSVA as the core indicator, a physically interpretable representation of pavement conditions was achieved. Experimental results show that the SVM model's classification outcomes are highly consistent with the RMSVA-threshold-based grading rules, with an overall agreement rate of 93.75%. Moreover, different pavement types exhibit a strong monotonic correspondence between RMSVA values and classification levels. These results demonstrate the stability and generalizability of the proposed method under complex road conditions. With advantages such as easy accessibility of equipment, low cost, and flexible deployment, the approach is suitable for rapid inspection and auxiliary maintenance decision-making on non-motorized roads. Future work will focus on expanding the sample size and incorporating multi-condition data to further enhance the model's generalization capability.

Acknowledgments

This work was supported by the Undergraduate Research Training Program of Henan University of Technology (No. 202510463129).

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