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Research Article

Analysis of Road Damages for Micro Mobility Vehicles Via Synthetic Data: Three-Axis Accelerometer-Based Machine Learning

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Keywords

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Data-driven,
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Abstract

The effect of road damages on the road surface on driver safety and comfort depends on the damping mechanism of the vehicle. Since micro mobility vehicles have small wheels, road damage affects them with varying severity. This study aims to determine road damage based on the response of bicycles, e-bikes, and e-scooters to the road surface. In order to achieve this goal, firstly synthetic data approach is adopted. There are 10 000 samples in this data set and it was produced on Google Colab based on Python. These samples simulate data collected with a three-axis accelerometer. In order for the road damage distributions to represent the real world, flat roads (undamaged), cracks and potholes are determined as 7 000, 2 000 and 1 000 samples, respectively. In order to prevent the distribution from being biased and to eliminate the overfitting problem, unbalanced class distribution and sensor noise are simulated. Random Forest algorithm is used for the classification of damages. The classification accuracy rate of the damages is 95%. In addition, the K-Means clustering algorithm helps analyze how each micro mobility vehicle type responds to road damages. The Silhouette Score is 0.543, which shows how intertwined the clusters are and how separate they are from each other. The results confirm that the proposed approach integrates well with real-world data. To validate model performance, researchers should collect real accelerometer data alongside simulated data.

1. Introduction

Sustainable and environmentally friendly solutions must be increasingly preferred in urban transportation [1,2]. Micro mobility vehicles are low-carbon footprint transportation alternatives such as bicycles, e-bikes, hoverboards, segways and e-scooters [3]. The classification groups these vehicles based on their type of transportation, motorization status, and assistance level. They are shown comparatively in the diagram given in Figure 1 [4]. It has the potential to reduce urban traffic congestion [5], reduce environmental pollution [6], solve the first-last mile problem [7], and make short-distance journeys more efficient [8]. Providing these positive effects contributes to cities being more sustainable. However, these vehicles have smaller wheel diameters and limited suspension systems compared to traditional motor vehicles [9].

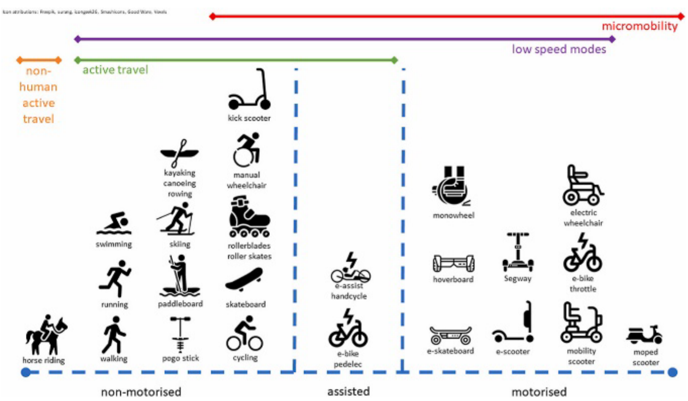

Figure 1. Transportation types and micro mobility categories

These features make these vehicles more sensitive to road surface deterioration. Road surface deterioration occurs due to external factors such as weather conditions, traffic composition and traffic volume [10]. In addition, internal factors such as the materials and workmanship used increase the deterioration. As a result of deterioration, many road damages such as potholes, cracks and alligator cracks occur in the road surface [11]. These damages negatively affect the driving dynamics of mobility vehicles, leading to loss of comfort, safety risks and accidents [12,13]. To do so, it is of great importance to detect road damage and integrate this information into the transportation infrastructure. Many studies have been carried out to detect road damage [14–17]. The methods used to detect road surface damage are expressed as object detection, laser beams, vibration-based and traditional [18].

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Traditional methods involve an expert manually scanning the road network by eye. This is an inefficient approach in terms of time and personnel. Nowadays, it has become common to perform road surface analysis using three-axis accelerometer sensors. These sensors allow determining the condition of the road surface by recording the vibration data of the vehicles. Object detection-based systems identify existing defects on the road surface in real time. However, it is a weak approach in providing information about pothole depths and crack widths. Researchers have primarily applied these approaches to motor vehicles. However, the degree to which micro mobility vehicles are affected by road damage is quite different.

This study develops a machine-learning model to detect road damages using three-axis accelerometer data from bicycles, e-bikes, and e-scooters. The aim was to test the applicability of this approach. In particular, obtaining and labelling accelerometer data with these vehicles is a very challenging process. First, we created a synthetic dataset of 10,000 samples using Python to simulate real-world road surface conditions. We modelled three different road surface conditions: undamaged, cracked, and pothole. The unbalanced data distribution in the datasets was simulated using sensor noise. Then, the classification of road damages was performed using the Random Forest (RF) algorithm. The difference in the wheel sizes of these vehicles causes the severity of the damages to be perceived differently. The K-Means clustering algorithm was applied to analyze the response of micro mobility vehicles to road surface conditions.

The research findings obtained from the analysis show the usability of the proposed solution approach in road surface evaluation processes. In the later stages of the study, it is aimed to evaluate the model performance more comprehensively by collecting real accelerometer data.

2. Research background

Detection of road damages with different methods is the focus of many researchers. In this section, studies carried out with accelerometers are mentioned. Vehicle vibration is the most obvious response to road damages. It has been proven by researchers that road anomalies can be detected from a relationship between the obtained vibration values and road surface properties [19–21]. Vibration-based methods are more economical and convenient than manual and laser-based inspections.

Lee et al. (2021) [22] detected road surface anomalies with accelerometer-based smartphone integration. 1896 road surface images were obtained and a road test was performed in which the corresponding three-axis acceleration data were obtained. The classification of road defects relies on the maximum change in Z-axis acceleration. The application of this system was carried out by attaching it to the windshield of a sports utility vehicle (SUV). Anaissi et al. (2019) [23] created a system that continuously monitors road conditions using on-board accelerometer sensors. Six months of data were obtained from this system installed on a school bus. The model detected road damage with 97.5% accuracy. A pothole detection system was developed by combining accelerometer data and in-car video data collected from participating users [24].

A road damage classification algorithm was developed using data collected from accelerometers. Since the aim was to detect potholes and ruts, the RF algorithm was used to classify these damages. A high accuracy of 97% and 85% was achieved, respectively [25]. To understand and detect the physical activities of different micro mobility vehicles, 502 trips were analysed. Thanks to the equipment provided to the drivers, the acceleration values at the time of driving were recorded and the driving differences of the micro mobility modes were shown [26].

Accelerometer-based road damage detection is limited in the literature. Some researchers have analysed the suspension systems of heavy vehicles using vibration data [27,28]. Today, the most commonly used approach to detect road damage is the image processing technique. Potholes and cracks are stated as the most dangerous road damage. Kaya and Çodur, (2025) [10] carried out the most comprehensive road damage detection study. They examined 10 road defects using road images obtained from eight different countries. Building an embedded system enabled the real-time detection of existing road damages. However, this solution approach cannot be used in snow and adverse weather conditions. In another study [29], the preference of micro mobility vehicles according to customer preferences was examined. The preference of different vehicles was analysed based on 16 evaluation criteria. The study emphasizes the comfort criterion as a key preference. Because the degree of micro mobility vehicles being affected by road damage is high.

Previous studies have primarily focused on traditional motor vehicles. Micro mobility vehicles continue to be seen as vulnerable traffic components in road networks. Micro mobility vehicles, such as bicycles, e-bikes, and e-scooters, have significantly smaller wheels and limited suspension systems, making them more sensitive to road surface irregularities. Due to their increasing penetration and lack of infrastructure, accidents occur. The burden of these accidents on the health system is increasing [30,31]. Despite these problems, the response of micro mobility vehicles to road damage has not been analysed. This study aims to fill this gap in the literature.

This study addresses this gap by:

- Developing a synthetic accelerometer dataset to analyse the impact of road damage on micro mobility vehicles.
- Applying Random Forest classification to detect different types of road defects.
- Using K-Means clustering to assess how micro mobility vehicles respond to road damages based on their vibration characteristics.
- By focusing on micro mobility vehicles, this research provides a novel perspective on road damage analysis and contributes to the development of safer infrastructure for sustainable urban mobility.

3. Material and Methods

In this study, three-axis accelerometer data were used to analyze the response of bicycles, e-bikes and e-scooters to road surface deteriorations. Since these vehicles have smaller wheel diameters compared to traditional motor vehicles, the intensity of vibrations they perceive from road damages is high. To do so, the relationship between road damages and micro mobility vehicles should be analyzed with accelerometers. Scanning road networks and obtaining data with each of these vehicles is difficult and costly. The proposed solution approach should be tested using synthetic data before real field data. The data expected to be obtained from accelerometer sensors was simulated to reflect real-world physical effects. The synthetic dataset consists of three different categories: smooth road (undamaged), cracks and potholes in order to model road surface conditions. Damages consist of 10,000 samples in order to represent real-world data. The dataset contains 7000, 2000 and 1000 samples for undamaged roads, cracks and potholes, respectively. The dataset created is modelled to mimic real data obtained from accelerometer sensors. The algorithms must prevent overfitting and eliminate extreme values. Factors such as sensor noise and unbalanced class distribution are taken into account to increase the suitability of the data for the real world.

3.1. Synthetic Data Production

Since the collection of real accelerometer data is a time-consuming and costly process, the authors in the study preferred the synthetic data generation approach. The synthetic dataset was designed to mimic the accelerometer data expected to be obtained from the real road surface of micro mobility vehicles. The use of synthetic data allowed us to overcome the difficulties of data collection, train the model with a large dataset, and examine the behaviour of the model in different scenarios. First, the road surface was modelled by separating different categories as undamaged road, cracks and potholes. The vibrations expected to come from the road surface were generated according to the X, Y, Z axes. Table 1 presents sample values from the generated synthetic data.

Table 1. An example of a synthetic data set containing three-axis acceleration data

Timestamp	X	Y	Z	Vehicle type	Road conditions
470	$6x10^{12}$	0.0901239997591614	0.042088757304590	0	0
570	$1x10^{12}$	0.1183516168820029	0.095451989872327	0	0
690	$1x10^{12}$	0.1516374522785384	0.033802202308532	0	0
700	$1x10^{12}$	0.1687465235759062	0.101078210391818	0	0
81070	$1x10^{12}$	0.595126984820803	0.017135741271423	1	1
0:bicycle 1:e-scooter 2:e-bike			0:undamaged 1:cracks 2:pothole		

The validation of synthetic data followed a three-stage process. First, the statistical distributions of the generated data were analyzed to determine whether they were compatible with real-world accelerometer data. In particular, statistical measures such as mean, standard deviation, and distribution shape were evaluated to ensure that the synthetic data were similar to real-world data in the literature. In the second stage, the model was tested on both synthetic and real data. The aim here is to see how well the model trained with synthetic data can generalize to real-world data and to compare the performance metrics of the model. If the model provides high accuracy on synthetic data but shows low performance when tested with real data, this may indicate that the synthetic data does not fully represent the real world. In the final stage, we planned field tests by collecting real-world accelerometer data. Thus, the validity of the model for practical applications will be verified and the model parameters will be re-optimized with real data when necessary. This process aimed to evaluate the real-world performance of the model trained with synthetic data and to resolve potential incompatibilities.

We designed the dataset simulation to replicate the accelerometer data of real-world micro mobility vehicles. The simulation process consists of three main stages. In the first stage, acceleration distributions were determined for different road surface conditions (flat road, cracks, and potholes) and acceleration models specific to each road surface type were created. These distributions were designed by referencing micro mobility studies in the literature and real-world observations. In the second stage, different acceleration responses were modelled for each micro mobility vehicle type (bicycle, e-scooter, e-bike). Different acceleration values were created in the X, Y, and Z axes by considering the suspension systems, wheel dimensions, and interactions of the vehicles with the road surface. In the third stage, sensor noise and measurement errors were modelled to ensure that the simulated data were closer to the real world. Low-frequency vibrations and device measurement deviations were simulated with the random noise addition method. This process ensured that the synthetic dataset reflected the real-world measurement dynamics as much as possible.

3.2. Random Forest

RF is an ensemble learning method based on decision trees. It provides strong results in terms of both accuracy and generalization performance. RF creates decision trees defined in accordance with the user dataset. It is created using a random subset of the training data. Data features are effective factors in tree creation and splitting [32]. Splitting is done in a way that minimizes the variance of the target variable in each result subset. There are criteria such as accuracy, precision, recall and F1-score for evaluating the model.

3.3. K-means clustering algorithm

K-Means is one of the most widely used methods among clustering algorithms, which is one of the unsupervised learning techniques [33]. It aims to divide data with similar characteristics into a certain number of clusters. First, the user selects K (number of clusters) random center points. Based on the training data, a distance metric such as Euclidean distance is used to assign the nearest cluster center. The system repeatedly executes this process to determine the final cluster centers. It is frequently preferred by researchers due to its fast, scalable, applicable and adaptability to various application areas.

4. Micro mobility vehicles and road damage detection results

RF algorithm was preferred to classify the damage status of the road surface using synthetic accelerometer data. The model was trained with training data (80%) and evaluated on test data (20%). Accuracy was used as the model evaluation metric. As a result of model training, 95% accuracy rate was obtained. This high accuracy rate shows that the model is successful in distinguishing road damages. In addition, precision, recall and F1-score metrics were used to measure the classification performance of the trained model and are given in Table 2. Researchers frequently use these evaluation metrics. Precision measures the rate at which the examples predicted as positive by the model are truly positive. TP (True Positive) represents the examples predicted as positive by the model and are truly positive, while FP (False Positive) represents the examples predicted as positive by the model but are actually negative. Recall measures how well the model captures the examples that are truly positive. FN (False Negative) represents the examples that the model predicted as negative but are actually positive. The F1 score shows the balance as the harmonic average of Precision and Recall. Accuracy is another metric that shows the ratio of the total correct predictions of the model to all predictions. The formulations of the metrics are given below [34–36].

$$\boldsymbol{P} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \tag{1}$$

$$\boldsymbol{R} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \tag{2}$$

$$\boldsymbol{F1} = \boldsymbol{2}.\frac{\boldsymbol{PxR}}{\boldsymbol{P+R}} \tag{3}$$

$$\boldsymbol{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

Table 2. Model evaluation metric results

Vehicle type	P	R	F1-score	Support
0	0,99	0,99	0,99	1409
1	0,98	0,98	0,98	416
2	0,99	0,98	0,99	175

Support value shows the number of samples in the test data for each class. Bicycle has the most samples, while e-bike has the least samples. The model makes very high accuracy predictions. P, R and FR scores indicate that the model performs well. P and R values close to 1 indicate that the model is overfitting. However, testing with real world data is required to determine this definitively. When the test results are examined, it is observed that the model can correctly distinguish damaged road conditions such as cracks and potholes. This accuracy is important for road safety.

In this study, an analysis was performed to compare the performances of Random Forest and Support Vector Machine (SVM) algorithms for the classification of road surface defects. While Random Forest provides a model with high generalization ability by combining a large number of decision trees, SVM is more successful in capturing nonlinear decision boundaries. Therefore, both methods were evaluated to understand the success of the model in predicting road damages by comparing different classification strategies. The classification of road damages was analyzed using the SVM algorithm. SVM results provide close values compared to the RF algorithm. The accuracy rate was found to be approximately 94%. Figure 2 presents a comparative graph of the two perceptions.

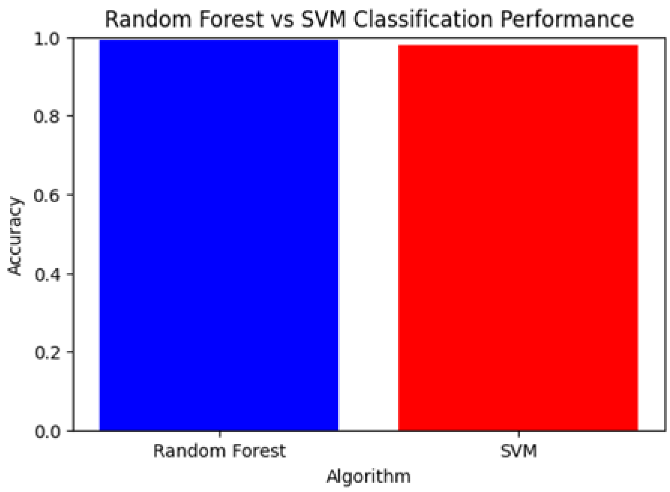

Figure 2. Comparison of classification algorithms

In this study, the K-Means clustering algorithm was applied to group the responses of bicycles, e-bikes and e-scooters to the road surface using three-axis acceleration data. The model determined 3 different clusters using the acceleration data on the X, Y and Z axes and the vehicle type. The K-Means algorithm created three different clusters determined as n_clusters=3. This process is the basic rule of the algorithm. The number of clusters was determined as a selection according to different road surface types and different responses of vehicle types. The clustering result allowed each data point to be assigned to a specific cluster. The cluster quality is evaluated with the silhouette score. The obtained Silhouette Score is 0.543, which provides information about the interconnectedness of the clusters and how separate they are from each other. The silhouette score shows that the clusters are reasonably separated from each other, but some points may have uncertainty between the classes. The distribution of the clusters on the X and Z axes is shown in Figure 3. The Z Axis represents the acceleration values of the vehicles on the vertical axis. It is the most important axis that shows the reactions that micro mobility vehicles receive from the road surface.

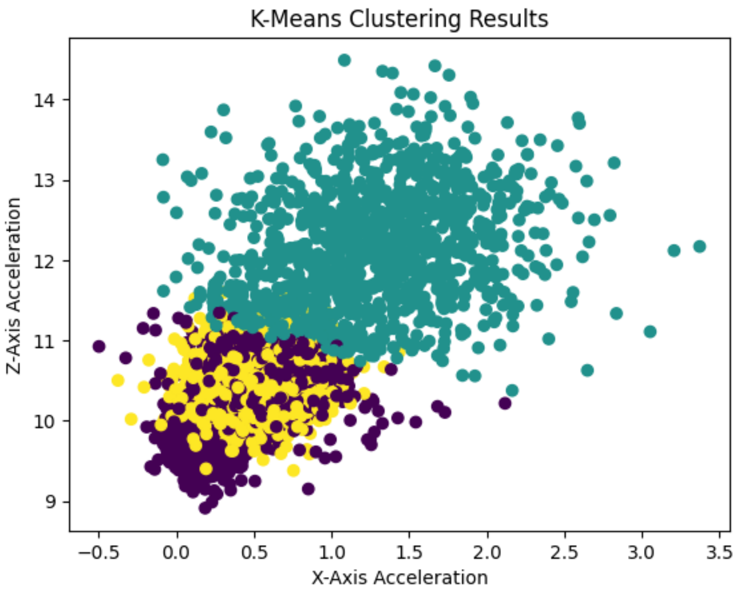

Figure 3. K-Means clustering visualization

In addition, K-Means clustering algorithm was applied for bicycle, e-scooter and e-bike vehicle types. After this process, the response of each vehicle to the road surface was analyzed. Silhouette scores for bicycle, e-scooter and e-bike were calculated as 0.3685698, 0.6013022 and 0.4144534, respectively. Figure 4 shows the clustering results for micro mobility vehicles. Since bicycles have small wheels and a suspension-free structure, they can be extremely sensitive to all road irregularities. These disadvantages caused the acceleration values to be more similar between the clusters. E-scooters have smaller wheels and a different suspension structure. Therefore, these features contributed to their clearer responses to different road damages. E-bikes are heavier and more stable vehicles than bicycles. Therefore, they have the ability to absorb shocks better.

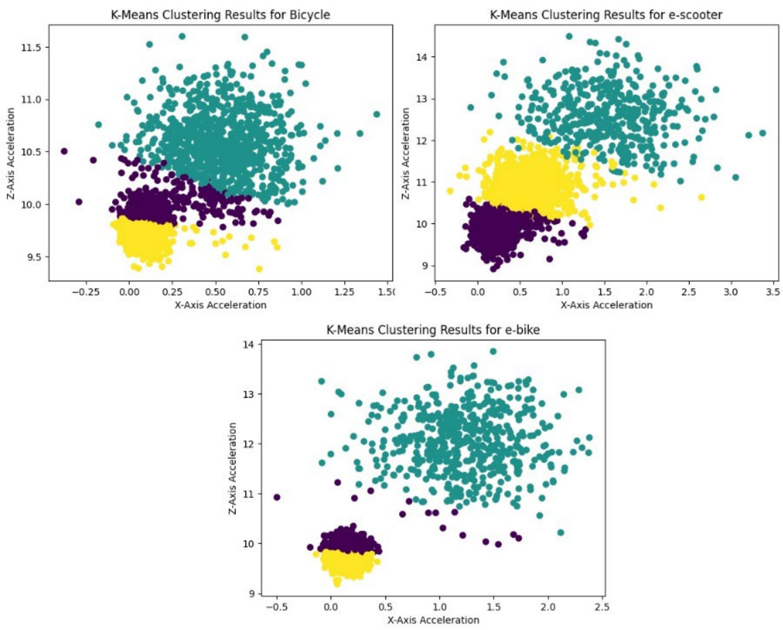

Figure 4. Clustering results for micro mobility vehicles

In the process of matching the clustering results for bicycles with road defects, cluster 0 contains mostly data from flat roads (1500 flat roads, very few broken roads). For cluster 1, there may be a group with moderately broken roads (low flat road ratio, balanced crack and pothole ratios). For cluster 2, it usually matches data points containing potholes and broken roads.

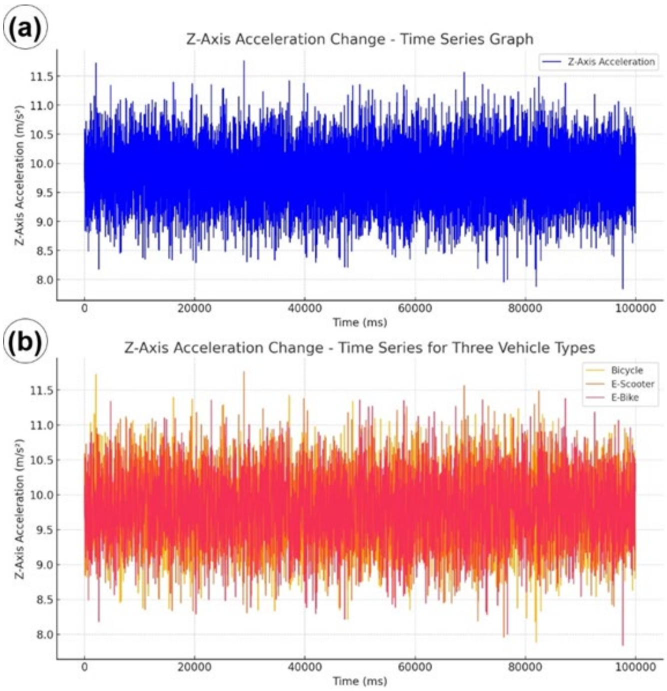

Figure 5. Z-Axis acceleration changes over time for different micro-mobility vehicles

The graphs illustrate the variations in Z-axis acceleration (m/s²) over time (ms) for bicycles, e-scooters, and e-bikes traveling on different road conditions. The Figure 5 (a) provides an overall representation of Z-axis acceleration fluctuations across the dataset, while the Figure 5 (b) differentiates between vehicle types. Each vehicle type exhibits distinct acceleration patterns, reflecting their varying suspension systems and wheel sizes.

In particular, bicycles tend to have smoother acceleration variations due to their larger wheels and better shock absorption. In contrast, e-scooters exhibit more pronounced fluctuations, as their smaller wheels and lack of suspension systems make them more sensitive to road irregularities. E-bikes show intermediate behaviour, benefiting from motorized assistance and improved suspension. These results highlight the importance of considering vehicle-specific dynamics when analyzing road surface conditions through acceleration data.

The data used in these graphs were synthetically generated based on Gaussian distributions with parameters derived from real-world accelerometer data. Additionally, sensor noise and random perturbations were incorporated to simulate real-world measurement conditions. This approach ensures that the dataset realistically captures the expected behaviour of micro-mobility vehicles under different road conditions, making it suitable for training and validating machine learning models.

It is normal for acceleration values to provide different results depending on the type of micro mobility vehicle. The fact that e-scooters have small wheels increases the severity of road damage. However, 95% accuracy rate was achieved in the classification made based on acceleration values. The values found in other studies in the literature using the object detection approach are discussed in this section. In a study, mAP values were found as 61.6 and 76.9, respectively, using YOLOv5 and YOLOv5s models [37]. In another study, F1 score was determined as 74.24% [16]. These values vary depending on many factors. Factors such as data structure, number of data, data quality, number of classes, used algorithm and user experience affect the accuracy of the models. In order to compare the models, testing should be performed on the same data set.

In summary, this study provides an important contribution to understanding how micro mobility vehicles are affected by road surface damage. Micro mobility vehicles have become one of the essential components of sustainable and environmentally friendly transportation solutions. However, current city infrastructures are generally designed with motor vehicles in mind, and the safety and comfort of small-wheeled vehicles such as bicycles, e-bikes and e-scooters are often neglected. This study provides valuable data to road maintenance teams, urban planners and policy makers to better understand the risks faced by micro mobility users and to develop safer transportation infrastructures. In addition, the findings obtained can contribute to the development of real-time road damage detection and user guidance systems by integrating them into smart city applications. Thus, sustainable transportation can be promoted, traffic accidents can be prevented and urban mobility can be made safer.

5. Conclusion

In this study, a machine learning based solution approach is proposed to understand the response of micro mobility vehicles such as bicycles, e-bikes and e-scooters to road surface conditions and to classify road defects. Three-axis accelerometer (X, Y, Z) vibration model is used to understand the relationship between road damage and micro mobility vehicles. Synthetic data generation is performed and road surfaces are detected using RF classification model. In addition, the response of different micro mobility vehicles to road surface defects is analyzed using K-Means clustering algorithm. The research findings obtained in the study are listed below.

- A 95% accuracy rate was achieved in the road surface classification using the RF model. This value provided by synthetic data shows that real accelerometer data can successfully distinguish road surface defects.
- The sensitivity of micro mobility vehicles to road defects was analyzed with the K-Means clustering algorithm.
- The model calculated the Silhouette score for e-scooters as 0.601. The analysis showed that e-scooters reacted to road defects with the clearest distinction.

- As a result of the clustering analysis, it was observed that the road surface conditions were clearly separated as undamaged road, cracks and potholes.

This study presented an effective solution approach to analyze the relationship between micro mobility vehicles and road damages and demonstrated the potential of the machine learning-based approach.

However, some limitations should be acknowledged. One of the primary limitations is the use of synthetic data instead of real-world accelerometer measurements. Although synthetic data generation ensures control over class distribution and sensor noise, real-world road conditions may introduce additional complexities such as environmental variations, different vehicle loads, and road surface inconsistencies. Another limitation is the focus on only three types of micro mobility vehicles (bicycles, e-bikes, and e-scooters), whereas other forms of micro mobility, such as hover boards and segways, may exhibit different responses to road damages. Furthermore, while the RF classifier demonstrated high accuracy, the generalizability of the model should be tested on real-world datasets to validate its robustness across different urban environments.

For future research, real-world accelerometer data should be collected to evaluate the performance of the proposed model under actual road conditions. Additionally, incorporating deep learning models, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), could enhance classification accuracy by capturing complex temporal patterns in accelerometer signals. Further studies may also explore integrating additional features, such as GPS data and environmental factors, to improve the reliability of road damage detection systems. Moreover, expanding the scope of vehicle types and testing the model in diverse urban and rural settings could provide deeper insights into the impact of road conditions on micro mobility safety and comfort.

Nomenclature

X-Axis: Measures left-right movements

Y-Axis: Measures forward-backward movements
Z-Axis: Measures up-down movements

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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