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Review

A Comprehensive Review of Smartphone and Other Device-Based Techniques for Road Surface Monitoring

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Abstract: Deteriorating road infrastructure is a global concern, especially in low-income countries where financial and technological constraints hinder effective monitoring and maintenance. Traditional methods, like inertial profilers, are expensive and complex, making them unsuitable for large-scale use. This paper explores the integration of cost-effective, scalable smartphone technologies for road surface monitoring. Smartphone sensors, such as accelerometers and gyroscopes, combined with data preprocessing techniques like filtering and reorientation, improve the quality of collected data. Machine learning algorithms, particularly CNNs, are utilized to classify road anomalies, enhancing detection accuracy and system efficiency. The results demonstrate that smartphone-based systems, paired with advanced data processing and machine learning, significantly reduce the cost and complexity of traditional road surveys. Future work could focus on improving sensor calibration, data synchronization, and machine learning models to handle diverse real-world conditions. These advancements will increase the accuracy and scalability of smartphone-based monitoring systems, particularly for urban areas requiring real-time data for rapid maintenance.

Keywords: road infrastructure; smartphone sensing; surface monitoring; data processing; machine learning

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1. Introduction

Recently, the integration of smartphone technology for civil infrastructure monitoring proved to be an innovative way to improve accuracy and timeliness in data collection. Smartphones provide an easily scalable, low-cost means due to their embedded sensors, including accelerometers, gyroscopes, and GPS modules for road surface condition assessment [1,2]. These capabilities are particularly useful in citizen-centered monitoring systems, where large datasets can be crowdsourced for more complete monitoring. Road infrastructure is among the so-called hard infrastructures underlying modern societies and economic development by efficiently connecting goods and people. Quality road infrastructure directly influences the economic performance of a nation's safety and its environmental sustainability. Pavement deterioration is a problem common to all parts of the world and one of the greatest challenges for road maintenance, especially in view of limited financial resources and advanced technologies in low-income countries [3–5].

1.1. The Role of Pavement Roughness in Infrastructure Performance

Pavement roughness usually remains the critical index with regard to comfort and the safety assurance of performance. It also has a direct impact on vehicle fuel consumption, the time spent by vehicles to travel, and maintenance costs, not to mention other wider implications at economic and environmental levels. The International Roughness Index (IRI) was developed in the 1980s during the World Bank-sponsored International Road Roughness Experiment in Brazil and has since been adopted as the world standard for the measurement of road surface roughness [6]. It is used over a wide area in Pavement Management Systems (PMS) for the assessment of functional and structural conditions during the decision on strategies of maintenance and rehabilitation [7,8].

Including the IRI data in the PMS is important because the roughness progression with time reflects the deterioration of pavement surfaces. Research has shown that IRI is not only a road quality indicator but also correlates well with vehicle operating costs and ride comfort; hence, it is an essential performance indicator [9,10]. Meegoda and Gao developed the IRI progression model, which estimated the growth of roughness based on the cumulative traffic load, structural number, and other environmental factors, such as precipitation and freeze index. The model, therefore, helps to estimate (for transport agencies) what is remaining of the service life of pavements and to carry out proper maintenance strategies. However, the collection of data about the IRI, even at present, is a very laborious and costly process despite its wide applicability [7,8].

Recent developments in pavement roughness prediction models based, for example, on Long-Term Pavement Performance (LTPP) data provide hope for reducing the data collection burden by giving better and better predictions using climate and traffic as inputs [9]. These models provide transportation agencies with tools to make informed decisions regarding appropriate and cost-effective maintenance interventions at both network and project levels. In addition, there is a simplification of the decision-making by using IRI as a performance indicator, since agencies can rely on roughness data when other forms of pavement distress measurements are not available [11]. This also makes IRI a major input in determining what sections of the roadways need maintenance or rehabilitation, particularly in instances where resources are limited and detailed distress measurement may not be feasible.

Correspondingly, IRI continues to play the same important role in summarizing pavement roughness as an integral part of infrastructure performance monitoring. Its role in PMS is to optimize resource allocation for road maintenance, supporting the sustainability of efficient transportation networks.

1.2. Traditional Road Roughness Measurement Techniques

Rod and level surveys, dipsticks, and profilographs are traditional road roughness measurement methods that have been in use over the past decades. These units usually depend on direct road profile measurements with manual or semi-automated data collection. Although they are very accurate, their major faults are that labor costs are high, the data collection rates slow, and their post-processing time is longer [6]. With the increase in the demand for better road monitoring, newer methods like lightweight profilers and high-speed inertial profilers came into being in order to generate data faster with more reliability without much loss to accuracy [7,12].

The May's Ride Meter and the Automatic Road Analyzer are examples of machines that estimate road roughness based on the response of the vehicle to the road. These are sensitive to the type of vehicle, weight of the vehicle, and the speed at which the vehicle is going, and are also susceptible to outside conditions. According to the ASTM E950 standards, roughness-measuring devices can be further classified into four classes. Class I consists of the precision profiling devices, including laser profilers, while Class II includes profilographs and high-speed inertial profilers, which are less precise but more commonly used. Class III devices are those that estimate the IRI by using correlation equations, while Class IV apply subjective ratings. However, these traditional methods are usually expensive and computationally cumbersome despite their reliability. They are thus not suitable for widespread applications, particularly in developing countries. Nevertheless, a shift towards automated and semi-automatic methods has lessened many of the problems. Automated systems reduce human effort and increase consistency, besides providing data at higher speeds, which is very important when monitoring extended road networks. However, even completely automated systems, like inertial profilers, are too expensive in terms of both equipment and maintenance costs and are hardly accessible in some regions.

Recent efforts have involved the development of more cost-effective systems that balance accuracy and affordability. For example, Bidgoli et al. (2019) [13] developed a sensor-based monitoring system equipped with accelerometers and a GPS module able to measure pavement roughness with enough accuracy at a small fraction of the traditionally spent costs. This low-cost approach has been particularly helpful in areas of low speed, where conventional high-speed profilers can hardly be effective. These advanced systems, with continued improvement in technology, are bound to find greater applications in road maintenance and management in the near future as a way of ensuring sustainability both for developed and developing nations [8,13–15].

1.3. The Emergence of Smartphone Sensors for Road Roughness Detection

Indeed, the increased pervasiveness of smartphones that are already equipped with on-board sensors has provided the means for a solution to detect road roughness at a very low cost with high scalability as shown in Figure 1. Unlike traditional measurement devices, the sensors in smartphones provide an easy, cheap way to collect data about the road surface in real time. These sensors, particularly the accelerometer and GPS, can capture the dynamics of a vehicle and its location to realize rough road surface detection and transient events, such as potholes and bumps, with a high degree of accuracy. Recent studies have shown [16,17] that smartphones are powerful tools in road roughness detection.

Li et al. [18] proposed a new crowdsourcing-based solution using the sensing capabilities provided by smartphones to collect data from a large number of users on the road surface. In this approach, the vertical acceleration caused by road irregularities is measured using an inbuilt accelerometer in the smartphone, while the GPS georeferenced each event, allowing the system to detect the event location and severity of the roughness events. The system picks up major changes in road quality and transient events (such as potholes) through the use of RMS values of accelerometers. Later, crowdsourced data are sent to the cloud-based server for aggregation and processing into comprehensive and real-time updates of road conditions. Accordingly, road maintenance agencies are able to make an effective determination of road quality and plan repairs accordingly in good time [19].

Compared to the traditional methods, smartphone-based road roughness detection presents some advantages. First, it reduces the cost of collecting data. Second, the innovative approach could allow continuous data collection since the users can passively contribute to road surface information during their daily commutes. While this approach improves the spatial and temporal coverage of roughness data, it also allows real-time updates that would enable authorities to monitor the state of roads in a more dynamic way and confront emerging problems [20]. Similarly, smartphone use enables new possibilities for better flexibility in road monitoring. This combination of an accelerometer and a GPS automatically georeferences the roughness measurements, facilitating the identification of problem sections of roads. Another great aspect of crowdsourcing in this technology is that even if one user navigates around a pothole, another might drive through it, enabling the system to detect and record the event with accuracy owing to multiple data points [21,22].

In the last decade, there has been an increasing acknowledgement of the capability of smartphone sensors in road condition monitoring through various research works such as [16,23,24]. The type of smartphone, the mounting position in the vehicle, the speed of the vehicle, and the vehicle's suspension system have all been identified to affect the accuracy and reliability of the roughness data collected using smartphones, as has been shown by Douangphachanh and Opara [25,26]. Figure 2 shows the general procedure for the real-time monitoring of road surface conditions from smartphones, which includes accelerometers that can capture vibrations caused by various forms of surface irregularities and a GPS selecting the position. For general preprocessing, which has to be carried out in order to have accurate and operational data, noise filtering and the reorientation of sensor data may be needed. Subfigure (a) represents the initial state where the smartphone's accelerometer records vibrations in the X, Y, and Z axes without any adjustments. This data reflects the raw acceleration values influenced by gravity and surface vibrations. Subfigure (b) illustrates the accelerometer readings reoriented to align with the vehicle's coordinate system, compensating for the effect of gravity during braking. This adjustment ensures that the X, Y, and Z axes now correspond accurately to the motion and orientation of the vehicle. Subfigure (c) demonstrates the final preprocessing step, where the GPS is activated to synchronize the accelerometer data with positional information. The reoriented accelerometer data (X', Y', Z') is now ready for further analysis of road surface conditions. For general preprocessing, which is essential to ensure accurate and reliable data, techniques such as noise filtering and the reorientation of sensor data are required [17,27]. These techniques become imperative for refining raw data from captured sensors and for helping to enhance the overall effectiveness of the monitoring system.

Figure 2 provides a diagrammatic representation of the use of smartphone sensors, such as accelerometers and GPS, to detect surface irregularities. In the figure, x represents the raw sensor data captured by the smartphone's accelerometer, while X is the preprocessed data after applying techniques like filtering and reorientation to enhance accuracy. X' denotes the final output, which represents the detected road irregularities, such as potholes or bumps, identified through machine learning models. This process ensures the accurate and reliable detection of surface anomalies for real-time road monitoring.

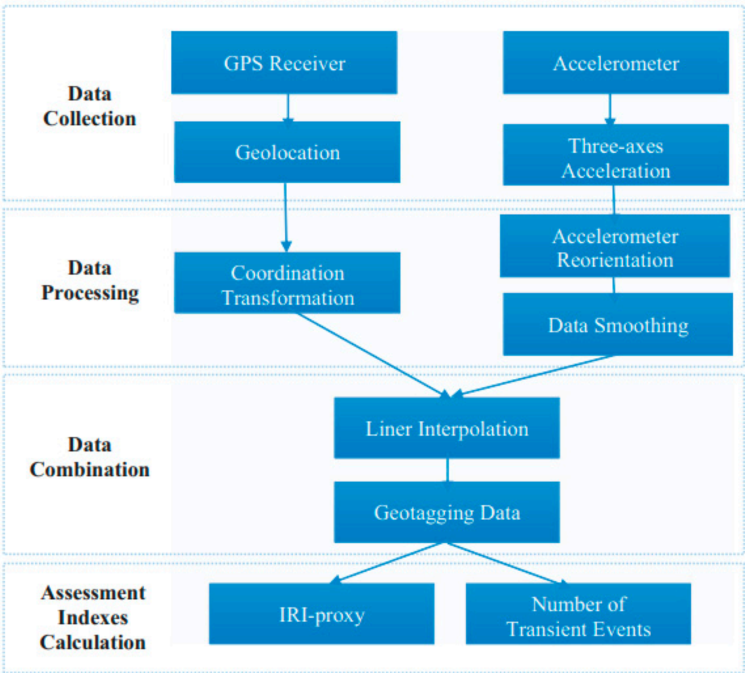

Figure 1. Integration of Global Positioning System (GPS) with smartphone sensors [28]. Reproduced with permission license number 589261145.

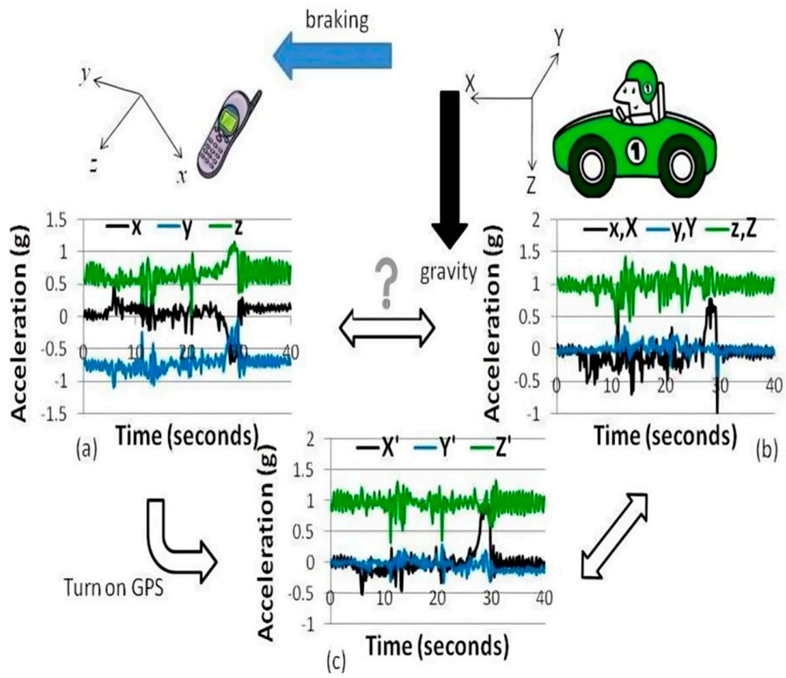

Figure 2. Real-time road surface condition monitoring using smartphones [29].

Despite significant development in the sensors of smartphones, issues such as the integration of data from accelerometers, gyroscopes, and GPS require further research for a better improvement in the precision of detection [30–32]. Nevertheless, while many research studies have used algorithms of machine learning to enhance the classification of road surface distress, variability in data quality and comprehensive training datasets still limits it [33–35]. Therefore, the paper originality and contribution lie in this novel comprehensive review of existing studies regarding the usage of smartphone sensors for the detection of road surface distresses by nurturing unexploited opportunities and novelties. This review goes beyond summarizing previous work by offering a critical assessment of the heterogeneous methodologies that were employed, such as sensor-based approaches that include accelerometers, gyroscopes, and GPS [36,37]. The strong and weak points are discussed for each methodology. Major challenges that have not been discussed in depth in the prior literature concern sensor data noise, accuracy on the diverse types of environmental conditions, and the complexity of real-time detection over varied road types.

Artificial intelligence (AI) and deep learning have transformed road anomaly detection, enabling more precise and efficient monitoring solutions. For instance, the YOLOv3 algorithm, as used in a study by Manalo et al., demonstrated its capability by achieving a mean average precision (mAP) of 96.16% for pothole detection, even with a limited dataset of 300 images [38]. This highlights the potential of deep learning in addressing traditional limitations, such as the need for extensive datasets and computational resources. Such advancements underscore the value of adopting AI-driven techniques to enhance the scalability and accuracy of road monitoring systems.

One of the highlights of this review is the discussion of the integration of novel technologies, such as machine learning algorithms, hybrid models joining supervised and unsupervised learning, and the possibility of fusing data coming from various sensors and devices, opening new opportunities towards higher detection precision and system scalability.

2. Methodologies for Road Surface Detection Using Smartphones

Traditionally, the roadmap for monitoring based on smartphones has focused on the gathering of accelerometer data, which measures the vertical movement of the vehicle. It relates to road roughness and transient events like potholes or bumps. Recent achievements have expanded the scope of smartphone-based road detection methodologies to image processing techniques and machine learning algorithms. For example, Ref. [39] have proposed a new methodology for road damage detection and classification through the use of deep neural networks (DNNs) from smartphone-captured images. In this approach, the camera in the smartphone takes pictures of the surface of the road, which, through a convolutional neural network (CNN), can recognize various types of damage: cracks, potholes, and surface wear. This tool has outgrown the usual sensor-based systems because of the visual analysis of road conditions, which results in a better accuracy of detection and, in particular, identification of damage types.

The authors of [39] trained the CNN model using the RAIJ dataset, which is composed of 9053 road images, to classify road damage into eight categories. The images of the road in real time are captured using a smartphone attached to the dashboard, while damage detection is directly carried out on the device or via cloud computing. This method reduces the processing cost overwhelmingly compared to more laborious traditional methods of road inspection, yet it allows for real-time data collection on a large scale, similar to the adopted crowdsourcing methodologies in the work of Li and Dey [18,40]. Image processing, integrated with sensor-based detection, brought in a more holistic approach to the monitoring of road surfaces. Whereas accelerometers measure the physical roughness of the road, images processed by deep learning algorithms give further information on the types and severity of road damage. This, in turn, has given a combined methodology for the more comprehensive assessment of road conditions and improved reliability in data collected through smartphone-based systems [41,42].

Apart from increasing the detection accuracy, crowdsourcing in those methods is the very factor that assists in scaling up road monitoring. Data obtained from various smartphone users can be integrated for continuous updates of real-world road conditions, thereby developing a dynamic and cost-effective solution for road infrastructure maintenance. Our view is supported by Singh [17]. Another example of major highway management using smartphones to detect damage to the roads, presented in the work of [39], can allow for immediate notification both to road maintenance authorities and drivers in order to improve road safety and decrease maintenance costs. That is, road surface detection with smartphones has moved from the simple sensor-based measurement of roughness to the elaboration of sophisticated systems that merge deep learning with image processing [43].

3. Challenges in Data Collection and Preprocessing

There are several fundamental issues with data collection and preprocessing in smartphone-based road surface detection. A major concern is sensor noise due to several issues, including but not limited to the mechanical causes of vehicle movement, environmental conditions, and even mounting position. It can occlude useful information from the data and hinder correct road anomaly detection, according to Douangphachanh and Singh [25,44]. Many research initiatives have, in turn, been carried out by applying preprocessing techniques like high-pass filtering and the reorientation of sensor data in order to remove noise and the irrelevant sampling of data points. Of course, there are many other noise reduction techniques that can be explored.

Another challenge is related to the dependency of sensor readings with respect to the speed. Sensor response will vary for the same road anomaly as vehicle speed changes. A pothole itself—a bump—can produce very different vibration patterns depending on the speed when the impact is there. This can be seen as one sort of inconsistency in data, making the development of good models for road surface detection challenging. To overcome this issue, some studies—like that of Seraj [45]—incorporated GPS speed data and combined it with accelerometer signals. Preprocessing techniques, such as wavelet decomposition and feature extraction techniques, may also be applied to reduce variability due to speed. This can be very useful to find meaningful features from sensor data independent of vehicle speed and can enhance the reliability of the overall anomaly detection systems. Besides speed, variations in roads, such as asphalt, concrete, or unpaved, and variations in environmental conditions, such as rain, snow, or other irregular surfaces, result in substantially differential sensor readings. Different conditions necessitated by such variability demand advanced data fusion techniques that are able to collaborate with the information obtained using multiple sensors, including gyroscopes and accelerometers, for consistent results over heterogeneous conditions, as illustrated in Figure 3 [16].

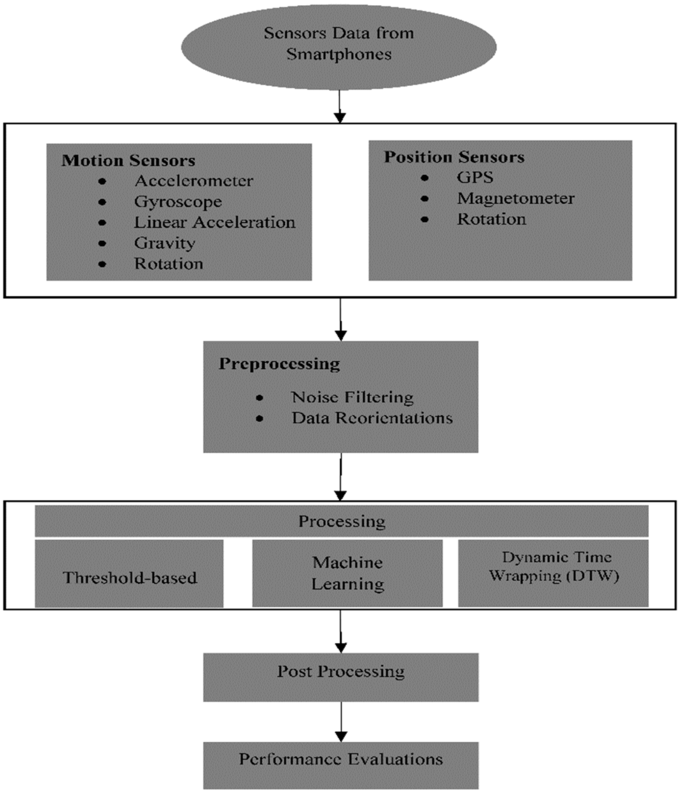

Figure 3. Smartphone distress detection process for road surface [16].

Finally, ensuring that the labeling of data is conducted accurately at the point of collection remains critical for the successful training of machine learning algorithms capable of correct classification of road anomalies. Seraj et al. [45] addressed this challenge by using an audio-visual technique to label data in such a way that the precision of the labeled datasets increases.

Meanwhile, the real-time processing of data remains one of the critical challenges in large-scale road monitoring systems. Large volumes of sensor data require advanced algorithms and efficient computing resources to process in real time. Other approaches utilize machine learning algorithms, such as support vector machines, to classify road anomalies in real-time into predefined categories using the data provided by these sensors [33,45]. However, due to the lack of rich, real-world training datasets, such machine learning models remain limited [34]. In summary, sensors on smartphones provide a highly feasible and easily scalable solution for detecting road surfaces. However, overcoming sensor noise, dependency related to traveling speeds, variability in data, and real-time processing are some of the issues associated with data. There is also much room for improvement in the development of preprocessing techniques, data fusion, and algorithms in machine learning that assist in overcoming these challenges and improving the accuracy and reliability of the smartphone-based road monitoring system.

Dynamic Time Warping (DTW) has been proposed as a solution to these limitations, offering an adaptive approach to anomaly detection. Unlike static thresholds or machine learning models, DTW effectively manages temporal and spatial variations in sensor data, making it ideal for resource-constrained devices like smartphones. For example, Singh et al. [17] demonstrated the utility of DTW in their “Smart Patrolling” system, achieving anomaly detection rates of 88.66% for potholes and 88.89% for bumps. This highlights the potential of combining DTW with crowdsourced data for accurate, real-time road monitoring.

3.1. Sensor-Based Data Collection Approaches

Advanced sensors provide ground for regarding smartphones as a cost-effective option for monitoring the road surface. All the important data points needed for the identification and classification of different road surface anomalies can be recorded using these sensors. Hardly any data point is missed that may relate to the presence of various types of defects or damage in the road surface, such as potholes, bumps, cracks, and roughness. The machine learning models deployed along with these sensors have made the smartphone-based road monitoring systems scalable and highly effective. The main purpose of an accelerometer is to measure the vertical instigation resulting from driving on anomalous road surfaces. It has been found to be one of the most effective methods for detecting road roughness, such as in the study by Zang et al. [32], where a high relation coefficient of r = 0.893 was recorded with professional-grade instruments for roughness assessment. Moreover, Douangphachanh and Oneyama [46] reported an accuracy as high as 70–90% in pothole detection when using accelerometer data. However, accuracy can be affected by mounting position of the smartphone and/or rider posture.

The gyro enhances the accelerometer by measuring rotational movements that generally increase the ability to detect road surface conditions. This sensor is effective in detecting lateral displacements such as ruts. Works, such as that by Allouch [47], have indeed identified that the use of gyroscope data in addition to accelerometer readings could raise the accuracy of detection to as much as 98.6%. This advantage in using a gyroscope may be hindered by the increased computational cost and higher energy consumption that such usage entails, an issue which may impact on real-time applications. Douangphachanh and Oneyama [46] emphasized the use of added information from a gyroscope as one avenue for the enhancement of accuracy in road roughness detection.

The GPS sensor provides valuable geolocation input data that allow to accurately tag and map road anomalies. This is relevant for generating high-resolution maps of road conditions to be used for planning purposes regarding repair priority. In fact, the usual accuracy of a GPS is from 5 to 10 m, but it can be interfered with by several factors, including signal interference and the urban environment. Li and Goldberg [28] stressed the contribution of GPS to accelerometer data when deciding on the reliable localization of road anomalies. However, signal interference owing to high-rise buildings is a persisting challenge.

The magnetometer, which gives the orientation to keep the axes of the smartphone aligned with the movements of the vehicle, improves accuracy in detection, particularly for roads with complex features like curves or inclines. Dey [40] showed that magnetometers, together with accelerometer data, could improve the performance of a road condition classifier to as high as 92% accuracy using machine learning approaches like support vector machines [48]. According to Mahajan and Dange [49], magnetometers improve the detection accuracy in difficult terrains like hilly areas. These sensor-based methods are further strengthened through preprocessing techniques that filter out noise and adjust the orientation of axes of the smartphone, hence providing a more accurate detection of road anomalies. Crowdsourcing data from multiple vehicles or users enhance the scalability of such monitoring systems, hence enabling wide coverage with no major investments in infrastructure. It enhances efficiency by improving the classification of road conditions through machine learning algorithms, such as K-means clustering, random forest, and convolutional neural networks. Each sensor contributes to an overall robust road surface monitoring system that offers scalability and cost-effectiveness, with the overall performance summarized in Table 1.

Table 1. Summary of sensor-based data collection approaches.

Sensor Type	Functionality	References	Pavement Defects	Detection Methodology	Accuracy Level	Limitations
Accelerometer	Measures vertical displacements for road roughness	[32]	Pothole, hump detection	Threshold-based, ML (SVM)	Strong correlation (r = 0.893)	Impacted by mounting position and rider posture
		[46]	Pothole detection	Threshold-based	70–90% accuracy	Susceptible to vehicle vibration noise
		[50]	Pothole detection	Participatory sensing, threshold-based	True positive rate up to 90%	Limited by smartphone hardware and software
		[27]	Pothole, hump detection	Threshold-based	100% detection up to 50 km/h	Severity estimation errors at high speeds
		[51]	Bumpy roads, braking events	Machine learning	High accuracy with ML (K-means, SVM)	Requires phone reorientation; affected by placement
		[47]	Pothole detection, smooth roads	C4.5 decision tree, machine learning	98.6% accuracy with decision tree	Requires combination with gyroscope
		[52]	Pothole, surface distortion, rutting, patching	Power Spectral Density (PSD), K-means clustering	84% accuracy with K-means clustering	Lower sampling rate to conserve battery life
GPS	Provides geolocation and speed data	[28]	Precise anomaly localization	Combined with accelerometer	5–10 m accuracy	Accuracy affected by signal interference and weather
		[50]	Localization of potholes	GPS localization integrated with accelerometer	Standard GPS accuracy (5–10 m)	Accuracy affected by signal strength, weather
		[53]	Geolocation for pothole detection	GPS coordinates used to map anomalies	Standard GPS accuracy	Impacted by signal strength and urban environments
		[16]	Provides geolocation for road anomalies	Combined with accelerometer	Standard GPS accuracy	GPS accuracy affected by urban environments and signal interference
		[52]	Geolocation for road anomalies	Combined with accelerometer	Standard GPS accuracy (4.9 m in open sky)	Signal interference in dense areas

Table 1. *Cont.*

Sensor Type	Functionality	References	Pavement Defects	Detection Methodology	Accuracy Level	Limitations
Gyroscope	Measures rotation to improve detection accuracy	[47]	Supports detection of potholes	Combined with accelerometer	98.6% accuracy with accelerometer	Adds computational overhead and energy consumption
		[53]	Supports detection of road irregularities	Statistical processing, DTW	High accuracy using statistical methods	Impacted by signal noise and environmental factors
		[16]	Enhances detection of road anomalies	Combined with accelerometer	Improved detection accuracy	High power consumption and complexity
		[46]	Road roughness	Combined with accelerometer for IRI estimation	R^2 up to 0.8	Higher computational power required
Magnetometer	Reorients phone's axes to align with vehicle	[51]	Indirect support for bump detection	Assists with accelerometer and GPS	Used for orientation	Susceptible to magnetic interference, power consumption
		[40]	Smooth roads, potholes, speed bumps, rumble strips	Machine learning (random forest, SVM)	High accuracy in combination with accelerometer (92%)	Susceptible to magnetic interference
		[49]	Potholes, road bumps	Combined with accelerometer for orientation	Improved accuracy with accelerometer combination	Susceptible to magnetic interference, particularly in urban environments
		[54]	Potholes	Black-box camera system	71% sensitivity, 88% precision	Affected by lighting; misses bright or flat potholes

3.2. Data Preprocessing Techniques

Data preprocessing is an important phase for making the data reliable and valid. A few filtering and transformation techniques are applied to the sensor data in order to remove noise and enhance the quality of the signals. The common techniques generally used in preprocessing sensor data are High-Pass Filtering, Low-Pass Filtering, Simple Moving Average (SMA), Reorientation, and Dynamic Time Warping (DTW), each of which has been found to be useful in enhancing certain aspects of monitoring road condition. Generally, high-pass filtering is used to filter out the low-frequency noise in the signals that may have been generated because of vehicle maneuvers, engine vibration, etc., or that may be due to external sources like wind. Figure 4 illustrates an example of a high-pass filter applied to sensor data, showing its effectiveness in reducing low-frequency noise; refs. [17,55] demonstrated in their 2017 work that there was an improvement of about 10% in the accuracy of pothole detection when high-pass filters were applied to accelerometer data. In a similar way, Qiqin Yu et al. [56] used high-pass filtering to exclude the low-frequency dynamics of the vehicle and improved road anomaly detection.

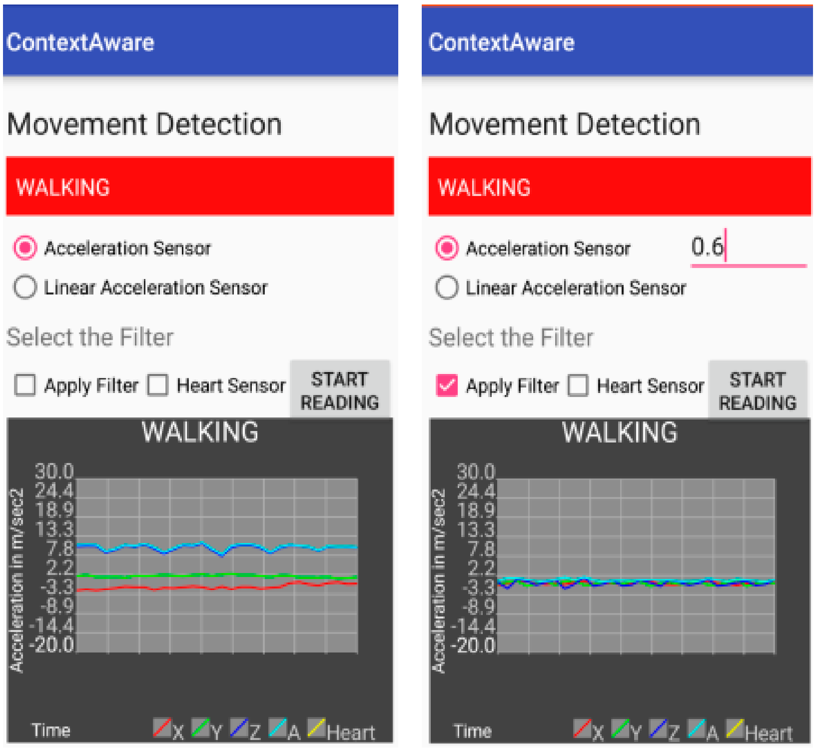

Figure 4. Example of a high-pass filter applied to sensor [55].

On the other hand, low-pass filtering removes the high-frequency noise while preserving the low-frequency signals useful for road surface anomalies. In fact, studies like that of Cabral et al. and Ronghua Du et al. [57,58] proved that low-pass filters eliminate irrelevant noises due to engine vibrations and improve the detection of low-frequency anomalies such as bumps. Qiqin Yu et al. [56] further emphasized its use in refining the accuracy of pavement roughness estimation.

Another smoothing technique, normally employed to the data to reduce its short-run fluctuation, is the Simple Moving Average (SMA). In this technique, successive equal periods' data are averaged together to bring out the underlying trend that may be hidden in transient noise. For instance, Shtayat et al. [59] discussed how the Simple Moving Average makes accelerometer data more consistent and hence helps to achieve higher accuracy for the road anomaly detection task, although there would be a trade-off between the extent of smoothing and the sharpness retention of significant features.

The reorientation of the smartphone when it does not align with the axes of the vehicle is crucial. This process adjusts the sensor data to align with the vehicle's coordinate system, ensuring accurate detection of road anomalies. This technique can transfer the sensor data into the vehicle coordinate system in a proper way for accurate road anomalies detection. According to Singh et al. and Achariyaviriya and Horanont [44,60], reorientation reduces directional errors and increases detectability, which may be affected if the position of the smartphone changes while collecting the data.

Finally, DTW is used for the similarity measurement of time-dependent sequences. Thus, DTW can be useful in finding out the pattern in sensor data. Zengwei Zheng et al. [61] have been able to successfully use DTW in conjunction with machine learning models for the detection and classification of the road anomalies and attained notably improved accuracy. Each of the above techniques plays a significant role in the preprocessing of raw sensor data, making it useful in many aspects and shedding influence on the ways in which smartphone-based road surface monitoring systems are highly accurate and efficient [62,63]. In Table 2, the key data preprocessing techniques that majorly find their place in smartphone-based road monitoring systems and their functionalities, advantages, and possible limitations are summarized.

Table 2. Summary of data preprocessing techniques.

Technique	Functionality	References	Application	Sensor Type	Effect on Accuracy	Limitations
High-Pass Filtering	Removes low-frequency noise	[17]	Enhances pothole detection	Accelerometer	+10% for pothole detection	May discard useful low-frequency data
		[64]	Filters out engine vibrations and suspension noise	Accelerometer	+10% for anomaly detection	May lose some useful low-frequency signals
		[59]	Reduces noise from vibration data for pavement monitoring	Accelerometer	Improves detection accuracy	Could discard some important signals
		[56]	Enhances anomaly detection by removing vehicle dynamics	Accelerometer	Improves anomaly detection	May miss certain low-frequency anomalies
Simple Moving Average (SMA)	Smooths out fluctuations to reduce noise	[17]	Reduces noise, retains significant changes	Accelerometer	+8% for pothole and bump detection	Can blur sudden anomalies
		[59]	Makes data consistent for analysis	Accelerometer	Improves data consistency	May blur minor details and anomalies
Reorientation	Aligns sensor data with vehicle axes	[17]	Reduces directional errors	Accelerometer, Gyroscope	Improves sensor accuracy	Requires vehicle orientation correction
		[60]	Ensures accurate data collection	Accelerometer, Magnetometer, GPS	Improves sensor accuracy	Can be complex to implement in real time
		[57]	Consistent sensor data collection	Accelerometer, Gyroscope	Improves sensor accuracy	Requires computational complexity
		[16]	Consistent data collection	Accelerometer	Improves detection accuracy	Requires correction algorithms
Low-Pass Filtering	Removes high-frequency noise	[57]	Reduces engine vibrations and irrelevant signals	Accelerometer	+7% for anomaly detection	Can discard important high-frequency details
		[16]	Enhances detection of low-frequency anomalies	Accelerometer	+7% for bump detection	Can lose high-frequency details
		[58]	Filters engine vibrations and other high-frequency noise	Accelerometer	+7% for road anomaly detection	May discard important high-frequency data
		[56]	Enhances pavement roughness estimation	Accelerometer	Improves roughness index accuracy	Could mask some high-frequency anomalies
Dynamic Time Warping (DTW)	Compares time-series data to detect patterns	[17]	Detects road anomalies (potholes, bumps)	Accelerometer	+12% for anomaly detection	Computationally intensive in real-time use
		[61]	Detects road anomalies such as potholes, bumps	Accelerometer, Gyroscope	+12% for anomaly detection	Computationally intensive for real-time use

Figure 5 shows the application of a Kalman filter, which is widely used to improve the accuracy of road roughness measurements by smoothing out noise and predicting the actual road profile based on sensor data.

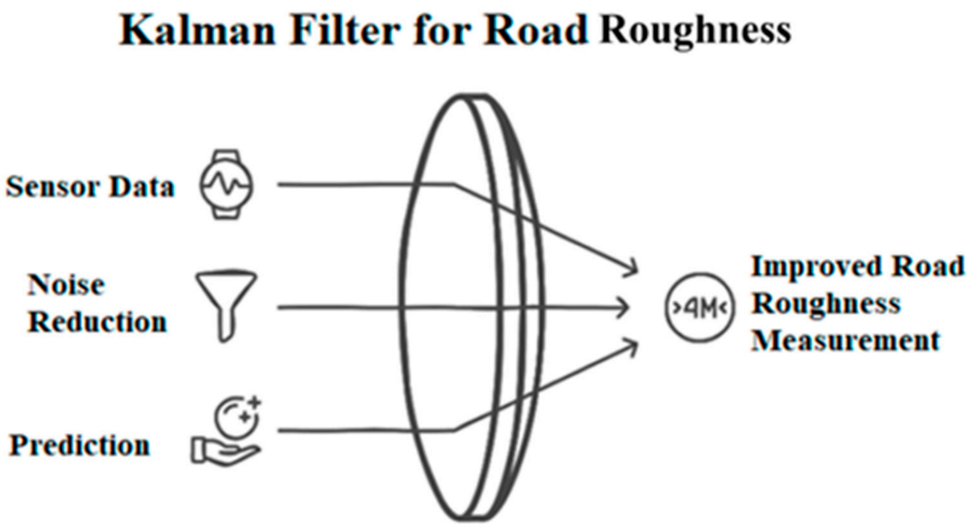

Figure 5. Application of a Kalman filter to improve sensor data accuracy.

Meanwhile, machine learning models applied for pavement and road surface condition monitoring make use of different technologies and preprocessing techniques. Decision trees and SVMs perform well in the classification of defects within the road surface. In particular, SVMs behave very well during winter conditions, while hybrid models are able to have better accuracy with transfer learning. Especially with the integration of transfer learning, CNNs turn out to be quite accurate in the detection and handling of surface damages and real-time road situations. RNNs, especially those with an LSTM-based nature, serve best for the analysis of temporal series data, such as pavement performance predictions or crowdsourced anomaly detection. A further comparison of the models is presented in Table 3, pointing out their accuracy, showing the adopted preprocessing methods used to enhance images and videos, and their results in different road and pavement conditions.

Table 3. Performance comparison of machine learning models for road surface detection.

Machine Learning Model	References	Functionality	Accuracy (%)	Robustness	Limitations
Decision Trees	[65]	Classifying mid-range road quality	75	Medium	Overfitting, mitigated with pruning
	[66]	Detecting pavement surface deformations	90 (after pruning)	Medium	Misclassification due to complex backgrounds
Support Vector Machines (SVMs)	[67]	Classifying hazardous road conditions (snow, ice, wet)	100 (training), <4 (generalization)	High	Reliance on external data (weather stations)
	[68]	Urban land-use classification	91	High	Struggles with noisy data in heterogeneous urban areas
	[69]	Asphalt pavement distress classification	95	Very High	Longer training times, dependent on image quality

Table 3. *Cont.*

Machine Learning Model	References	Functionality	Accuracy (%)	Robustness	Limitations
Convolutional Neural Networks (CNNs)	[70]	Road sign detection and surface damage classification	89	Very High	High computational cost, requires large datasets
	[71]	Road boundary and surface damage detection	98.7 (sensitivity)	Very High	Difficulty with low-height curbs and occlusions by vehicles
	[72]	Detecting cracks and potholes in tramway environments	98.7 (sensitivity)	Very High	Difficulty with small or large objects and scale variations
	[73]	Pothole detection and dimension estimation	96.3 (mAP)	Very High	Reliance on clear lane markings
	[74]	Pothole detection in bituminous roads	96	Very High	Dependent on well-constructed image datasets
	[75]	Real-time road situation recognition	91	Very High	High computational demand, delays in real-time processing
Recurrent Neural Networks (RNNs)	[76]	Detecting road surface anomalies from crowdsourced data	N/A	High	Noise and inconsistencies in crowdsourced data
	[77]	Predicting pavement performance (PCI and IRI)	R^2 of 0.81 for PCI, 0.79 for IRI	Very High	High data variability, requires extensive computational resources

3.3. Influence of Vehicle Dynamics

Prevalent vehicle dynamics, like speed, characteristics of the suspension system, and even aerodynamics, are very important in the topic of smartphone-based monitoring of road surfaces. These aspects sometimes may affect the data collected from sensors mounted on a smartphone and hence reduce the precision of detecting the road conditions. The transient aerodynamic effects would affect how accurately the smartphone sensors are able to capture the road anomalies. For example, the interaction of aerodynamics and vehicle suspension can generate changes in the vertical loading conditions of the vehicle axles, impacting accelerometer data utilized in roughness detection. Besides this, the suspension system acts to dampen the road irregularities to the dynamics of the vehicle. At the same time, vehicles with stiffer suspensions can easily transmit more vibration to the accelerometers of the smartphone, making them more sensitive to road roughness. On the other hand, those with softer suspensions will more likely dampen such vibrations, leading to underestimation in the severities of the road anomalies. The dynamic interaction between the road surface, the vehicle's suspension system, and the smartphone sensors causes variability in the data collected [78].

Moreover, the speed of travel influences directly the amplitude and frequency of oscillations sensed by in-car smartphone sensors. Indeed, at greater speeds, the vehicle may turn out to react differently to road irregularities—a fact that amplifies the effect of transient aerodynamic forces. Indeed, Aschwanden et al. [79] arrived at the conclusion that these transient forces might well result in greater changes in the downforce on the axles, both in the front and in the back, ultimately impacting the general handling of the vehicle. It becomes tough to standardize the roughness measurement across different vehicle speeds and driving conditions with this variability. In other words, the important role that may affect the accuracy of a smartphone-based road surface monitoring system involves vehicle dynamics: more specifically, the aerodynamics of motion, the characteristics of suspension, and speed [80]. Improvement in the reliability of these systems could be achieved by accounting for such variables through advanced data preprocessing techniques and vehicle-specific calibrations to make sure that the road roughness data indeed represents the actual condition of the road surface under different dynamic conditions.

4. Machine Learning for Road Surface Classification

In the 'Machine Learning for Road Surface Classification' section, the images used for crack classification were collected using smartphone cameras mounted on vehicle dashboards, ensuring consistent height and angle. Images were captured at a resolution of 1080p in JPEG format, with frame rates of 30 fps for dynamic collection during vehicle motion. The dataset includes various types of cracks (e.g., transverse, longitudinal, and alligator cracking) and was collected under different lighting and weather conditions to enhance model robustness. Preprocessing steps, including noise filtering and cropping, were applied to ensure image quality and relevance. These images were georeferenced using GPS to correlate crack types with specific locations, providing additional metadata for analysis.

After preprocessing, feature extraction and classification are critical steps in identifying specific types of road surface distress. Feature extraction identifies patterns within the sensor data that correspond to distinct anomalies on the road, as demonstrated by [34,81–83]. For example, the amplitude of the accelerometer may give information about the depth of a pothole, while frequency can be indicative of mostly small and numerous cracks. Figure 6 demonstrates the impact of vehicle speed on the accuracy of roughness measurements, highlighting how sensor data interpretation must account for speed variations to ensure the accurate classification of anomalies [16]. Machine learning algorithms have received considerable interest in the classification of road surface features, particularly for the detection of anomalies in the form of potholes, cracks, and smooth surfaces [16,84,85].

Figure 6 also illustrates the impact of vehicle speed on the accuracy of roughness measurements. The three lines represent different conditions under which roughness data were collected:

- The first line (solid) indicates measurements taken at low speeds (<30 km/h), where the accuracy is highest due to reduced vehicle dynamics and vibration effects.
- The second line (dashed) shows measurements at medium speeds (30–60 km/h), where moderate accuracy is observed.
- The third line (dotted) represents measurements at high speeds (>60 km/h), where accuracy decreases significantly due to increased noise and dynamic effects on the vehicle.

This graph highlights the importance of controlling vehicle speed during data collection to improve the reliability of roughness measurements.

Supervised learning methods include SVMs and decision trees that are greatly used in model training using labeled datasets to classify fresh data efficiently [28,51,85]. For example, Bhoraskar et al. [51] demonstrated that coupled with GPS, accelerometer data could detect potholes with a very high level of accuracy using sensors from smartphones. Similarly, Li and Goldberg [28] found that there was a marked efficiency in the way SVMs could distinguish these variances in distress on the road surface when accelerometer data and GPS were combined together. The results showed that, after being trained, the performance of SVMs in classifying road surface anomalies for potholes and cracks was quite good.

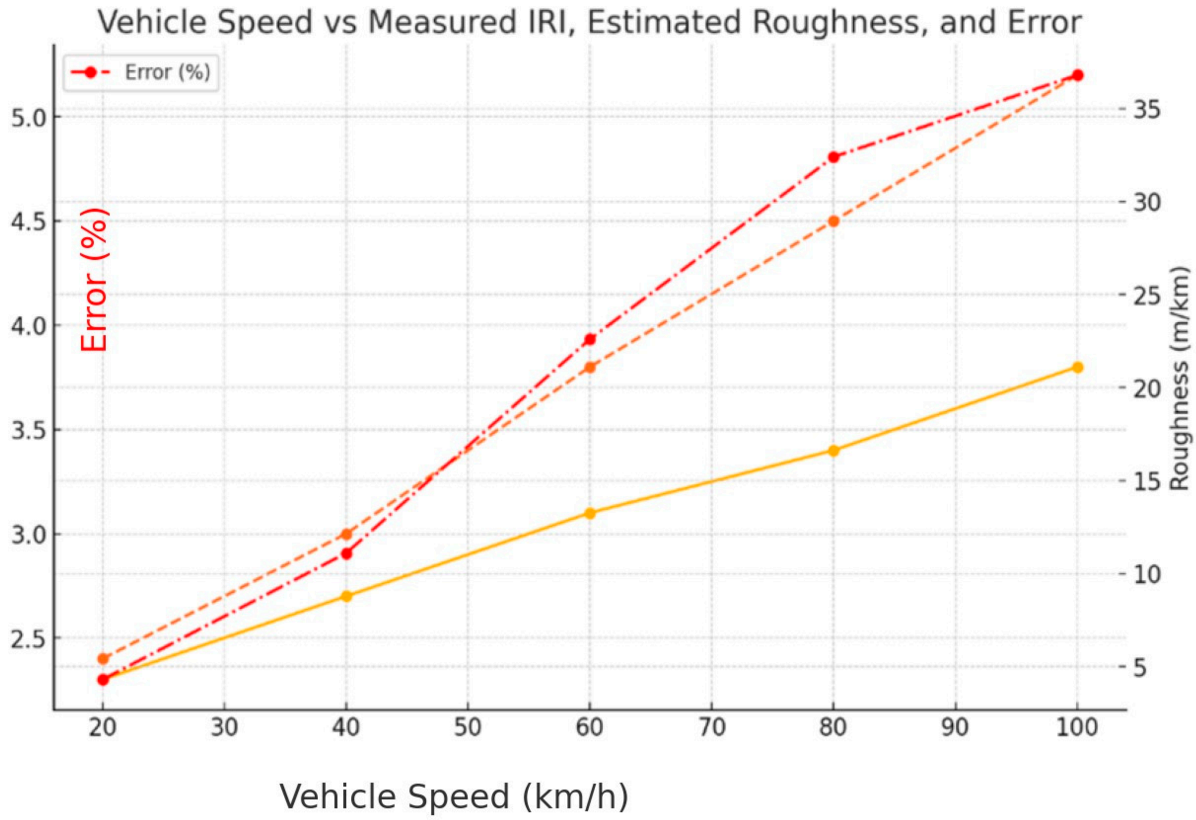

Figure 6. Impact of vehicle speed on roughness measurement accuracy.

Jalili et al. [86] addressed the limitations of SVMs and other linear models by utilizing Artificial Neural Networks (ANNs) to model non-linear relationships between vertical acceleration data and the International Roughness Index (IRI). Their approach incorporated crowdsourced smartphone data, using Root Mean Square of Acceleration (RMSA) and vehicle speed as inputs. The study reported a Mean Squared Error (MSE) of 0.56 and a Pearson correlation of 0.91, significantly outperforming traditional regression and SVM-based models. This work underscores the potential of combining ANN with crowdsourced data to enhance scalability and accuracy in road roughness monitoring.

Nguyen et al. [87] extended the application of Artificial Neural Networks (ANN) to estimate onboard bus ride comfort by utilizing multi-dimensional data. Their model included 20 input variables such as vehicle parameters (speed, acceleration, and jerk) and passenger-related attributes (posture, location, and anthropometric data). The ANN model achieved a high correlation coefficient (R = 0.83) and a low mean squared error (MSE = 0.03), effectively capturing non-linear interactions between objective and subjective factors. These results highlight ANN's adaptability to dynamic, real-world transportation challenges, further reinforcing its utility in transportation research.

Other decision tree-based works for the classification of road surface defects were proposed by Viner et al. and Zhang et al. [34,85]. The key feature of their decision trees was simplicity and real-time performance, and these performed quite well in distinguishing between smooth and distressed surfaces with large datasets in a very minimal processing time. Other authors compared SVMs with random forests. Sabir et al. [23] remark that SVMs yielded better performances concerning the identification of surface anomalies, while random forests are more versatile if dealing with noisy or unstructured data.

The efficiency of both approaches, using SVM and decision trees, was also confirmed by Fernández et al. (2016) [88]. They say that in the case of small cracks, SVM performance was relatively good, though the decision trees showed the best results in identifying big road defects like potholes. These collectively point to the massive potential of integrating machine learning models with data from smartphone sensors in the development of scalable, real-time road surface distress monitoring and detection solutions.

Figure 7 shows the structure of the decision tree model used in classifying each crack in the pavements. Based on the six features x1 through x6, the model identifies different types of cracks—longitudinal, transverse, and block cracks—and eliminates noise. The decision tree represents all possible decisions for each feature, providing a structured guide for the classification process. While descending in the tree, at every branch, this splits the data by these features until it reaches the terminal node, where it classifies the type of crack or noise. Thereby, the structure ensures effective and correct classification by narrowing down the possible outcomes systematically according to the features extracted from the crack images [89].

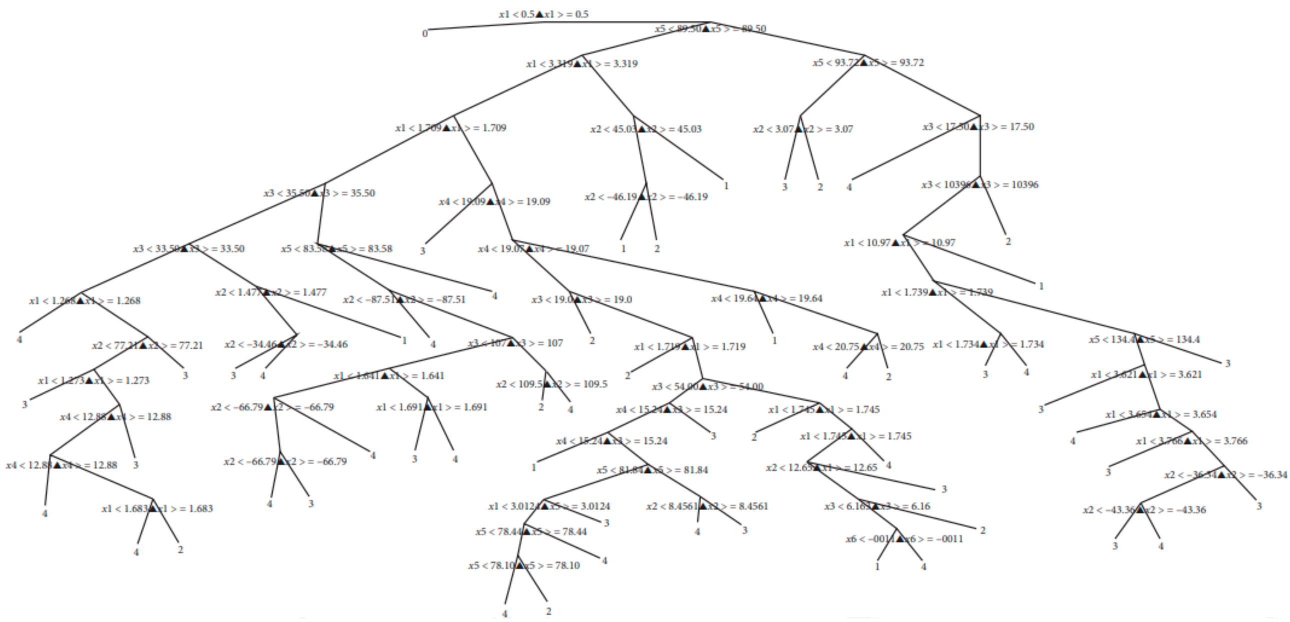

Figure 7. Decision tree model for classifying road surface distress [90].

In contrast with these models, unsupervised learning approaches, like K-means clustering, do not require labeled data in any form. Such methods are then applied for the classification of similar patterns with regard to the data, which can help in recognizing new types of road surface issues or when labeled data are not that abundant within certain environments [32,33,91]. For instance, Fernández, A., et al. (2016) [88], by using unsupervised learning, were able to classify sensor data into various sets of groupings, which enabled the detection of unknown road wear patterns. Similarly, Vlahogianni and Barmpounakis (2017) showed that unsupervised learning may be useful in detecting newly emerging conditions of the road surface that cannot be included in any of the classes of a classification system. Recently, there have been hybrid approaches that combine both unsupervised and supervised learning with tremendous potential for improving the accuracy and robustness of the detection of road surface distress; these techniques leverage the complementary strengths of both approaches in coming up with a more complete anomaly detection methodology. First, unsupervised learning is applied to find patterns that are hidden in the data from sensors or to cluster and find new types of road surface anomalies that would go otherwise unrecognized. This will reduce the dimensions of the data and group similar patterns, hence the ability to apply more accurate supervised learning classification to the clusters.

Several works have demonstrated that this kind of hybrid mechanism outperforms the traditional completely supervised models. For example, Sattar et al. (2018) [16] identified that their hybrid model, which used K-means clustering followed by decision trees, enhanced the accuracy by about 15% in comparison to decision tree classifiers alone. Similarly, Ref. [34] also reported that the K-means clustering as a preprocessing method reduced the noise and irrelevant data before enabling the decision tree to focus on the most important features, increasing pothole and crack detection accuracy by 12%. Another important aspect of using unsupervised clustering in the current approach is that it provides the possibility of discovering new road surface distress types that have previously never been labeled in training data, which increases the adaptability power of a model.

The use of hybrid models was also pointed out by Iakovidis, D. K., et al. (2021) [84] as reaching the foreground with substantial efficiency in real-world applications when labeled datasets were not available or incomplete. The hybrid models cluster unlabeled data in such a way that they identify the anomalies, feeding this to the supervised models for classification with greater precision. This helps to improve the detection of both common and rare types of road surface distress. Viner, H., et al. (2006) [85] emphasized that the combination of the unsupervised learning discovery power with the accuracy of classifications by means of supervised learning presents a more robust framework for large-scale monitoring systems.

Machine learning methods are only as good as the amount and quality of the data that they are being trained on. Indeed, it has been observed in a variety of works that larger, more diverse data results in more accurate models with great generalization toward new environments [33,81,92]. However, this extensive training data used in real-world applications is resource-intensive to collect and label and hence has a limitation in nature [23,34,85,93].

While the methodologies concerned with the detection of road surfaces based on mobile phones are promising, there is yet a constellation of challenges. Each method has its strong and weak points; in relation to this, the methodology chosen for any road maintenance project often depends on what is required: accuracy, scalability, processing in real-time, etc. [46,94,95]. Table 4 summarizes various machine learning techniques and their effectiveness in detecting different types of road surface distress. Future studies should be directed towards enhancing methods for data preprocessing, developing more sophisticated feature extraction methods, and improving the adaptability of machine learning models for various road conditions [31,33,84,88]. As detailed in Table 4, combining multiple methodologies could further capitalize on their respective strengths, offering more reliable and cost-effective solutions [85,91].

Added to this is the issue of the different sampling rates introduced by the different models of smartphones, hence the need to standardize data [28,50]. Another issue is the variability in hardware across smartphones: different models of smartphones have different types and qualities of fitted sensors; this heterogeneity will show variations in the data collected. It is this variability that calls for the development of algorithms to either normalize or compensate for these differences in a manner that would allow consistent road quality assessments from different devices [17,81].

Table 4. Machine learning techniques for road surface distress detection.

Machine Learning Model	References	Pavement Defects	Technology	Accuracy (%)	Preprocessing	Outcomes
Decision Trees	[65]	Surface defects (potholes, cracks, subsidence)	Accelerometer, gyroscope	75	High-pass filtering, linear interpolation, power spectrum analysis	Effective classification of mid-range road quality (Class 3)
	[66]	Pavement surface deformations (cracks, potholes)	UAV	90 (after pruning)	Gaussian filtering, Canny edge detection, morphological operations (opening and closing)	Effective for detecting pavement deformations from UAV images

Table 4. *Cont.*

Machine Learning Model	References	Pavement Defects	Technology	Accuracy (%)	Preprocessing	Outcomes
Support Vector Machines (SVMs)	[67]	Winter roads (snow, ice, wet)	MARWIS (mobile road weather sensors), vehicle sensors	100 (training), <4 (generalization)	Standardization of weather and road surface features	Accurate classification of hazardous road surface conditions, improving traffic safety
	[68]	Urban settings (built-up, bare land, vegetation, water bodies)	Satellite imagery (Landsat 8)	91	Geometric corrections, data standardization	Good classification of built-up areas and vegetation
	[69]	Asphalt pavement distresses (block cracking, fatigue cracking, potholes, rutting)	Pre-trained DL networks (AlexNet, ResNet50)	95	Transfer learning for feature extraction, followed by SVM classification	Superior classification performance with hybrid models, F1-score up to 0.96
Convolutional Neural Networks (CNNs)	[70]	Road sign detection, surface damage detection	Video-based data, UAV	89	Augmentation, normalization, anchor box calculation	High accuracy for road sign and surface damage detects
	[71]	Cracks, road boundaries, curbs, surface damage in urban environments	LiDAR, MMS	98.7 (sensitivity)	Ground filtering, slope and height difference detection	High accuracy and real-time detection of road boundaries
	[72]	Cracks, potholes, surface damage in urban roads crossed by tramway lines	LiDAR	98.7 (sensitivity)	Augmentation, normalization, inverse perspective mapping, Kalman filtering	High accuracy and real-time detection of pavement damage
	[73]	Pothole detection and dimension estimation on paved roads	Built-in vehicle camera, Lane-Keeping Assistance System	96.3 (mAP)	Data augmentation (flipping, rotation, zoom, brightness, etc.)	Cost-effective real-time pothole detection and dimension estimation using built-in vehicle technologies
	[74]	Potholes in bituminous roads	Built-in vehicle cameras, pre-trained AlexNet CNN	96	Background removal, noise reduction, feature extraction	Effective and efficient detection of potholes in bituminous roads using transfer learning
	[75]	Urban road situations (driving reverse, pedestrian detection, object falling)	Video surveillance cameras	91	Data augmentation, frame extraction, resizing, normalization	Effective at real-time road situation classification with high accuracy and precision
Recurrent Neural Networks (RNNs)	[76]	Urban roads (potholes, cracks, speed breakers)	Smartphone sensors (GPS, accelerometer, orientation)	N/A	Wavelet scattering transformation, spatial transformation	Effective for detecting road surface anomalies from crowdsourced trajectories
	[77]	Asphalt pavement sections (PCI, IRI prediction)	LTPP d	R^2 of 0.81 for PCI, 0.79 for IRI	Data filtering, normalization, one-hot encoding, feature extraction	Superior pavement performance prediction using LSTM with Attention mechanism

5. Data Fusion and Crowdsourcing in Road Surface Monitoring

Recently, crowdsourcing-based approaches have emerged as one of the major paradigms in road surface monitoring, leveraging data from thousands of smartphone users to effectively build real-time maps of road conditions on a wide area. Since these systems collect data from multiple users, scalability is vastly improved, allowing for an economical solution to be derived regarding large-scale road infrastructure monitoring. However, in turn, with the increasing variety of smartphone models, variability in sensor quality, driving habits, vehicle kinds, and road conditions, serious challenges to heterogeneity are posed to the incorporated data. Such conditions were emphasized in the work of Douangphachanh and Oneyama 2014b; Martinez-Ros et al. (2022) [25,95].

Recent research to meet these challenges has concentrated on probabilistic data aggregation and sensor fusion approaches that come from multiple sources, merging them as such for improved accuracy in the outlier detection. A probabilistic crowdsourcing technique for aggregating road surface anomalies through filtering out the false positives or negatives can be used. This enhances reliability because different smartphones and vehicles might vary greatly in their sensor quality. The system will rely on a spatiotemporal clustering of detected anomalies to integrate both the spatial and temporal information of reporting events for effective long-term road condition monitoring.

Indeed, data fusion can help to overcome the limitations of standalone smartphone sensors. Using accelerometer data together with inputs from other sensors, such as GPS, gyroscopes, or even in-vehicle cameras, generally leads to better detection accuracy [96]. The effectiveness of multi-sensor fusion of accelerometer data with video feeds to help reduce the noise and variability often associated with pure accelerometer signals has already been investigated. This offers enhanced detection, regardless of changes brought about by vehicle speeds or mounting positions of the smartphone. Equally worth noting in Sattar et al. (2022) and Xin et al. (2023) [97,98] is that advanced machine learning models create avenues for the enhancement of anomaly detection. Sattar et al. (2022) employed a DPGMM for the classification of road surface anomalies from hyperspectral images into minor and severe classes. Its nonparametric nature adapts this model to the variability of data and allows better discrimination between minor and severe anomalies. Similarly, it was proposed by Xin et al. that the LSTM network will increase the classification accuracy since it considers the time-dependent nature of road surface data.

Besides data fusion and machine learning, crowdsourcing is used to perform large-scale, real-time road condition monitoring. Data aggregation from a large number of users allows dynamic map generation where road conditions are continuously updated in real time. This dynamic mapping system is hugely valuable for any PMS whereby authorities can capture real-time insights into road conditions that enable them to prioritize repairs and optimize maintenance schedules accordingly. The advantage of such a system is that it reduces dependence on expensive traditional road monitoring techniques; furthermore, it is flexible and scalable for large-scale road infrastructural maintenance.

While crowdsourcing brings its own set of challenges about data consistency and variability, the development of probabilistic data aggregation, spatiotemporal clustering, and sensor fusion techniques has markedly enhanced the accuracy and reliability of such systems. With the further development of machine learning and data fusion technologies, crowdsourced road surface monitoring has emerged as a consistently powerful tool for cities and municipalities to manage the roads efficiently and economically.

Figure 8 illustrates a crowdsourced large-scale road surface monitoring architecture. In this model, several smartphone users collect sensor readings, such as acceleration, angular velocity, and GPS readings while driving. The data are sent to a centralized database where it is aggregated and analyzed over various locations to monitor road conditions. This architecture enables the continuous real-time monitoring of road surfaces at a much lower cost by harnessing user contributions to build an extensive map of road quality in large geographic areas.

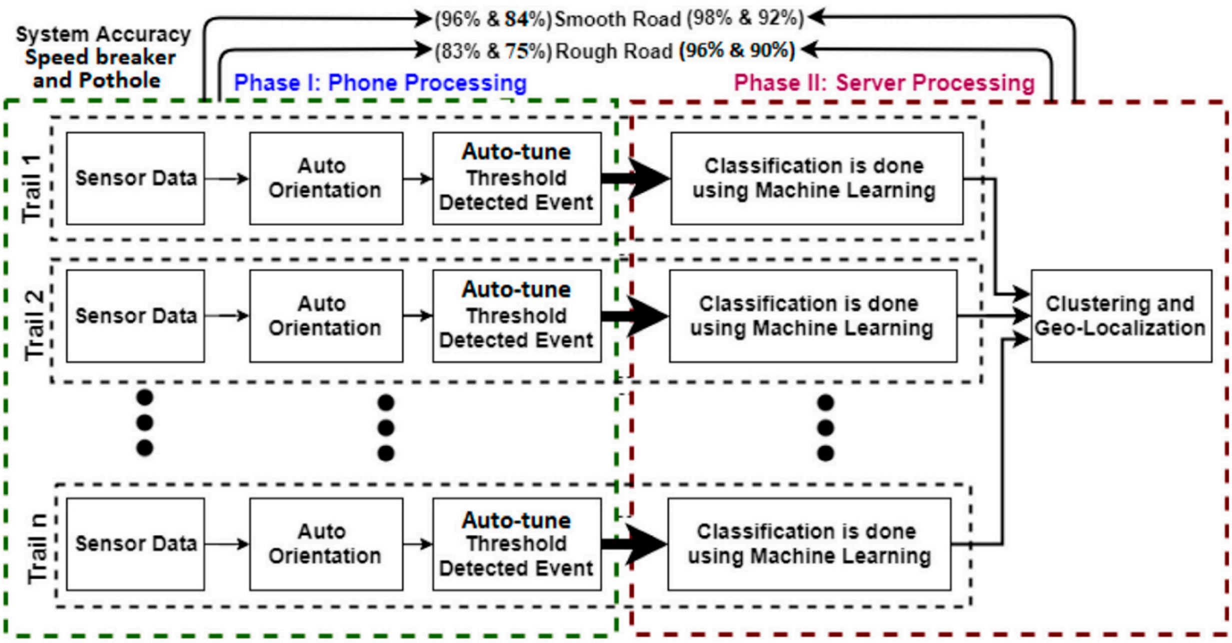

Figure 8. Crowdsourced data collection architecture for road surface monitoring [99]. Reproduced with permission license number 5892630995208.

Figure 9 compares different strategies of data aggregation in crowdsourced road monitoring. Different methods are assessed to consolidate sensor data from multiple users with respect to achieving accurate and reliable assessments of road conditions. It shows the strengths and weaknesses of various methods, such as weighted averaging, voting mechanisms, and advanced machine learning techniques. These strategies aim to address issues related to data heterogeneity, such as variability in smartphone sensors, driving behavior, and environmental factors, to improve accuracy in large-scale road conditions [1,51,93].

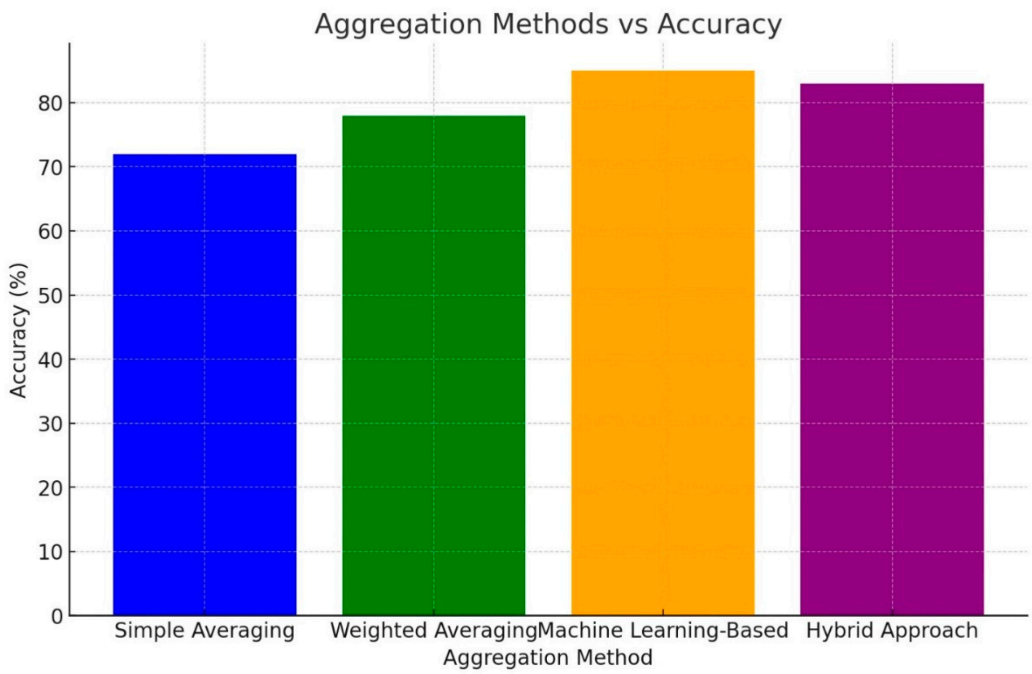

Figure 9. Comparison of data aggregation strategies in crowdsourced road monitoring.

6. Recent Technological Advancements in Road Surface Monitoring

Recent technological developments have gone a long way in improving the monitoring of the road surface, especially with regard to the integration of smartphone-based systems and sensor technologies. Among the fastest-developing solutions, one may distinguish Inertial Measurement Units, whose integration with GPS data allows the performance of road roughness assessment in a more accurate and reliable way. These systems have really prevailed in urban areas, where many roadways make it difficult for the more traditional monitoring systems to work. By adding multi-axis, vehicle motion-measuring IMUs and GPS for accurate geolocation, the accuracy of road condition assessments increased significantly [33,85].

Modern road surface monitoring systems should be able to integrate multiple sensors, such as accelerometers, gyroscopes, and GPS receivers. Figure 10 presents a typical system configuration, combining in-vehicle and smartphone sensors for the identification of road anomalies. These sensors collect data on vehicle motion and position, which again are synchronized and time-tagged by GPS data. The resulting data can be used to find anomalies in roads with high accuracy in real time. Setting up multiple IMUs and GPS receivers within multiple vehicles and smart devices facilitates the collection of data at a larger scale, hence offering a much more robust monitoring structure for more types of driving conditions. The result further enhances the ability of the system to perform real-time assessments of the state of the road condition [100,101].

Deep learning has also contributed much to the improvement in the accuracy and efficiency of smartphone-based monitoring. For example, using IRI-Net, a type of convolutional neural network, to estimate the International Roughness Index leads to extremely good results in measuring road roughness from real-world applications. These systems help in the real-time gathering of data from several vehicles, thus offering the ability to supply the continuous monitoring of huge-scale road surfaces [102]. With all these developments, the road surface monitoring philosophy should drift more into smart city applications that will deliver real-time data from vehicles, smartphones, and infrastructure to enhance urban mobility and maintenance planning [63,103].

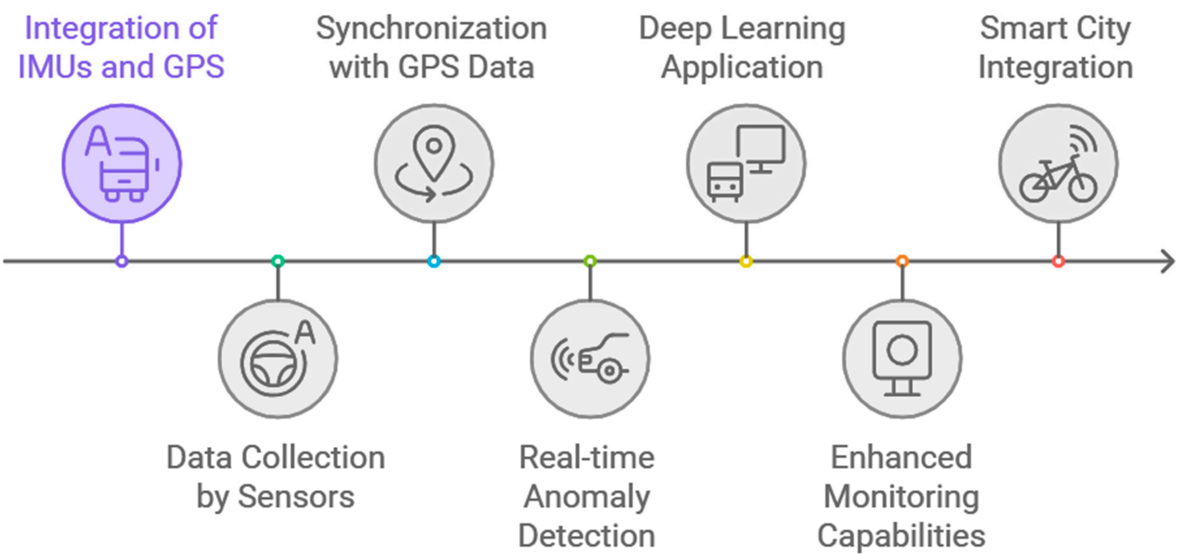

Figure 10. Integration of IMUs and GPS for enhanced road surface monitoring.

Zhao et al. [104] introduced a robust two-stage machine learning model for road anomaly detection and classification, combining random forest for anomaly detection and Gaussian Process Classifiers for detailed classification. A notable aspect of their methodology is the transformation of time-series data into geospatial series, enabling speed-independent anomaly detection. This approach achieved an accuracy of 87%, demonstrating its potential for real-world applications and dynamic conditions.

Furthermore, the elaboration of real-time data processing techniques has enabled the evaluation of road conditions in real time, crucial for applications like autonomous driving or real-time traffic management. These improvements signify a real leap in system usability and performance with regard to the road surface monitoring system based on smartphones [33,93].

6.1. Advancements and Future Opportunities in Smartphone-Based Road Surface Monitoring

The very fast evolution of road surface monitoring based on smartphones opens new perspectives for further technological development: hybrid sensor networks will merge data coming from smartphones with other sources, such as satellites and drones. In this way, integration could enable more complete assessments of the conditions of roads and closer-to-reality estimates of infrastructure, as Zhang et al. (2022) and Singh et al. (2017) [17,34] present. In this regard, the combination of smartphone sensor data with high-resolution satellite imagery and drone-based remote sensing can ensure greater spatial coverage and detail to enhance the detection of road anomalies. This is in respect to the work of Ranyal et al. (2022) [105].

Equally gaining increased attention is the enhancement of machine learning models. Conventional models are normally incapable of handling the inherent noise and variability in data from diverse environments and a plethora of vehicle types. Recent developments have checked on ensemble learning methods, which incorporate various enhanced models for increased accuracy and robustness in making their predictions. These ensemble methods apply a variety of algorithms that can process complex sensor data for more reliable assessments of the road [23,84,106].

Except for those conventional machine learning-based techniques, threshold-based methods are still in wide usage due to computational efficiency. These methods rely on the fundamentals of data analysis usually using a smartphone accelerometer, which provides readings for vertical accelerations that indicate road anomalies. To overcome the limitations of static thresholding, adaptive thresholding methods are alternatives. Looking ahead, hybrid techniques that combine the ease of threshold-based methods with the accuracy of machine learning could offer an effective and efficient solution toward the real-time detection of road conditions.

Integrating such a smartphone-based monitoring system into smart city infrastructure is another area that opens up possibilities for better urban mobility and road maintenance. Dynamic maps created with updates of the latest road condition data prove to be quite potent for municipalities in streamlining efforts pertaining to maintenance and improving resources [27,34,106]. Further technological advances in smartphones may offer new sensors, such as thermal imaging and LiDAR, in smartphone-based systems and give even more details regarding the condition of roads. Such sensors would be applicable for detecting not only superficial but also sub-surface defects in the roads to have a holistic understanding of the quality of roads [105,107].

While there are still many challenges, particularly related to scaling these systems and maintaining consistent data quality across varied environments, increasingly novel approaches to data processing and the integration of diverse sensor types have helped overcome many issues. Coupled with advanced machine learning algorithms and hybrid techniques, crowdsourced data contributes to the increasing accuracy, scalability, and feasibility for smartphone-based road monitoring systems. With continued research, such systems will play an important role in the maintenance of road infrastructure and urban developments through the provision of cost-effective and scalable solutions for the large-scale monitoring of road conditions [108].

6.2. Data Fusion, Signal Processing and Machine Learning Techniques

Of course, data fusion has been an important technique for advancing the systems associated with road surface monitoring. It can, for example, reduce noise and amplify the quality of the signal by fusing data from multiple sensors like IMUs, GPS, and accelerometers. The measurements from these sensors are often given finer details using advanced filtering techniques like Kalman filtering. Recent studies have shown that the use of a Kalman filter can drastically reduce the error margin during road surface monitoring by smoothing sensor data and predicting the real road profile [109–111].

Table 5 presents a comparison between some signal processing methods of a Kalman filter, particle filter, orthogonal wavelet transform, and envelope threshold by highlighting their effectiveness in improving data accuracy towards typical monitoring applications of road surfaces.

Table 5. Comparison of signal processing techniques for road surface monitoring.

Technique	Error Reduction	Computational Complexity	Applications
Kalman Filtering	High	Moderate	Real-time monitoring, autonomous vehicles
Particle Filtering	Moderate	High	Complex environments, navigation systems
Wavelet Transform	High	Moderate	Signal denoising, anomaly detection

Figure 11 is an example of a trained machine learning model used for anomaly detection in roads from data fused using IMUs and GPS. The model embeds the combination of feature extraction and classification techniques to detect different types of road surface defects with high accuracy.

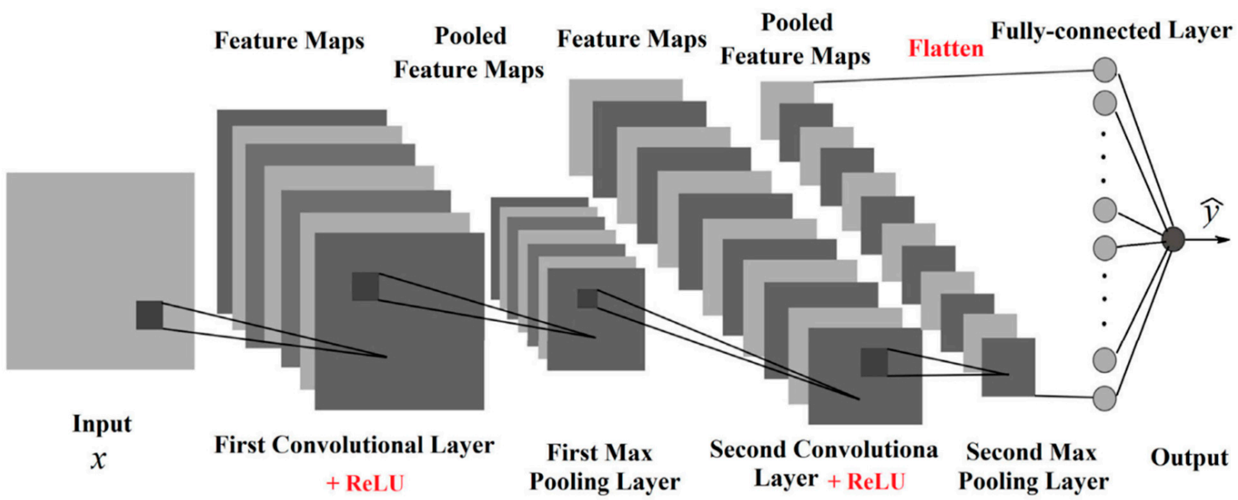

Figure 11. Machine learning model for road anomaly detection [112].

7. Real-World Applications of Smartphone-Based Road Monitoring

Advanced road surface monitoring systems have proved effective in several practical applications. Recently deployed systems have been using multi-sensor data along with machine learning to monitor road conditions in real time over a large metropolitan area. This deployment also improved the accuracy of road surface condition assessments and delivered valuable data for urban planning and maintenance. These advanced methodologies resulted in higher accuracies of detection and efficiencies in processing data as summarized in Table 6, presenting results across various real-world applications. Besides the systems based on IMU, GPS, and machine learning, the concept of smartphone-based road monitoring has gained momentum in recent times because it incorporates economics and can be scaled more easily [113]. Crowdsourcing in this respect can be a very good option to obtain continuous data regarding the condition of roads from drivers. Smartphones can easily detect road roughness, potholes, and other surface anomalies in real time with the help of a range of sensors such as accelerometers, gyroscopes, and GPS, making them highly important tools for the management of urban infrastructure [50].

IRI-Net, proposed by Jeong and Jo (2023) [102], is a convolutional neural network developed to estimate the International Roughness Index with the help of vehicle vibrations measured using smartphones. Later, it was validated with larger-scale ground truth data from 29 vehicles, 9 variants of smartphone models, and 5 different mounting configurations of smartphones. IRI-Net estimated ground truth road roughness under various conditions: different vehicle types, driving speeds, and mounting positions of the smartphone—an area that opens up new possibilities towards practical road monitoring with deep learning.

The variabilities of the sensor data depending on different types of vehicles, driving behavior, and smartphones' mounting positions create a negative influence on data accuracy. Jeong and Jo in 2023 [102] came up with an effective new GPS processing approach that enhances the accuracy with a couple of interpolation and grid-snapping techniques. This approach overcomes the low-resolution problem of crowdsourced GPS data, creating road anomaly mapping at far higher resolutions that simultaneously enhance the reliability of the system in the interest area. As [7,16,114] pointed out, crowdsourcing data are based on the condition of urban roads since they aid in broader urban planning and maintenance. Field applications proved their worth by enhancing the precision of defect detection in roads, time efficiency in processing data, and quality information for maintenance and urban planning concerns.

Table 6. Outcomes of advanced road surface monitoring applications [115].

Application	Location	Technology Used	Detection Accuracy
Urban Road Monitoring	New York, NY, USA	IMUs, GPS, Machine Learning	92%
Autonomous Vehicle Road Surface Analysis	Tokyo, Japan	IMUs, Kalman Filtering	89%
Rural Road Maintenance	Bavaria, Germany	GPS, Signal Processing	85%

8. Conclusions

This research has tried to demonstrate the new horizons opened by smartphone-based road surface monitoring systems as scalable and inexpensive alternatives to more traditional approaches. An accuracy as high as that reached by more traditional devices can be achieved using sensors contained in smartphones, such as accelerometers, gyroscopes, and GPS, which are able to detect any given road surface anomaly, from potholes and pavement cracks to surface roughness. Machine learning algorithms further enhance the detection capabilities, hence making those systems even more robust and reliable. Presently, they are fraught with challenges; this technology can be further developed, at least when integrated into smart city frameworks and interwoven with other new technologies such as 5G and artificial intelligence. The following represents the key findings and future directions from the study:

- Smartphones are capable of detecting road surface anomalies with high accuracy, such as potholes, cracks, and roughness, using accelerometers, gyroscopes, and GPS sensors.
- The detection accuracy of the road surface anomalies has been significantly increased by the integration of some machine learning algorithms, especially the CNNs and

SVMs. Hybrid models which merge DL with traditional ML techniques achieve superior performance and scalability in classification.

- Crowdsourcing collects data with the contribution of multiple smartphone users who provide real-time and large-scale data on road surfaces and increases the spatial coverage. Transportation agencies are now able to continuously monitor the actual conditions of their roads for timely maintenance interventions.
- Preprocessing techniques such as high-pass filtering, low-pass filtering, and DTW increase the accuracy and reliability of sensor readings. Data fusion from accelerometers, gyroscopes, and GPS increases the robustness of monitoring systems, thereby allowing adaptation to diverse conditions.
- Some of the challenges ahead include sensor noise, hardware variability, and inconsistency in data coming from crowdsourcing, amongst many which are still underway and will require further research to devise more sophisticated algorithms to solve these issues.
- If a smartphone-based vehicle monitoring system is integrated within smart city frameworks, i.e., ITS, this will improve the management of urban infrastructure. This may be further expanded to involve other high-resolution tools, including satellite imagery and drone-based systems, in addition to smartphone data for road surface monitoring. The further development of technologies like AI and edge computing may allow them to perform real-time data gathering metered with predictive maintenance.

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References

1. Alavi, A.H.; Buttlar, W.G. An overview of smartphone technology for citizen-centered, real-time and scalable civil infrastructure monitoring. *Futur. Gener. Comput. Syst.* **2019**, *93*, 651–672. [CrossRef]
2. Asaduzzaman; Rana, S. Smart Monitoring of Pavement Condition Utilizing Vehicle Vibration and Smartphone Sensor. In *Lecture Notes in Civil Engineering*; Springer Science and Business Media Deutschland GmbH: Singapore, 2022; pp. 199–209. [CrossRef]
3. Crist, P.; Kauppila, J.; Vassallo, J.; Wlaschin, B. Asset Management for Sustainable Road Funding. 2013. Available online: https://www.econstor.eu/bitstream/10419/97083/1/747110255.pdf (accessed on 9 December 2024).
4. Hunt, P.D.; Bunker, J.M. Analysis of Unbound Granular Pavement Deterioration for Use in Asset Management Modelling. Available online: https://eprints.qut.edu.au/215882/ (accessed on 9 December 2024).
5. Frisoni, R.; Dionori, F.; Casullo, L.; Vollath, C.; Devenish, L.; Spano, F.; Sawicki, T.; Carl, S.; Lidia, R.; Neri, J.; et al. *EU Road Surfaces: Economic and Safety Impact of the Lack of Regular Road Maintenance*; EPRS—European Parliamentary Research Service: Brussels, Belgium, 2014.
6. Sayers, M.W. *On the Calculation of International Roughness Index from Longitudinal Road Profile*; Transportation Research Board: Washington, DC, USA, 1995.
7. Islam, S.; Buttlar, W.G.; Aldunate, R.G.; Vavrik, W.R. Measurement of pavement roughness using android-based smartphone application. *Transp. Res. Rec. J. Transp. Res. Board* **2014**, *2457*, 30–38. [CrossRef]
8. Smith, K.; Ram, P. *Measures and Specifying Pavement Smoothness*; FHWA: Washington, DC, USA, 2016.
9. Meegoda, J.N.; Gao, S. Roughness progression model for asphalt pavements using long-term pavement performance data. *J. Transp. Eng.* **2014**, *140*. [CrossRef]
10. Levesque, W.; Bégin-Drolet, A.; Lépine, J. Effects of Pavement Characteristics on Rolling Resistance of Heavy Vehicles: A Literature Review. *Transp. Res. Rec. J. Transp. Res. Board* **2023**, *2677*, 296–309. [CrossRef]
11. Madanat, R.; Mäkinen, T.J.; Moritz, N.; Mattila, K.T.; Aro, H.T. Accuracy and precision of radiostereometric analysis in the measurement of three-dimensional micromotion in a fracture model of the distal radius. *J. Orthop. Res.* **2005**, *23*, 481–488. [CrossRef]
12. Onuorah, C.A. Evaluation of Pavement Roughness and Vehicle Vibrations for Road Surface Profiling. Ph.D. Thesis, University of Hertfordshire, Hatfield, UK, 2017.
13. Bidgoli, M.A.; Golroo, A.; Nadjar, H.S.; Rashidabad, A.G.; Ganji, M.R. Road roughness measurement using a cost-effective sensor-based monitoring system. *Autom. Constr.* **2019**, *104*, 140–152. [CrossRef]
14. Lane, N.D.; Miluzzo, E.; Lu, H.; Peebles, D.; Choudhury, T.; Campbell, A.T. A Survey of Mobile Phone Sensing. *IEEE Commun. Mag.* **2010**, *48*, 140–150. [CrossRef]
15. Shon, H.; Cho, C.-S.; Byon, Y.-J.; Lee, J. Autonomous condition monitoring-based pavement management system. *Autom. Constr.* **2022**, *138*, 104222. [CrossRef]

16. Sattar, S.; Li, S.; Chapman, M. Road surface monitoring using smartphone sensors: A review. *Sensors* **2018**, *18*, 3845. [CrossRef]
17. Singh, G.; Bansal, D.; Sofat, S.; Aggarwal, N. Smart patrolling: An efficient road surface monitoring using smartphone sensors and crowdsourcing. *Pervasive Mob. Comput.* **2017**, *40*, 71–88. [CrossRef]
18. Li, X.; Chen, R.; Chu, T. A Crowdsourcing Solution for Road Surface Roughness Detection Using Smartphones UAS for Agriculture View Project Multi-Sensor System Based Positioning and Navigation View Project. 2014. Available online: https://www.researchgate.net/publication/289564027 (accessed on 9 December 2024).
19. Hossain, M.I.; Tutumluer, E.; Nikita; Grimm, C. Evaluation of Android-Based Cell Phone Applications to Measure International Roughness Index of Rural Roads. In Proceedings of the International Conference on Transportation and Development 2019, Alexandria, VA, USA, 9–12 June 2019.
20. Sujon, M.; Dai, F. Application of weigh-in-motion technologies for pavement and bridge response monitoring: State-of-the-art review. *Autom. Constr.* **2021**, *130*, 103844. [CrossRef]
21. Aleadelat, W.; Ksaibati, K.; Wright, C.H.G.; Saha, P. Evaluation of pavement roughness using an android-based smartphone. *J. Transp. Eng. Part B Pavements* **2018**, *144*, 04018033. [CrossRef]
22. Salau, H.B.; Onumanyi, A.J.; Aibinu, A.M.; Onwuka, E.N.; Dukiya, J.J.; Ohize, H. A Survey of Accelerometer-Based Techniques for Road Anomalies Detection and Characterization. *Int. J. Eng. Sci. Appl.* **2019**, *3*, 8–20.
23. Sabir, N.; Memon, A.A.; Shaikh, F.K. Threshold Based Efficient Road Monitoring System Using Crowdsourcing Approach. *Wirel. Pers. Commun.* **2019**, *106*, 2407–2425. [CrossRef]
24. Yang, X.; Hu, L.; Ahmed, H.U.; Bridgelall, R.; Huang, Y. Calibration of smartphone sensors to evaluate the ride quality of paved and unpaved roads. *Int. J. Pavement Eng.* **2022**, *23*, 1529–1539. [CrossRef]
25. Douangphachanh, V.; Oneyama, H. Exploring the use of smartphone accelerometer and gyroscope to study on the estimation of road surface roughness condition. In *ICINCO 2014—Proceedings of the 11th International Conference on Informatics in Control, Automation and Robotics*; SciTePress: Setúbal, Portugal, 2014; pp. 783–787. [CrossRef]
26. Opara, K.R.; Brzezinski, K.; Bukowicki, M.; Kaczmarek-Majer, K. Road Roughness Estimation Through Smartphone-Measured Acceleration. *IEEE Intell. Transp. Syst. Mag.* **2021**, *14*, 209–220. [CrossRef]
27. Harikrishnan, P.M.; Gopi, V.P. Vehicle Vibration Signal Processing for Road Surface Monitoring. *IEEE Sens. J.* **2017**, *17*, 5192–5197. [CrossRef]
28. Li, X.; Goldberg, D.W. Toward a mobile crowdsensing system for road surface assessment. *Comput. Environ. Urban Syst.* **2018**, *69*, 51–62. [CrossRef]
29. Mohan, P.; Padmanabhan, V.N.; Ramjee, R. Nericell: Rich monitoring of road and traffic conditions using mobile smartphones. In Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems, New York, NY, USA, 5–7 November 2008.
30. Lima, L.C.; Amorim, V.J.P.; Pereira, I.M.; Ribeiro, F.N.; Oliveira, R.A.R. Using Crowdsourcing Techniques and Mobile Devices for Asphaltic Pavement Quality Recognition. In Proceedings of the 2016 VI Brazilian Symposium on Computing Systems Engineering (SBESC), João Pessoa, Brazil, 1–4 November 2016; pp. 144–149.
31. Wang, H.; Nagayama, T.; Su, D. Estimation of dynamic Tire Force By Measurement of Vehicle Body Responses with Numerical and Experimental Validation. *Mech. Syst. Signal Process.* **2019**, *123*, 369–385. [CrossRef]
32. Zang, K.; Shen, J.; Huang, H.; Wan, M.; Shi, J. Assessing and mapping of road surface roughness based on GPS and accelerometer sensors on bicycle-mounted smartphones. *Sensors* **2018**, *18*, 914. [CrossRef]
33. *Ubiquitous Intelligence and Computing*; Springer Nature: Dordrecht, The Netherlands, 2011; ISBN 9780387347684.
34. Zhang, Z.; Zhang, H.; Xu, S.; Lv, W. Pavement roughness evaluation method based on the theoretical relationship between acceleration measured by smartphone and IRI. *Int. J. Pavement Eng.* **2022**, *23*, 3082–3098. [CrossRef]
35. Bhandari, R.; Nambi, A.U.; Padmanabhan, V.N.; Raman, B. Driving Lane Detection on Smartphones using Deep Neural Networks. *ACM Trans. Sens. Netw.* **2020**, *16*, 1–22. [CrossRef]
36. Ho, C.-H.; Snyder, M.; Zhang, D. Application of Vehicle-Based Sensing Technology in Monitoring Vibration Response of Pavement Conditions. *J. Transp. Eng. Part B Pavements* **2020**, *146*, 04020053. [CrossRef]
37. Zhang, P.; Huang, J.; Chen, S. Research on Evaluation Technology of Pavement Roughness Based on Smartphone. In Proceedings of the 2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA), Dalian, China, 25–27 August 2020; pp. 123–126.
38. Manalo, J.M.C.; Alon, A.S.; Austria, Y.D.; Merencilla, N.E.; Misola, M.A.; Sandil, R.C. A Transfer Learning-Based System of Pothole Detection in Roads through Deep Convolutional Neural Networks. In Proceedings of the 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 23–25 March 2022; pp. 1469–1473.
39. Maeda, H.; Sekimoto, Y.; Seto, T.; Kashiyama, T.; Omata, H. Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images. *Comput. Civ. Infrastruct. Eng.* **2018**, *33*, 1127–1141. [CrossRef]
40. Dey, M.R.; Satapathy, U.; Bhanse, P.; Mohanta, B.K.; Jena, D. MagTrack: Detecting Road Surface Condition using Smartphone Sensors and Machine Learning. In Proceedings of the IEEE Region 10 International Conference TENCON, Kochi, India, 17–20 October 2019; pp. 2485–2489.
41. Hadj-Attou, A.; Kabir, Y.; Ykhlef, F. Hybrid deep learning models for road surface condition monitoring. *Measurement* **2023**, *220*, 113267. [CrossRef]
42. Wahlström, J.; Skog, I.; Händel, P. Smartphone-Based Vehicle Telematics: A Ten-Year Anniversary. *IEEE Trans. Intell. Transp. Syst.* **2016**, *18*, 2802–2825. [CrossRef]

43. Kuutti, S.; Bowden, R.; Jin, Y.; Barber, P.; Fallah, S. A Survey of Deep Learning Applications to Autonomous Vehicle Control. *IEEE Trans. Intell. Transp. Syst.* **2019**, *22*, 712–733. [CrossRef]
44. Singh, G.; Bansal, D.; Sofat, S. A smartphone based technique to monitor driving behavior using DTW and crowdsensing. *Pervasive Mob. Comput.* **2017**, *40*, 56–70. [CrossRef]
45. Seraj, F.; Van Der Zwaag, B.J.; Dilo, A.; Luarasi, T.; Havinga, P. RoADS: A Road Pavement Monitoring System for Anomaly Detection Using Smart Phones. 2014. Available online: https://www.fhwa.dot.gov/research/tfhrc/labs/ (accessed on 9 December 2024).
46. Douangphachanh, V.; Oneyama, H. A study on the use of smartphones under realistic settings to estimate road roughness condition. *EURASIP J. Wirel. Commun. Netw.* **2014**, *2014*, 114. [CrossRef]
47. Allouch, A.; Koubaa, A.; Abbes, T.; Ammar, A. RoadSense: Smartphone Application to Estimate Road Conditions Using Accelerometer and Gyroscope. *IEEE Sens. J.* **2017**, *17*, 4231–4238. [CrossRef]
48. Sothe, C.; De Almeida, C.M.; Schimalski, M.B.; La Rosa, L.E.C.; Castro, J.D.B.; Feitosa, R.Q.; Dalponte, M.; Lima, C.L.; Liesenberg, V.; Miyoshi, G.T.; et al. Comparative performance of convolutional neural network, weighted and conventional support vector machine and random forest for classifying tree species using hyperspectral and photogrammetric data. *GIScience Remote. Sens.* **2020**, *57*, 369–394. [CrossRef]
49. Mahajan, D.V.; Student, P.G.; Dange, T. Estimation of Road Roughness Condition by using Sensors in Smartphones. *Int. J. Comput. Eng. Technol. (IJCET)* **2015**, *6*, 41–49.
50. Mednis, A.; Strazdins, G.; Zviedris, R.; Kanonirs, G.; Selavo, L. Real time pothole detection using Android smartphones with accelerometers. In Proceedings of the 2011 International Conference on Distributed Computing in Sensor Systems (DCOSS), Barcelona, Spain, 27–29 June 2011; pp. 1–6.
51. Bhoraskar, R.; Vankadhara, N.; Raman, B.; Kulkarni, P. Wolverine: Traffic and road condition estimation using smartphone sensors. In Proceedings of the 2012 Fourth International Conference on Communication Systems and Networks (COMSNETS 2012), Bangalore, India, 3–7 January 2012.
52. Dong, D.; Li, Z. Smartphone Sensing of Road Surface Condition and Defect Detection. *Sensors* **2021**, *21*, 5433. [CrossRef]
53. Alqudah, Y.A.; Sababha, B.H. On the analysis of road surface conditions using embedded smartphone sensors. In Proceedings of the 2017 8th International Conference on Information and Communication Systems (ICICS), Irbid, Jordan, 4–6 April 2017; pp. 177–181.
54. Jo, Y.; Ryu, S. Pothole Detection System Using a Black-box Camera. *Sensors* **2015**, *15*, 29316–29331. [CrossRef]
55. Chaurasia, S.K.; Reddy, S. Design and Implementation of Data Collection & Analysis Tool for Healthcare Parameter Monitoring using Inverse Low Pass Filter. *EAI Endorsed Trans. Pervasive Health Technol.* **2018**, *4*, e5. [CrossRef]
56. Yu, Q.; Fang, Y.; Wix, R. Pavement roughness index estimation and anomaly detection using smartphones. *Autom. Constr.* **2022**, *141*, 104409. [CrossRef]
57. Cabral, F.S.; Pinto, M.; Mouzinho, F.A.L.N.; Fukai, H.; Tamura, S. An automatic survey system for paved and unpaved road classification and road anomaly detection using smartphone sensor. In Proceedings of the 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 31 July–2 August 2018; pp. 65–70.
58. Du, R.; Qiu, G.; Gao, K.; Hu, L.; Liu, L. Abnormal road surface recognition based on smartphone acceleration sensor. *Sensors* **2020**, *20*, 451. [CrossRef] [PubMed]
59. Shtayat, A.; Moridpour, S.; Best, B.; Daoud, H. Application of noise-cancelling and smoothing techniques in road pavement vibration monitoring data. *Int. J. Transp. Sci. Technol.* **2023**, *14*, 110–119. [CrossRef]
60. Achariyaviriya, W.; Horanont, T. Crowd-Sourcing Based Road Surface Evaluation Using Mobile Sensing. Ph.D. Thesis, Thammasat University, Bangkok, Thailand, 2016.
61. Zheng, Z.; Zhou, M.; Chen, Y.; Huo, M.; Sun, L.; Zhao, S.; Chen, D. A Fused Method of Machine Learning and Dynamic Time Warping for Road Anomalies Detection. *IEEE Trans. Intell. Transp. Syst.* **2020**, *23*, 827–839. [CrossRef]
62. Gibert, K.; Sànchez–Marrè, M.; Izquierdo, J. A survey on pre-processing techniques: Relevant issues in the context of environmental data mining. *AI Commun.* **2016**, *29*, 627–663. [CrossRef]
63. Gupta, A.; Afrin, T.; Scully, E.; Yodo, N. Advances of UAVs toward Future Transportation: The State-of-the-Art, Challenges, and Opportunities. *Futur. Transp.* **2021**, *1*, 326–350. [CrossRef]
64. Dong, D.; Li, Z. Road Surface Condition Monitoring and Defect Detection with Smartphones. 2020. Available online: https://www.researchgate.net/publication/364029383 (accessed on 9 December 2024).
65. Nagy, R.; Kummer, A.; Abonyi, J.; Szalai, I. Machine learning-based soft-sensor development for road quality classification. *J. Vib. Control* **2024**, *30*, 2672–2684. [CrossRef]
66. Ibrahim, H.B.; Salah, M.; Zarzoura, F.; El-Mewafi, M. Smart monitoring of road pavement deformations from UAV images by using machine learning. *Innov. Infrastruct. Solut.* **2024**, *9*, 1–18. [CrossRef]
67. Moon, J.; Park, W. Using Support Vector Machines to Classify Road Surface Conditions to Promote Safe Driving. *Sensors* **2024**, *24*, 4307. [CrossRef]
68. Chowdhury, S. Comparison of accuracy and reliability of random forest, support vector machine, artificial neural network and maximum likelihood method in land use/cover classification of urban setting. *Environ. Chall.* **2024**, *14*, 100800. [CrossRef]
69. Apeagyei, A.; Ademolake, T.E.; Anochie-Boateng, J. *Hybrid Transfer Learning and Support Vector Machines Models for Asphalt Pavement Distress Classification*; Transportation Research Board: Washington, DC, USA, 2024.

70. Merolla, D.; Latorre, V.; Salis, A.; Boanelli, G. Automated Road Safety: Enhancing Sign and Surface Damage Detection with AI. *arXiv* **2024**, arXiv:2407.15406.
71. Suleymanoglu, B.; Soycan, M.; Toth, C. 3D Road Boundary Extraction Based on Machine Learning Strategy Using LiDAR and Image-Derived MMS Point Clouds. *Sensors* **2024**, *24*, 503. [CrossRef]
72. Guerrieri, M.; Parla, G.; Khanmohamadi, M.; Neduzha, L. Asphalt Pavement Damage Detection through Deep Learning Technique and Cost-Effective Equipment: A Case Study in Urban Roads Crossed by Tramway Lines. *Infrastructures* **2024**, *9*, 34. [CrossRef]
73. Ruseruka, C.; Mwakalonge, J.; Comert, G.; Siuhi, S.; Ngeni, F.; Anderson, Q. Augmenting roadway safety with machine learning and deep learning: Pothole detection and dimension estimation using in-vehicle technologies. *Mach. Learn. Appl.* **2024**, *16*, 100547. [CrossRef]
74. Vinodhini, K.A.; Sidhaarth, K.R.A. Pothole detection in bituminous road using CNN with transfer learning. *Meas. Sens.* **2024**, *31*, 100940. [CrossRef]
75. Dofitas, C.; Gil, J.-M.; Byun, Y.-C. Multi-Directional Long-Term Recurrent Convolutional Network for Road Situation Recognition. *Sensors* **2024**, *24*, 4618. [CrossRef] [PubMed]
76. Lyu, H.; Zhong, Q.; Huang, Y.; Hua, J.; Jiao, D. Urban Road Surface Condition Sensing from Crowd-Sourced Trajectories Based on the Detecting and Clustering Framework. *Sensors* **2024**, *24*, 4093. [CrossRef] [PubMed]
77. Chen, L.; Li, H.; Wang, S.; Shan, F.; Han, Y.; Zhong, G. Imporved model for pavement performance prediction based on recurrent neural network using LTPP database. *Int. J. Transp. Sci. Technol.* **2024**. [CrossRef]
78. Sprague, W. A Hybrid Approach to Condition Assessment of Paved Roads. Ph.D. Thesis, Lakehead University, Thunder Bay, ON, Canada, 2021.
79. Aschwanden, P.; Müller, J.; Travaglio, G.C.; Schöning, T. The Influence of motion aerodynamics on the simulation of vehicle dynamics. *SAE Int. J. Passeng. Cars—Mech. Syst.* **2008**, *1*, 545–551. [CrossRef]
80. Bridgelall, R.; Huang, Y.; Zhang, Z.; Deng, F. Precision enhancement of pavement roughness localization with connected vehicles. *Meas. Sci. Technol.* **2016**, *27*, 025012. [CrossRef]
81. Eriksson, J.; Girod, L.; Hull, B.; Newton, R.; Madden, S.; Balakrishnan, H. *The Pothole Patrol: Using A Mobile Sensor Network for Road Surface Monitoring*; ACM Digital Library: New York, NY, USA, 2008.
82. Basavaraju, A.; Du, J.; Zhou, F.; Ji, J. A Machine Learning Approach to Road Surface Anomaly Assessment Using Smartphone Sensors. *IEEE Sens. J.* **2020**, *20*, 2635–2647. [CrossRef]
83. Roberts, R.A. A New Approach to Road Pavement Management Systems by exploiting Data Analytics, Image Analysis and Deep Learning. Ph.D. Thesis, University of Palermo, Palermo, Italy, 2021.
84. Iakovidis, D.K.; Ooi, M.; Kuang, Y.C.; Demidenko, S.; Shestakov, A.; Sinitsin, V.; Henry, M.; Sciacchitano, A.; Discetti, S.; Donati, S.; et al. Roadmap on signal processing for next generation measurement systems. *Meas. Sci. Technol.* **2022**, *33*, 012002. [CrossRef]
85. Viner, H.; Abbott, P.; Dunford, A.; Dhillon, N.; Parsley, L.; Read, C. Surface Texture Measurement on Local Roads. 2006. Available online: https://www.researchgate.net/publication/265006175 (accessed on 9 December 2024).
86. Jalili, F.; Ghavami, S.M.; Afsharnia, H. An Artificial Neural Network approach to assess road roughness using smartphone-based crowdsourcing data. *Eng. Appl. Artif. Intell.* **2024**, *138*, 109308. [CrossRef]
87. Nguyen, T.; Nguyen-Phuoc, D.Q.; Wong, Y.D. Developing artificial neural networks to estimate real-time onboard bus ride comfort. *Neural Comput. Appl.* **2021**, *33*, 5287–5299. [CrossRef]
88. Fernández, A.; Usamentiaga, R.; Carús, J.L.; Casado, R. Driver Distraction Using Visual-Based Sensors and Algorithms. *Sensors* **2016**, *16*, 1805. [CrossRef] [PubMed]
89. Mathavan, S.; Kamal, K.; Rahman, M. A Review of Three-Dimensional Imaging Technologies for Pavement Distress Detection and Measurements. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 2353–2362. [CrossRef]
90. Han, H.; Deng, H.; Dong, Q.; Gu, X.; Zhang, T.; Wang, Y. An Advanced Otsu Method Integrated with Edge Detection and Decision Tree for Crack Detection in Highway Transportation Infrastructure. *Adv. Mater. Sci. Eng.* **2021**, *2021*, 9205509. [CrossRef]
91. Vlahogianni, E.I.; Barmpounakis, E.N. Driving analytics using smartphones: Algorithms, comparisons and challenges. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 196–206. [CrossRef]
92. Sattar, S. A Crowdsourcing Technique For Road Surface Monitoring Using Smarthphone Sensors. Ph.D. Thesis, Toronto Metropolitan University, Toronto, ON, Canada, 2018.
93. Devan, M.; Shanmugam, L.; Tomar, M. AI-Powered Data Migration Strategies for Cloud Environments: Techniques, Frameworks, and Real-World Applications. *Aust. J. Mach. Learn. Res. Appl.* **2001**, *1*, 79–111.
94. Ganti, R.K.; Ye, F.; Lei, H. Mobile crowdsensing: Current state and future challenges. *IEEE Commun. Mag.* **2011**, *49*, 32–39. [CrossRef]
95. Martinez-Ríos, E.A.; Bustamante-Bello, M.R.; Arce-Sáenz, L.A. A Review of Road Surface Anomaly Detection and Classification Systems Based on Vibration-Based Techniques. *Appl. Sci.* **2022**, *12*, 9413. [CrossRef]
96. Lee, T.; Chun, C.; Ryu, S.-K. Detection of road-surface anomalies using a smartphone camera and accelerometer. *Sensors* **2021**, *21*, 561. [CrossRef]
97. Sattar, S.; Li, S.; Chapman, M. Probabilistic-Based Crowdsourcing Technique for Road Surface Anomaly Detection. *ISPRS—Int. Arch. Photogramm. Remote. Sens. Spat. Inf. Sci.* **2022**, *XLIII-B4-2022*, 281–286. [CrossRef]

98. Xin, H.; Ye, Y.; Na, X.; Hu, H.; Wang, G.; Wu, C.; Hu, S. Sustainable Road Pothole Detection: A Crowdsourcing Based Multi-Sensors Fusion Approach. *Sustainability* **2023**, *15*, 6610. [CrossRef]
99. Alam, M.Y.; Nandi, A.; Kumar, A.; Saha, S.; Saha, M.; Nandi, S.; Chakraborty, S. Crowdsourcing from the True crowd: Device, vehicle, road-surface and driving independent road profiling from smartphone sensors. *Pervasive Mob. Comput.* **2020**, *61*, 101103. [CrossRef]
100. Khanmohamadi, M.; Guerrieri, M. Advanced Sensor Technologies in CAVs for Traditional and Smart Road Condition Monitoring: A Review. *Sustainability* **2024**, *16*, 8336. [CrossRef]
101. Dabous, S.A.; Feroz, S. Condition monitoring of bridges with non-contact testing technologies. *Autom. Constr.* **2020**, *116*, 103224. [CrossRef]
102. Jeong, J.-H.; Jo, H. Toward Real-World Implementation of Deep Learning for Smartphone-Crowdsourced Pavement Condition Assessment. *IEEE Internet Things J.* **2023**, *11*, 6328–6337. [CrossRef]
103. Al-Sabaeei, A.M.; Souliman, M.I.; Jagadeesh, A. Smartphone applications for pavement condition monitoring: A review. *Constr. Build. Mater.* **2024**, *410*, 134207. [CrossRef]
104. Zhao, K.; Xu, S.; Loney, J.; Visentin, A.; Li, Z. Road Pavement Health Monitoring System Using Smartphone Sensing with A Two-Stage Machine Learning Model. *Autom. Constr.* **2024**, *167*, 105664. [CrossRef]
105. Ranyal, E.; Sadhu, A.; Jain, K. Road Condition Monitoring Using Smart Sensing and Artificial Intelligence: A Review. *Sensors* **2022**, *22*, 3044. [CrossRef]
106. Chhabra, R.; Singh, S. A survey on smart phone-based road condition detection systems. In Proceedings of the International Conference on Emerging Technologies: AI, IoT, and CPS for Science & Technology Applications, Chandigarh, India, 6–7 September 2021.
107. Dey, K.C.; Mishra, A.; Chowdhury, M. Potential of Intelligent Transportation Systems in Mitigating Adverse Weather Impacts on Road Mobility: A Review. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 1107–1119. [CrossRef]
108. Outay, F.; Mengash, H.A.; Adnan, M. Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges. *Transp. Res. Part A Policy Pract.* **2020**, *141*, 116–129. [CrossRef]
109. Punzo, V.; Formisano, D.; Torrieri, V. Part 1: Traffic Flow Theory and Car Following: Nonstationary Kalman Filter for Estimation of Accurate and Consistent Car-Following Data. *Transp. Res. Rec. J. Transp. Res. Board* **2005**, *1934*, 1–12. [CrossRef]
110. Haigermoser, A.; Luber, B.; Rauh, J.; Gräfe, G. Road and track irregularities: Measurement, assessment and simulation. *Veh. Syst. Dyn.* **2015**, *53*, 878–957. [CrossRef]
111. Li, J.; Wang, L.; Miao, Y.; Tong, X.; Ye, Z. Road Roughness Detection Based on Discrete Kalman Filter Model with Driving Vibration Data Input. *Int. J. Pavement Res. Technol.* **2023**. [CrossRef]
112. Luo, D.; Lu, J.; Guo, G. Road Anomaly Detection Through Deep Learning Approaches. *IEEE Access* **2020**, *8*, 117390–117404. [CrossRef]
113. Loprencipe, G.; Filho, F.G.V.d.A.; de Oliveira, R.H.; Bruno, S. Validation of a low-cost pavement monitoring inertial-based system for urban road networks. *Sensors* **2021**, *21*, 3127. [CrossRef]
114. El-Wakeel, A.S.; Li, J.; Noureldin, A.; Hassanein, H.S.; Zorba, N. Towards a Practical Crowdsensing System for Road Surface Conditions Monitoring. *IEEE Internet Things J.* **2018**, *5*, 4672–4685. [CrossRef]
115. Sheykhmousa, M.; Mahdianpari, M.; Ghanbari, H.; Mohammadimanesh, F.; Ghamisi, P.; Homayouni, S. Support Vector Machine Versus Random Forest for Remote Sensing Image Classification: A Meta-Analysis and Systematic Review. *IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens.* **2020**, *13*, 6308–6325. [CrossRef]