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TOPICAL REVIEW

# Crowdsensing for Road Pavement Condition Monitoring: Trends, Limitations, and Opportunities

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**ABSTRACT** Road Pavement Condition Monitoring (RPCM) is indispensable for proactive maintenance, especially amidst increasing traffic and unpredictable weather patterns. The demand for cost-efficient solutions leveraging emerging technologies such as the Internet of Things (IoT), Machine Learning (ML), and cloud computing is increasing. This work examines the evolution of RPCM solutions, examines the challenges, and proposes future improvements. An extensive literature review is presented which exposes the challenges with existing RPCM solutions. The assessment criteria are the sensory platform, algorithms employed, detected road deformities, and performance. The approaches employed in RPCM are examined including their advantages and limitations. A holistic assessment of RPCM methodologies is presented which includes threshold, dynamic time warping, computer vision, and ML approaches. It is determined that smartphone-based monitoring solutions incorporating data acquisition and ML are superior to other methods. Future research directions are presented considering the limitations of existing solutions and the goal of cost-effective and efficient RPCM solutions.

**INDEX TERMS** Cloud computing, computer vision, Internet of Things (IoT), machine learning, road monitoring, sensors.

## ABBREVIATIONS

| | |
|---|---|
| Acc | Accelerometer. |
| AI | Artificial Intelligence. |
| Ard | Arduino. |
| AWS | Amazon Web Services. |
| Cam | Camera. |
| CNN | Convolutional Neural Network. |
| DNN | Deep Neural Network. |
| DT | Decision Trees. |
| EV | Ensemble Voting. |
| GB | Gradient Boosting. |
| GIS | Geographic Information System. |
| GPR | Ground Penetrating Radar. |
| GPS | Global Positioning System. |
| Gyro | Gyroscope. |
| IoT | Internet of Things. |
| IRI | International Roughness Index. |
| IOVT | Internet of Video Things. |
| ICT | Information and Communications Technology. |
| KNN | K-Nearest Neighbors. |
| LR | Logistic Regression. |
| MLP | Multi-layer Perception. |
| ML | Machine Learning. |
| NB | Naive Bayes. |
| NN | Neural Network. |
| OBD | On Board Diagnoistics. |
| PCI | Pavement Condition Index. |
| PCR | Pavement Condition Rating. |
| RPCM | Road Pavement Condition Monitoring. |

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| | |
|---|---|
| RPi | Raspberry Pi. |
| RPN | Region Proposal Network. |
| SP | Smartphone. |
| SVM | Support Vector Machine. |
| TPR | True Positive Rate. |
| USen | Ultrasonic Sensor. |

## I. INTRODUCTION

Roads play a vital role in transportation facilitating safe and efficient movement of people and goods [1]. Environmental conditions such as rain, heat, moisture, snow, and water, flooding, and human factors such as accidents, traffic volume, overloading, construction quality, and maintenance contribute to road deterioration [2], [3], [4], [5]. These factors lead to the formation of cracks in the pavement, whose size and dimensions vary as shown in Figure 1 [6]. If left unattended, these cracks can widen and deepen, resulting in road deformities such as longitudinal cracks, transverse cracks, alligator cracks, road bumps, and dents, ultimately leading to potholes [7], [8]. Other impediments such as manholes, bridge joints, railroad crossings, and road bottlenecks also disrupt normal driving behavior [9]. Although road deformities can take different forms, pavement cracks are typically the earliest signs, and their presence often precludes the development of more severe deformities [7], [10].

Deteriorated roads contribute significantly to traffic congestion, accidents, driver aggression, and vehicle damage, all of which disrupt the smooth flow of traffic [8], [10], [11]. Potholes, in particular, have been identified as a major cause of road accidents [2], [12], [13], [14], [15], [16], [17], [18]. According to the World Health Organization, traffic injuries are a leading cause of death and disability globally, resulting in over 1.3 million deaths and 20-50 million injuries annually [12], [19], [20]. Poor road conditions, including potholes, cracks, and uneven surfaces, increase the risk of accidents and contribute to these alarming statistics [21].

Road Pavement Condition Monitoring (RPCM) has safety implications as well as significant economic and productivity impacts. Efficient transportation of goods and people relies heavily on well-maintained roads, and disruptions or delays can have adverse economic consequences [22], [23]. Poor road conditions can lead to vehicle damage, increased maintenance costs, and reduced productivity for businesses [3], [10], [19], [24], [25], [26]. Moreover, congestion resulting from road closures or repairs can cause delays and higher transportation costs, hampering economic efficiency [27], [28]. Therefore, RPCM is crucial for identifying and prioritizing repairs, minimizing disruptions, and ensuring the smooth flow of goods and people.

Data-driven preventive maintenance schedules based on RPCM can greatly enhance road quality and conserve energy. For instance, road roughness increases energy losses caused by Pavement-Vehicle Interaction (PVI). Implementing road remediation solutions that reduce such losses by 50% would improve vehicle fuel economy by 2%, thereby decreasing energy consumption and greenhouse gas emissions [29]. Crowdsensing for RPCM has gained attention due to its ability to harness diverse technologies and provide cost-effective solutions. By leveraging crowd-contributed data and advancements in the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing, monitoring and assessment of road conditions can be enhanced, leading to improved road safety, fuel efficiency, and environmental sustainability.

### A. RESEARCH CONTEXT

With advancements in Information and Communications Technology (ICT), RPCM has transitioned from manual inspection to automated monitoring. The IoT has facilitated RPCM through the integration of devices including sensors [30], [31], [32]. The increasing number of IoT devices which now exceeds 30 billion presents new opportunities for Intelligent Transportation Systems (ITS) in general [33], [34], [35], [36] and RPCM in particular [30], [31]. Real-time information about road conditions can be shared with authorities to enable timely repair of damaged road surfaces. RPCM solutions typically employ one of the three data acquisition methods given below [37].

1) 1D Time-Series Data Acquisition: This method employs low-cost sensors such as accelerometers, magnetometers, gyroscopes, and GPS to collect vibration, tilt, velocity, orientation, and location data. The widespread adoption of smartphones with embedded sensors has made it cost-effective to crowdsource personal sensing platforms for RPCM. These platforms collect data on road surfaces which is then transferred to a cloud platform for further processing and storage. The results can be used to identify road anomalies such as potholes, cracks, and bumps. GPS data allows for the precise mapping of these anomalies on mobile maps, enabling drivers to adjust their routes and speeds accordingly.
2) 2D Visual Data Acquisition: This method involves the use of cameras to capture visual data. The performance depends on the quality and resolution of the camera used. This approach allows for the extraction of dimensions, including length, width, and pattern, of road anomalies [38]. However, it relies heavily on camera calibration and orientation, which can be challenging in practice.
3) 3D Depth Data Acquisition: This method utilizes Light Detection and Ranging (LiDAR), Ground Penetrating Radar (GPR), laser, and thermal imaging sensors to acquire 3D depth data [3], [13], [14], [24], [30], [39]. In addition to the parameters extracted from images, this method can provide depth information about road anomalies. LiDAR, in particular, is gaining in popularity for RPCM due to its high accuracy and resolution at a relatively low cost. However, weather

and environmental conditions like rain, snow, and fog can impact the effectiveness of this method.

Table 1 presents the types of sensors employed. The sensors commonly used in the literature are camera, thermal, laser, vibration and GBR, and the advantages and disadvantages are given in the table. These results indicate that the most cost effective solution is using vibration sensors.

In the literature, vibration sensors and image processing are the most commonly employed strategies for RPCM. However, regardless of the sensor type, GPS data is essential for locating road deformities [8], [10], [30]. Techniques such as image and videography analysis, as well as laser spectroscopy, are used to detect and analyze potholes, including depth, size, volume, and shape [14]. This information can be used to determine suitable maintenance measures. Therefore, selecting an appropriate sensing method is crucial, and should consider the application requirements and limitations of each method.

In recent years, crowdsensing has emerged as a promising solution for RPCM due to the widespread availability of personal sensing platforms such as smartphones which have the potential to collect data on a large scale [15], [40]. Crowdsensing offers a more efficient, cost-effective, and scalable approach compared to traditional methods for collecting data on road pavement conditions. Furthermore, it can be used for real-time data collection and can gather data from a wider range of locations. Smartphones with GPS can provide more precise and comprehensive information on road conditions than traditional methods. Thus, crowdsensing is a very promising methodology for RPCM by providing real-time, cost-effective data collection with broad coverage and detailed information.

### B. SCOPE AND OBJECTIVES

Several literature reviews have considered aspects of RPCM [18], [37], [41], [42], [43], [44], [45], [46], but they have a narrow focus, i.e. sensor platforms, individual sensors, and specific road anomalies [18], [41], [45], or software related to RPCM [42], [43]. Thus, there is a need for a survey considering the wider applicability of crowdsensing for RPCM within a real-world context. This study satisfies this need by providing a comprehensive investigation of crowdsensing for RPCM. The specific objectives are as follows.

1) Determine the trends and limitations inherent in the using crowdsensing for RPCM.
2) Assess the cost-effectiveness and feasibility of employing crowdsensing for RPCM.
3) Evaluate the performance and reliability of data derived from crowdsensing in the context of RPCM.
4) Provide recommendations for future development and deployment of crowdsensing solutions for RPCM.

Addressing these objectives will yield valuable insights to guide both researchers and practitioners in improving the efficiency and effectiveness of RPCM. The significance of this study lies in its potential to contribute to the improvement of road networks, traffic flow, and transportation systems in general, as well as the associated societal benefits. This will alleviate traffic congestion, reduce accident rates, and decrease vehicle emissions. The cost-effectiveness, feasibility, and reliability of crowdsensing for RPCM will also be examined. These results will inform the design and implementation of precise and efficient solutions, leading to safer and more sustainable road infrastructure.

The remainder of this paper is organized as follows. Section II presents an overview of the literature review conducted including search terms, research questions, and criteria for selecting articles for inclusion. In Section III, the methodologies employed in RPCM are discussed, highlighting their strengths and limitations. Section IV presents an examination of future research directions. Finally, Section V provides a summary of the results obtained.

## II. LITERATURE REVIEW

In this section, a literature review is presented for the analysis of the research on crowdsensing for RPCM. The goal is to gain insights into the potential of crowdsensing for use in real-world scenarios. The review process involves research questions, search strategy, and paper inclusion and exclusion criteria. This process will identify relevant studies that address the research questions and contribute to the advancement of RPCM using crowdsensing technologies.

### A. RESEARCH QUESTIONS

The following questions were considered to guide the literature review on crowdsensing for RPCM.

1) What types of sensing platforms are used for RPCM through crowdsensing?
2) Which AI and ML algorithms are being employed with these platforms?
3) What type of road anomalies are being detected and what is the performance?
4) What are the challenges, limitations, and opportunities associated with the current methods used for RPCM?

By answering these questions, the literature review provides a comprehensive overview of the state-of-the-art technologies and methodologies used for RPCM.

### B. SELECTION CRITERIA

The following criteria were used in deciding to include a paper in the literature review.

1) The paper must provide answers to the research questions.
2) The paper must have been published between 2017 and 2022.
3) The paper must be published in English.
4) The paper should be readily available online.
5) The paper should contain a sufficient number of references from reliable sources.
6) The paper must appear in the Web of Science and/or Scopus databases.

**TABLE 1. Sensor technologies used for RPCM.**

| Parameter | Camera | Laser | GPR | Thermal | Vibration |
|---|---|---|---|---|---|
| Technology | 2D, 3D image processing | 3D image based on reflections | 3D image of underground surfaces via radio waves | 2D, 3D image of spatial distribution of temperature differences | 1D Acc Gyro |
| Processing | complex image processing algorithms | acquisition of 3D point cloud | acquisition of depth images and simulation data required | acquisition of surface heat variations | data is used directly |
| Processing Time | data acquisition and analysis is fast but response time is processor dependent | data acquisition is fast with speeds as high as 100 km/hr | slow due to data size but acquisition is automated | data acquisition and analysis is robust | poor due to the required data processing |
| Real-Time Application | depends on processor | yes | yes | yes | not suitable for real-time detection |
| Sensing Time | while moving towards distress | while moving towards distress | while moving towards distress | while moving towards distress | after experiencing distress |
| Characterization of Distress | relies on shape and size | relies on 3D images | relies on 3D images | relies on heat maps | only along wheel path as data is 1D |
| Light Sensitivity | sensitive to illuminance level and light source position | negligible | negligible | not sensitive to light but affected by surface temperatures | none |
| Performance | depends on algorithm | high | high | high | very susceptible to errors |
| Cost | low | high | very high | very high | negligible |

7) Either the IoT or a smartphone must be used for data collection. Papers that only present algorithms were excluded.

### C. RESULTS

A systematic search was first conducted in pertinent databases to ensure all relevant work was considered. The search was confined to papers published between January 2017 and December 2022, and papers whose titles did not align with the focus on IoT and RPCM were excluded. A total of 320 papers were initially identified. Then, 39 duplicate studies were removed, followed by the exclusion of 164 additional papers based on a detailed evaluation of their titles and abstracts. The full text of the remaining 117 papers was examined and 58 papers were selected. An additional 17 papers were added through a snowballing technique resulting in 75 papers being included in this study. The selection process is illustrated in Figure 2. The distribution of the selected papers for RPCM using crowdsensing is given in Figure 3. Although crowdsensing based RPCM has been explored in the past, these results show a significant increase in interest over the last five years with about 60% of the publications in 2020.

## III. SENSING PLATFORMS FOR RPC MONITORING

This section examines crowdsensing for RPCM by leveraging accelerometer and gyroscope sensors along with IoT solutions. Mobile applications or platforms allow individuals to capture road vibration and motion data while in vehicles. This data can be transmitted to a central server or cloud platform for analysis to identify and characterize anomalies including potholes, cracks, and bumps, as illustrated in Figure 4. The integration of GPS data from smartphones plays a pivotal role in accurately locating road anomalies on road network maps. This spatial information allows authorities and maintenance teams to prioritize areas requiring immediate attention and repair. Sensing platforms often employ AI and ML algorithms to detect road anomalies through crowdsensing as discussed below.

### A. THRESHOLD-BASED MONITORING

Crowdsensing for RPCM using sensors including accelerometers, magnetometers, gyroscopes, and USens has become popular [22]. Threshold-based methods, known for their computational efficiency, involve setting limits or thresholds for parameters such as roughness, texture, and cracking. By integrating these sensors with personal sensing platforms like smartphones, real-time monitoring of road surface conditions becomes possible, enabling the detection of anomalies such as potholes, cracks, and bumps. The collected data is then transmitted to a cloud platform for further processing and storage. While threshold-based monitoring has its limitations, such as not considering all factors that affect road surface quality, it enables the monitoring of a larger number of roads and the efficient detection of anomalies [22]. The threshold-based methods are presented in Table 2 and discussed below.

Ultrasonic Sensors (USens) are commonly used to measure the distance between a vehicle and the road for RPCM applications [22]. In [22], USen data was employed to

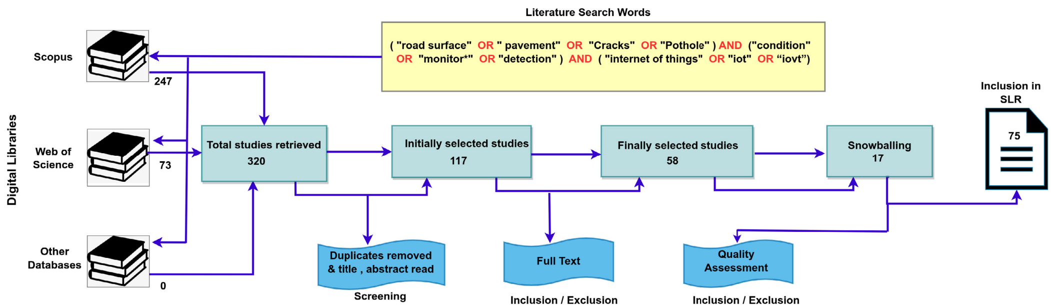


**FIGURE 1.** The paper selection process.

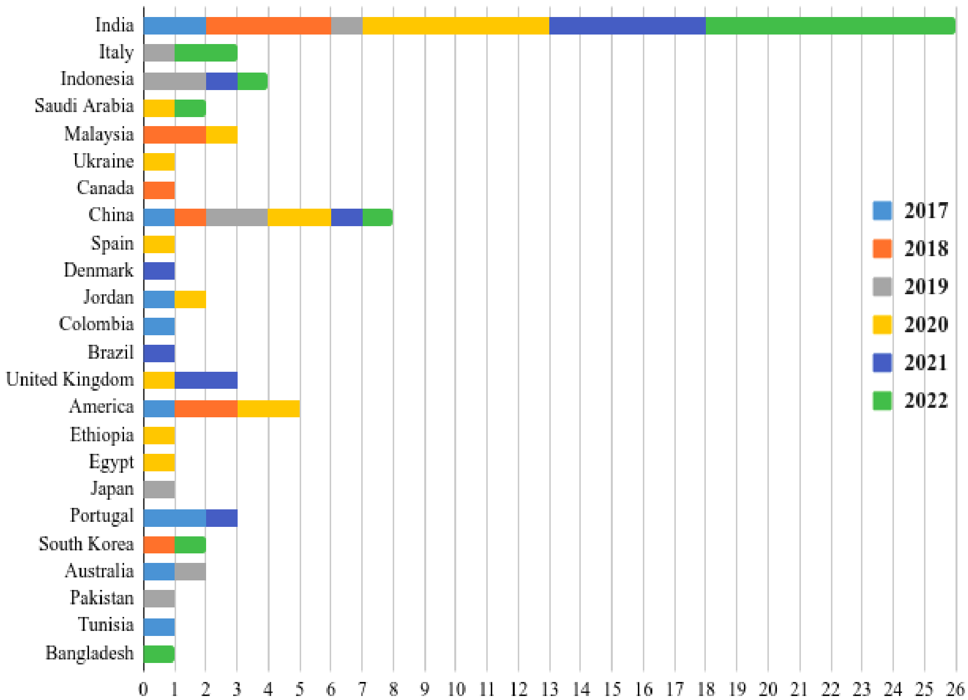


**FIGURE 2.** Literature survey distribution for 2017-2022.

detect and measure potholes. The data is streamed to an AWS platform to alert drivers through a mobile app. In [47], the location of detected potholes was marked on Google Maps and shared with drivers via a mobile app. The height and depth of road abnormalities were estimated in [48] in addition to detecting potholes. In [49], an intelligent road damage detection system called TRACTS-Net was presented that leverages USens for pothole detection.

Numerous RPCM solutions have been proposed that use accelerometer vibration data as the primary input [8], [13], [14], [21], [50], [51]. For example, the vehicle-as-a-sensor solution presented in [8] was used to classify road pavement into different categories, e.g. smooth, rough, and bumpy, and detect potholes. The sensor data is transmitted to the OneM2M cloud platform. An Android app solution was proposed in [50] that streams pothole information to a web application developed in Scala Play to provide information to drivers. In [51], a road ride quality score was obtained using accelerometer data in the $x$, $y$, and $z$ directions. Data cleansing and time synchronization with GPS were used to ensure accurate results. A score was then assigned to road sections and displayed on a web interface for driver access. An embedded system with environmental sensors was used in [13] to monitor vehicle emissions. The data obtained is streamed to the AWS cloud platform for analysis and user notification. In [21], smartphone sensors and an OBD-II device were used to detect vehicle speed, RPM, vibrations, and orientation. A $z$ axis threshold algorithm was developed to classify potholes and other anomalies. In [14], an intelligent real-time pothole detection and warning system was proposed for two-wheelers. It records the location, severity, and images of potholes, and this data is sent to a cloud server for analysis.

 

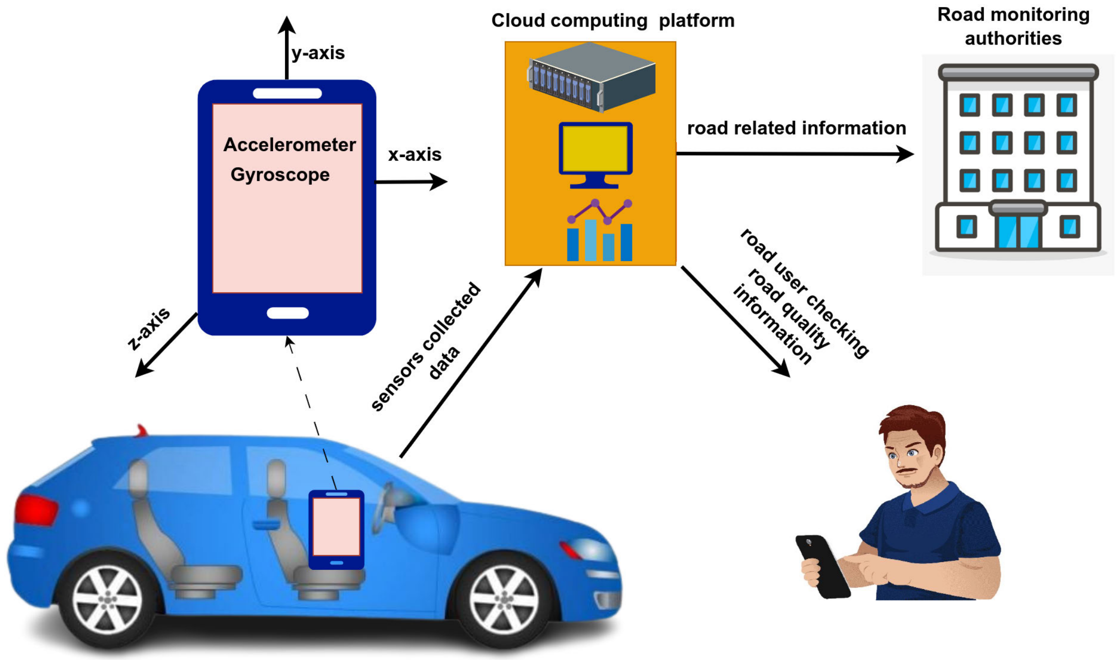


**FIGURE 3.** Crowdsensing for RPCM using a sensing platform.

**TABLE 2.** Threshold-based methods for RPCM.

| Tools | Sensors | Sharing | Anomalies | Reference |
|---|---|---|---|---|
| RPi, SP | USen | AWS | potholes | [22] |
| SP | Acc ($z$ axis) | ONeM2M | potholes, bumps | [8] |
| RPi, MQ sensors | Acc ($z$ axis) | AWS | potholes, bumps | [13] |
| SP | Acc | web server | potholes | [50] |
| RPi 3, Cam, SIM808 | ADXL345 Acc ($x, y, z$ axes) | AWS | potholes | [14] |
| NodeMCU, RPi 3B+ | MPU6050 Acc ($z$ axis) | Google Firebase | potholes, road surface quality | [51] |
| Ard UNO | USen HC-SR04, GPS Neo-6M | mobile app | potholes | [47] |
| RPi 3B, GSM | USen HC-SR04 | cloud, mobile app | potholes, bumps, speeders | [48] |
| SP, OBD-II, Cam | Acc ($z$ axis) | cloud | potholes | [21] |
| Ard UNo | USen HC-SR04 | — | potholes | [49] |
| NodeMCU | USen, Acc ($x, y, z$ axes) | ThingSpeak | potholes | [53] |
| SP | Acc ($x, y, z$ axes), GPS | Google Cloud | potholes | [54] |

### *B. DTW*

DTW (Dynamic Time Wrapping) is a technique used in crowdsensing-based RPCM to detect and track road conditions. It is a distance measuring method that matches time series data considering variations in speed or timing between sequences [40], [52]. In the context of RPCM, DTW is employed to compare vibration signals from vehicles traveling on a road with reference signals representing a smooth road surface. Deviations or disparities between the collected vibration and reference signals can be identified and labeled as potholes or road anomalies. This facilitates accurate detection and tracking of potholes in real-time, allowing road maintenance authorities to promptly address and repair damaged sections of the road network. The methods that employ DTW are presented in Table 3 and discussed below.

A scalable platform for pavement sensing, data analytics, and visualization was presented in [29]. It employs an embedded system to collect road condition data, and DTW is used to detect road anomalies such as potholes, cracks, and bumps. The collected data is processed and visualized in real-time on a dashboard to provide a comprehensive overview of the pavement condition. The data is stored on AWS to allow further analysis for the detection of road surface anomalies.

A comparison between two types of embedded systems (ARM Cortex MQ and RPi), and a smartphone-based Android app was conducted in [31]. The variations in International Roughness Index (IRI) values obtained from these systems were explored, and it was found that the placement of the monitoring system, with the smartphone mounted on the vehicle dashboard and the embedded system mounted on the vehicle axle, affected these values. This highlights the significance of the placement and orientation of the monitoring system when assessing road conditions. An embedded solution for RPCM specifically designed and installed on a bicycle was introduced in [55]. To ensure accurate results, the sensed data underwent cleansing using envelop detection and offset correction methods. The selected road was divided into distinct segments, and polynomial curve fitting techniques were applied to each segment to provide the corresponding pavement condition.

An SP app to assess and map road surface roughness was developed in [26]. Road surface roughness was classified into four categories and an accuracy of over 90% was achieved compared to data from a vehicle-mounted laser pavement scanner. These results demonstrate the potential of smartphones as cost-effective tools for evaluating road conditions and assessing road surface roughness accurately. A mathematical model for road pavement condition classification was proposed in [56] to distinguish between good, poor, and bad conditions. The model employs multiple parameters including $z$-axis data from accelerometers, vehicle speed and width, and tire width. To examine the variations in accelerometer parameters, a road was selected for field testing and divided into segments. The segments contained anomalies such as potholes and road surface irregularities, as well as raised crosswalks and bridge entry/exit points. The relationships between speed and $z$-axis data, and road elevation and $z$-axis data, were explored.

A mobile app was presented in [30] that employs a mathematical model incorporating noise filtering to mitigate the effects of SP motion. It effectively tracked $y$ axis accelerometer variations to detect road surface irregularities and potholes. The app was tested on different road types, including straight, ascending, and descending roads, and demonstrated accurate detection of irregularities and potholes. In [58], a method for detecting and classifying road surface quality was presented which employs an accelerometer mounted on a vehicle. Vibration data was processed using a Butterworth low-pass filter followed by feature extraction and classification of road quality. This method was shown to be effective in identifying road conditions such as cracks, potholes, bumps, and surface (e.g. dirt, paved, and rough). A method for road condition characterization was proposed in [40] that uses SP gyroscope data. The variance of gyroscope rotation was shown to be a reliable indicator of road pavement condition. The DTW algorithm was then employed to detect potholes by comparing the vibration signals with reference signals, and real-world data was used to demonstrate the effectiveness of the proposed method.

An embedded solution for RPCM which focuses on accident detection and prevention was introduced in [60]. The module is installed in vehicles and data mapping is used to analyze sensor data, including GPS and accelerometer data, for accident detection and monitoring the road condition. DTW is employed to classify road anomalies, such as speeders and potholes, based on vehicle speed and acceleration. An IoT-based road surface sensing and communication system was presented in [59] to monitor and analyze road conditions for safe driving, particularly in adverse weather conditions like rain, flooding, and snow. The system incorporates multiple sensor nodes deployed across the road network. These nodes gather data on road surface state such as temperature, humidity, and friction coefficient. This data is transmitted wirelessly to a central server where it is analyzed to generate road surface state information. The system enables drivers to be alerted about hazardous conditions and assists authorities responsible for road maintenance in making informed decisions. The use of non-contact microwave sensing for uniform distribution of salt on icy roads was examined in [57] using Frequency Modulated Continuous Wave (FMCW) signals reflected by the road surface. The proposed system has the potential to improve road safety and reduce maintenance costs for road infrastructure.

### C. MACHINE LEARNING

ML techniques are now widely employed for crowdsensing-based RPCM. The methods presented in Table 4 highlight the effective use of crowd-sourced data, SP technologies, sensors, and ML algorithms to achieve accurate detection and classification of road anomalies. In this table, the performance indicated is Accuracy (A), Precision (P), Recall (R), and F1 score (F1), and the technique providing the best performance is denoted by *. This table indicates the diversity of contributions to enhancing road safety and maintenance practices.

In [24], an embedded system utilizing RPi was employed to stream sensed parameters to a local server for analysis. It incorporates the K-means clustering algorithm to classify road data into two classes, enhancing pothole detection. Another embedded solution for pothole detection was proposed in [61] that uses the K-means clustering algorithm. This solution employs a module that connects to a smartphone via Bluetooth to capture images of potholes. The data and images are then streamed to a central government server for analysis to support road maintenance. An IoT-based real-time application for road pothole detection and classification was introduced in [17]. The system incorporates a data processing unit that employs the K-means clustering algorithm to predict road conditions. A mobile app is also provided for users to report road conditions. The system effectiveness was evaluated using a dataset collected from sensors placed on a test road section. A crowdsourcing solution for abnormal road surface estimation using a Gaussian background model was proposed in [62]. The solution employs the K-means and K-medoids algorithms for data clustering, and the K-means algorithm was reported as more suitable.

**TABLE 3.** DTW methods for RPCM.

| Tools | Sensors | Sharing | Anomalies | Reference |
|---|---|---|---|---|
| Ard Nano | ADXL 335, Acc ($z$ axis) | SD card | potholes, bumps | [55] |
| SP | Acc ($y$ axis) | local | potholes, road surface irregularities | [30] |
| FCMW radar | — | — | salt distribution on roads | [57] |
| SP | Acc ($z$ axis) | Google Cloud | pavement condition | [56] |
| RPi 3B, Teensy | MPC-9250 IMU Acc ($z$ axis) | AWS | road surface quality | [29] |
| SP, two embedded systems | MPU6050 Acc ($z$ axis) | — | IRI | [31] |
| EVAL-ADXL345Z board | ADXL345 Acc ($x, y, z$ axes) | — | road surface quality | [58] |
| Smart Mobile Box | Acc, Gyro, magnetometer ($x, y, z$ axes), temperature and humidity sensors | cloud | road surface quality in adverse weather | [59] |
| SP | Acc ($z$ axis) | — | IRI | [26] |
| SP | Gyro ($x$ axis) | — | pavement condition | [40] |
| RPi Zero W, NEO-6M GPS | MPU9250 IMU Acc and Gyro ($x, y, z$ axes) | cloud | potholes, speeders | [60] |

A method that leverages crowd-sourced data from mobile devices was proposed in [15]. Low-pass filtering and a lane detection algorithm are used to eliminate high-frequency noise and separate data from different lanes. SVM is then employed to classify road regions with potholes. D&RSense was proposed in [63] as a solution for bike riders. It uses four smartphones and two bikes to build the dataset. SVM is employed for pothole and road surface irregularity detection, and an impressive accuracy of 95.4% was achieved. In [10], multiple sensor nodes were mounted on test vehicles to capture real-world road data. Statistical, time, and frequency domain features were extracted to distinguish road anomalies, and SVM was utilized for classification, yielding an accuracy of 90%. A Virtual Road Network Inspector (VRNI) was developed in [64] to continuously monitor, detect, and locate potholes based on adaptive one-class SVM models with vertical and lateral acceleration data as inputs. This method consistently achieved a high detection rate of 97.5% with a low false alarm rate of 4%. An IoV-fog-cloud framework was proposed in [16] to detect road anomalies. This framework combines sensors, edge devices, fog nodes, and cloud servers to collect and analyze data on road anomalies in real-time. The SVM-based Non-Linear Anomaly Detection and Diagnosis (SVM-nAVDD) approach was employed, and the results demonstrate that it can detect and classify road anomalies with an average precision of 91% and accuracy of 92% in depth/height detection.

The accelerometer in smartphones was used in [65] to capture vehicle vibrations and a data mining algorithm based on Gaussian modeling was employed to detect road abnormalities. $x - z$ ratio filtering was used for event classification to distinguish between potholes and humps. An algorithm was also developed to estimate severity based on the relationship between vertical acceleration and relative vertical displacement of the vehicle. An embedded solution using integrated accelerometers and USens for pothole and hump detection was presented in [25]. Accelerometer data was combined with ultrasonic data to address variations in signal magnitude caused by road roughness. Honey Bee Optimization was employed to optimize the sensor data. A pothole detection solution was introduced in [66] and evaluated using a publicly available dataset. A fast greedy clustering algorithm was used to group pothole candidates and an accuracy of 80% was achieved in classifying potholes into seven classes, namely small potholes, large potholes, pothole clusters, drain pits, gaps, bumps, and road surface irregularities. A cost-effective and computationally efficient model to categorize potholes and bumps using SP data was proposed in [67]. A CNN approach to analyzing SP accelerometer data and road images for pothole detection was proposed in [68]. An impressive F1 score of 89.9% was obtained. In [69], an edge computing system was introduced that uses CNN-based real-time classification of acoustic data from road surfaces. The system classifies road surfaces as good, ruined, silent, or unknown, and an accuracy of 90% was achieved. A real-time road condition assessment solution called LiRA was proposed in [70]. It employs vehicle sensors to detect road anomalies from abnormalities in vehicle movement. Although still under development, LiRA aims to become a comprehensive pavement management system.

#### 1) COMPARATIVE STUDIES

In [23], a solution for road pavement monitoring in Indonesia was proposed. A vehicle was driven at various speeds on a test road to obtain pavement data. Two ML algorithms, SVM and DT, were employed and it was found that SVM

**TABLE 4.** ML-based methods for RPCM.

| Tools | Sensors | Techniques | Sharing | Performance | Anomalies | Reference |
|---|---|---|---|---|---|---|
| RPi 3B+ | MPU6050 Acc ($x, y, z$ axes) Gyro ($x, y, z$ axes) | RF*, SVM, LR, KNN, NV, DT, EV | — | 86.8 (A)% | potholes | [2] |
| RPi | Acc ($z$ axis) | SVM*, DT | SEMAR cloud database | 98% (A) | potholes and bumps | [23] |
| SP | Acc ($x, y, z$ axes) | CNN | cloud | $<$ 80 (A)% | pavement condition | [12] |
| SP, tablet | Acc ($x, y, z$ axes) | SVM | — | 90% (TP) | road condition (mild, severe), potholes | [10] |
| Ard, RPi | speed, ADXL345 Acc($x, z$ axes) | K-means | local server | — | potholes | [24] |
| Ard Nano 33 IoT | Acc ($x, y, z$ axes) | TinyML Algo (TEDA) | local server | 78% (F1) | potholes, bumps | [73] |
| SP | Acc ($x, z$ axes) | Gaussian model based mining | — | speed dependent | potholes, humps | [65] |
| SP | Acc ($z$ axis) | K-means, Gaussian background model | — | — | abnormal road surfaces | [62] |
| SP | Acc($z$ axis) | SVM*,CNN, MLP | — | 98% (A) | road segment classification | [71] |
| Ard Uno, MPU6050 | Acc ($z$ axis) | SVM*, KNN, RF | — | 99% (A) | pavement condition | [74] |
| Ard UNO | Acc, ultrasonic | HBO | cloud | — | potholes and humps | [25] |
| SP | Acc ($x, y, z$ axes) | SVM, Fast DTW | cloud | 97.5% (A) | potholes and bumps | [63] |
| SP | Acc | fast greedy algorithm | cloud | 80% (A) | potholes | [66] |
| SP | Acc ($x, z$ axes) | Inception V3 | — | 100% (A) | potholes, bumps | [67] |
| sensor node, Cam | Acc ($x, z$ axis) | SVM | local | 97.5% (TP) | potholes | [64] |
| PIC18F26K22 microcontroller | speed, ADXL362 Acc($x, y, z$ axes) | SVM*, NB, RF, CNN | — | 95.2% (TP) | potholes, manholes, bumps, cat eyes | [72] |
| SP | Acc ($x, y, z$ axes) | RF*, LR, SVM | Google Firebase | 88.5% (P) | potholes | [52] |
| SP | speed, Acc ($x, y, z$ axes) | SVM | cloud | speed dependent | potholes | [15] |
| SP | Acc ($x, y, z$ axes) | C4.5 DT*, SVM, NB | — | 98.6% (A) | pavement condition | [19] |
| SP | Acc ($z$ axis) | fuzzy logic | local server | — | IRI | [75] |
| SP | speed, Acc ($x, y, z$ axes) | GB*, DT, MLP, NB | — | 87% (A) | manholes, short and long bumps | [27] |
| RPi 3B, OBD-II | vehicle data, Acc | CNN | — | — | pavement condition | [70] |
| SP | Cam, Acc ($x, y, z$ axes) | CNN | server | 89.9% (F1) | potholes | [68] |
| SP | Gyro ($x, y, z$ axes) | NN*, threshold, KNN | Google Firebase | 84% (A) | pavement condition | [76] |
| Ard | HC-SR04 ultrasonic | K-means | local server | — | potholes | [61] |
| Ard Mega | MPU6050 Acc and Gyro ($x, y, z$ axes), speed | SVM-nAVDD | cloud | 91.2% (P) | potholes, road surface irregularities | [16] |
| NodeMCU, NEO-6M | MPU-92/65 Acc, Gyro | K-means | SP | — | potholes | [17] |
| publicly available data | — | NB*, RF, LR, SVM, DT | — | 92% (A) | pavement condition | [20] |
| Ard | MPU6050 Acc ($x, y, z$ axis) and Gyro ($x, y, z$ axis) | NN*, threshold | Google Cloud | 86% (A) | pavement condition | [77] |
| RPi 3B | CMA-4544PF-W microphone | Tiny CNN | — | 90% (A) | road surfaces | [69] |

achieved a higher accuracy of 98%. An Android app for RPCM was proposed in [71]. Three ML algorithms, namely SVM, CNN, and MLP, were considered to classify road sections as normal, patched, bad, pothole, or bumpy. The results indicated that SVM achieved the highest accuracy of 98%, outperforming CNN and MLP which had 96% and 68% accuracy, respectively. A low-cost system for RPCM was presented in [72] that utilizes ML algorithms to classify road anomalies. GPS and accelerometer sensors were used to collect road surface condition data which was then processed using the SVM, RF, and KNN algorithms. The performance was evaluated using a dataset of road anomalies collected on a test route, and SVM achieved the highest TPR of 95.2%, while NB, RF, and KNN achieved TPRs of 92.4%, 78.6%, and 88.1%, respectively.

An edge computing solution called DeepBus was introduced in [2] for pothole detection and reporting. Eight ML models were considered including LR, SVM, KNN, NB, DT, RF, and EV, and RF achieved the highest accuracy of 86.8%. An SP app was developed in [52] to collect sensor data while driving to identify potholes using ML algorithms. Features based on accelerometer and gyroscope data were used to distinguish between normal road conditions and potholes. ML models including LR, SVM, and RF, were considered and RF provided the best pothole classification with a precision of 88.5% and a recall of 75.0%.

In [76], a SP application was presented that utilizes built-in sensors to classify roads based on their condition, specifically good, moderate, and poor. The threshold, KNN, and NN algorithms provided road pavement classification accuracies of 72.3%, 85.3%, and 90.2%, respectively. Field testing showed that the NN model achieved an accuracy of 84%. An IoT-based system was presented in [77] which employs Ard, an IMU sensor, and GPS to detect road conditions. Multiple sensor nodes were placed on vehicles to collect data and transmit it to a central server for analysis. The threshold and NN algorithms achieved accuracies of 82% and 86%, respectively.

In [27], a data mining approach was presented that leverages GPS and accelerometer data to identify road anomalies. The proposed methodology involves preprocessing the data followed by feature extraction. The GB, DT, MLP, and NB algorithms were used to evaluate the performance. An intelligent IoT-based accident avoidance system was proposed in [20] for adverse weather and road conditions. The goal is to use publicly available data to detect hazardous road conditions such as snow, ice, and heavy rain and assess their impact on road accidents. Five ML algorithms, namely NB, Random Forest (RF), LR, SVM, and DT, were employed to classify the data, and they provided accuracies of 92%, 91.5%, 91%, 90%, and 86%, respectively. In [19], the SP application Roadsense was developed to estimate road conditions using accelerometer and gyroscope data. Signal processing techniques were employed to extract features that indicate the road condition. The C4.5 DT, SVM, and NB algorithms were employed to estimate road conditions using these features. The reported accuracies for C4.5 DT, SVM, and NB were 98.6%, 95.3%, and 96.9%, respectively.

### D. COMPUTER VISION ALGORITHMS

The rapidly evolving field of computer vision, combined with advancements in IoT, deep learning, and image processing techniques, has opened up new possibilities for RPCM. These approaches have shown promising results in accurately identifying and monitoring road anomalies such as cracks, potholes, and other pavement defects. Table 5 presents the computer vision-based methods for RPCM and they are discussed below. In this table, the performance indicated is Accuracy (A), Precision (P), Recall (R), and F1 score (F1), and the technique providing the best performance is denoted by *.

Several computer vision-based solutions have been proposed for road anomaly detection. An IoVT approach incorporating a deep learning model was utilized in [78] to detect potholes in road images with an impressive accuracy of 99%. The system captures road images with a sensor node and processes them using OpenCV and TensorFlow. The embedded solution proposed in [38] employs IR images captured by a Kinect sensor and image processing to estimate the depth and severity of potholes. The results are then streamed to Dropbox for further analysis. In [79], an image-based solution was presented for pothole classification and open manhole detection. This system uploads images to a web server for use by the general public. Road anomalies are classified at predefined intervals and the authorities are contacted as necessary. In [67], a solution for edge-based crack detection was introduced. It combines a crack detection model called Real-time Segmentation using Effective Feature Extraction (Rsef) with edge computing on the NVIDIA Jetson TX2 platform. This model is based on EfficientNet and U-Net, and employs semantic segmentation for crack detection. The edge-based system, called Rsef-Edge, uses both an IoT device and an edge server with a powerful GPU. It was shown to significantly reduce latency by a factor of up to 17.4 without sacrificing accuracy (reported to be 97.3%). This makes it an ideal solution for performance-limited IoT devices that require low latency. In [81], an IoT-enabled system for pothole and road crack detection was presented. This system consists of a hardware module that uses image processing to detect potholes and road cracks. The detected anomalies are then transmitted to a cloud server via Wi-Fi for further analysis. A web application is employed for real-time notification.

Several approaches that leverage the IoT and CNNs for road crack and pothole detection have been proposed [11], [82], [83], [84]. In [11], an IoT approach utilizing BCD-CNN, a bio-inspired co-evolutionary deep-CNN, was proposed for road crack detection. The model is trained on road images captured by an SP camera and optimized using BCD-CNN. The algorithm was evaluated with a dataset of road images captured under different lighting conditions and angles. An edge computing solution for pothole detection employing a CNN was introduced in [83]. The CNN was trained on a large dataset of pothole images using transfer learning. The system uses a Jenteson Nano and an AI accelerometer for real-time processing of road images collected from a moving vehicle. However, the accuracy of this solution decreases as the vehicle speed increases. In [84], a 6G-enabled connected vehicle framework was proposed for intelligent road maintenance using deep learning data fusion. This framework incorporates various sensing results, including road images and accelerometer data, to monitor road conditions. Data fusion is used to integrate data from multiple sensors to improve the detection of potholes with different sizes and shapes in a variety of environmental and lighting conditions. An IoT-based system for road obstacle detection and identification using a CNN was presented in [85]. This system captures real-time road images with a camera. IoT technology is used to notify relevant departments of the presence of obstacles through a mobile application. In [82], an IoVT solution mounted on the front of a vehicle was proposed for road anomaly detection. Road images captured by an RPi and camera were streamed to an online database where a CNN algorithm was used to detect anomalies.

The use of DNNs for pothole and road crack detection was proposed in [3], [7]. In [3], a DNN learning-based approach was presented for pothole detection using images captured by a vehicle-mounted camera. A CNN is used for image processing and an RPN is employed to identify potential potholes. Road images were captured at a rate of 5 to 6 frames per second using an automotive camera integrated with the Nvidia DrivePX2 platform while the vehicle was traveling at 60 km/h. Four DNN models, namely Inception v2, ResNet101, Inception-ResNet v2, and SSD Mobilenet v2, were considered and ResNet101 provided the

**TABLE 5.** Computer vision-based methods for RPCM.

| Tools | Techniques | Sharing | Performance | Anomalies | Reference |
|---|---|---|---|---|---|
| public dataset | BCD-CNN | — | 99.7% (A) | road cracks (high, medium, low severity) | [11] |
| Nvidia DrivePX2, automotive grade Cam | ResNet101*, Inception v2, Inception-ResNet v2, SSD Mobilenet v2 | — | 83.5% (P) | potholes | [3] |
| RPi, Pi Cam | CNN | web server | — | potholes, cracks, ruts | [82] |
| RPi, Kinect sensor | — | Dropbox | — | potholes | [38] |
| vehicle mounted Cam | Inception-v4*, ResNet-50, Inception-ResNet-v2, RF, SVM, KNN, NB, CapsuleNet | local server | 91.7% (A) | road cracks | [7] |
| Canon IXUS 190 Cam | VGG*, GoogLeNet, DenseNet, DCGAN, logistic, NB, SVM | local server | 88.8% (F1) | road cracks | [4] |
| RPi Zero, IMU sensor, Pi Cam | OpenCV, Tensorflow | local server | 99% (A) | potholes | [78] |
| public images | Faster-RNN | web server | — | potholes, open manholes | [79] |
| Jetson Nano, AI accelerator, Cam | CNN | — | 25% (TP) | pothole detection | [83] |
| ESP8266, USB Cam | CNN | local server | — | potholes, cracks | [85] |
| SP Cam, Acc | CNN | local server | 89.9% (F1) | pothole detection | [84] |
| Nvidia Jetson Tx2 | Rsef-Edge | — | 97.3% (A) | crack detection | [80] |
| RPi, Cam | Otsu's Thresholding | — | 93.8% (A) | potholes | [81] |

highest precision and accuracy. An embedded solution for road crack detection and classification was proposed in [7]. Ten models were investigated including both shallow models (RF, SVM, KNN, NB, and linear discriminant analysis) and deep learning models (ResNet-50, Inception-v4, Inception-ResNet-v2, and CapsuleNet). The performance of these models was evaluated with and without preprocessing of image data and Inception-v4 was identified as the best choice with an accuracy of 91.7%.

In [4], an embedded solution for road pavement image processing was presented. The system transmits road pavement images to a local server via an SP Wi-Fi hotspot. Image processing is performed on a workstation equipped with a 2.1 GHz Intel Xeon Silver 4110 CPU and GPU cards, including NVIDIA GV100 and TITAN V. The GoogLeNet, VGG, DenseNet, deep convolution generative adversarial network (DCGAN), LR, NB, and SVM algorithms were considered, and the accuracy with and without image preprocessing was determined. VCG achieved the highest accuracy of approximately 88%.

## IV. DISCUSSION AND CHALLENGES

In this section, the above results are examined with a focus on their implications, limitations, and significance. We present the trends in crowdsensing-based RPCM and then consider the challenges identified and give research directions for the future.

### A. TRENDS

Crowdsensing-based RPCM has experienced a significant increase in interest. The corresponding trends reflect the evolution of RPCM and its applications. The major trends are as follows.

1) Sensing Platforms: RPCM using dedicated IoT solutions was previously considered but the widespread use of smartphones has resulted in the development of mobile apps for RPCM. This allows the general public to report road anomalies encountered during their daily travels. These apps can utilize sensors on the smartphones such as the camera, accelerometer, and GPS, to capture relevant data about road conditions. SP-based RPCM is a cost-effective solution compared to dedicated IoT-based solutions.
2) Data Aggregation and Analysis: The data collected from SP users can be aggregated and analyzed to identify road anomalies. ML and data mining techniques are employed to process the large volumes of crowdsensed data and extract insights. ML-based solutions are increasing because of their accuracy and cost-effectiveness compared to threshold and computer vision solutions. Public cloud platforms are also being utilized for data aggregation and analysis.
3) Real-time Monitoring and Alert Systems: One of the key advantages of crowdsensing-based RPCM is the ability to provide real-time monitoring of road

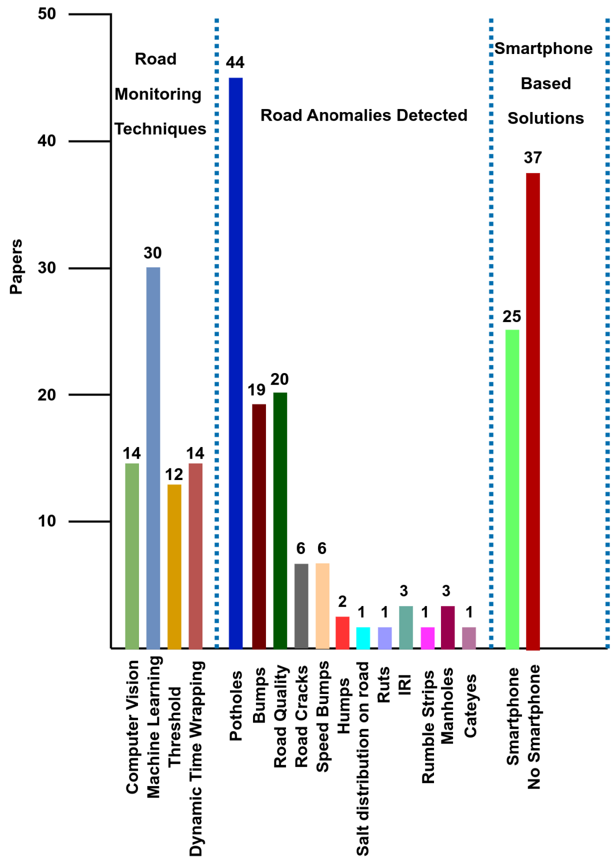


**FIGURE 4.** Crowdsensing platforms and algorithms in the literature.

conditions. The data collected from a large number of users can be leveraged by authorities to quickly detect and respond to road anomalies. Alert systems are used to notify relevant stakeholders such as road maintenance teams and drivers about the presence of road defects.

4) Integration with GIS and Mapping Systems: Crowdsensing data can be integrated with GIS and mapping platforms to create interactive maps that visualize the distribution and severity of road anomalies. This integration enables better decision-making to prioritize maintenance and optimize resource allocation.
5) Citizen Engagement and Participation: Crowdsensing-based RPCM promotes citizen engagement by involving the public in monitoring and reporting road anomalies. Their participation not only improves data collection but also increases public awareness and accountability regarding road conditions.

### *B. LIMITATIONS*

While crowdsensing has emerged as a promising approach for RPCM, it has limitations. In particular, crowdsensing-based monitoring relies on user participation which can be inconsistent and may not cover all areas of a road network, leading to potential gaps in data coverage. However, crowdsensing-based RPCM using GPS data remains a valuable tool for identifying and addressing road surface issues as it allows for the collection of real-time data that can help authorities prioritize maintenance and repairs for improved road safety.

#### 1) GPS

GPS technology is commonly used to locate road anomalies in crowdsensing-based RPCM. It employs a network of satellites orbiting Earth to provide location information. There are 27 satellites, with 24 in operation and three spares. GPS was initially developed for military applications but it has since been made available for civilian use [47]. A GPS receiver in a device such as an SP obtains signals from multiple satellites to calculate its location through a process called trilateration. Distances from at least four satellites are required to obtain accurate positions [47]. However, GPS-based RPCM solutions have several limitations that need to be addressed.

1) GPS Data Accuracy: The accuracy of GPS data can vary depending on factors like signal strength and environmental conditions. As a result, inconsistencies may arise in the location data collected by different users, making it challenging to precisely identify and locate road anomalies [10].
2) Frequency Mismatch Between Accelerometer and GPS Data: In crowdsensing-based RPCM, accelerometers are often used to measure vehicle acceleration which provides insights into road surface roughness. Accelerometer data is typically collected at a frequency of 100 Hz. In contrast, GPS data is commonly collected at a much lower frequency, usually once per second (1 Hz) [26], [52], [68]. This disparity in data frequency can lead to synchronization issues, leading to inaccurate road surface condition results [16].
3) Smartphone GPS Accuracy: The built-in GPS in smartphones is generally less accurate than standalone GPS devices. While using a separate GPS device may offer greater accuracy, it also adds complexity and increases costs. The accuracy of GPS location data from smartphones can be affected by weather conditions, the number of satellites available, and obstructions like tall buildings. It is typical for GPS data to have an error margin of 5 m or more [26], [27], [41].

#### 2) VEHICLE SPEED

Crowdsensing-based RPCM solutions are limited by factors such as vehicle speed [24], [65]. It can impact GPS data and vehicle vibration intensity.

The accuracy of GPS data is influenced by the time interval between consecutive updates, as they rely on satellite signals. At higher speeds, vehicles travel greater distances between GPS updates [16]. For instance, if a vehicle is traveling at 30 km/h with GPS updates every second (1 Hz), there will be approximately 8.3 m between updates, while at 50 km/h, 60 km/h, and 80 km/h, it will cover approximately 13.9 m, 16.7 m, and 22.2 m between updates, respectively. Thus, as the vehicle speed increases, the distance between GPS updates becomes larger, potentially reducing the accuracy in locating road anomalies.

Vehicle vibration can also affect the accuracy of road anomaly detection. Factors such as road condition, and the vehicle suspension system and dynamics contribute to these vibrations [8]. The vibration intensity will also vary with speed. Higher speeds can amplify vibrations and increase sensor noise, potentially degrading detection accuracy. Therefore, it is crucial to consider the relationship between vehicle speed and vibration when analyzing road anomaly data. Accounting for the impact of vibrations on sensor data and employing suitable mitigation strategies will improve anomaly detection accuracy.

The effects of vehicle speed on GPS updates and vehicle vibrations on detection accuracy should be considered when developing crowdsensing solutions for RPCM. Understanding and addressing these limitations will improve the accuracy and reliability of road anomaly detection systems. Sensor sensitivity and data collection frequency should be adjusted to ensure accurate and reliable data collection irrespective of vehicle speed. It is also important to prioritize the safety of the driver and other road users during data collection by adhering to responsible practices.

#### 3) SENSING PLATFORM PLACEMENT

The placement and orientation of the sensing platform within a vehicle will affect the performance of crowdsensing-based RPCM [8], [12], [41], [52]. For example, placing an SP on the dashboard or a fixed location within the vehicle may not accurately capture vehicle vibrations and movements, resulting in incomplete and/or poor results [41]. An effective strategy to mitigate this issue is to hold the SP or place it in a specially designed holder attached to the vehicle suspension system. Directly integrating the sensing platform with this system will provide data that better reflects vehicle dynamics thus improving road monitoring [51].

It is important to acknowledge the potential biases introduced by using smartphones as sensing platforms. Different SP models possess varying sensor capabilities and sensitivities which can impact the quality and consistency of the data collected [30], [41]. Further, accelerometer data obtained from smartphones often contains noise which can lead to inaccurate analysis. Thus, it is important to carefully design the system for data collection and analysis taking into account potential biases.

#### 4) VEHICLE PARAMETERS

Vibration-based RPCM can provide significant advantages in assessing pavement conditions. However, several factors can impact the accuracy and reliability of this technique. These factors include the test vehicle dimensions, weight, shock absorbers, tire properties (width, tread, air pressure), and the test road [86].

The effect of tire properties on vehicle vibrations and thus RPCM accuracy has been reported in the literature. Tire width and air pressure have a considerable influence on these vibrations, so any changes can affect RPCM results. In [86], an RPCM method was introduced that employs a non-invasive Dynamic Tire Pressure Sensor (DTPS). Comparison with results using conventional ground-mounted accelerometers and directional microphones showed that DTPS is a promising alternative. It is better at detecting fluctuations due to tire pressure and eliminating environmental noise. Moreover, the ground acceleration obtained from DTPS measurements is close to that with ground-mounted accelerometers. The importance of tire-pavement interaction for highway safety was examined in [87], particularly in the context of autonomous driving and RPCM. In [88], an ANN was used for RPCM and it was found that including data on tire properties such as air pressure, tire type, and vehicle load can improve classification accuracy.

Vehicle dimensions and weight play a role in RPCM since they determine the force on the road surface. Heavy vehicles will increase the vibrations while the force of light vehicles may be insufficient to accurately measure the road condition. In [89], a smartphone accelerometer was used to measure the road roughness. It was concluded that the vehicle suspension system plays an important role in RPCM because it affects the vibrations experienced by the vehicle body. Air suspension systems can produce different vibration results for a road surface compared to traditional hydraulic shock absorbers [90]. They are used in many vehicles because they provide a more comfortable ride.

Avoiding road anomalies while driving can impact RPCM as the data will be incomplete. Drivers tend to avoid potholes as they can cause discomfort and potential damage to the vehicle. However, this will affect RPCM accuracy, especially when using accelerometer-based systems that rely on vehicles passing over road anomalies to detect them [91]. For example, it was found in [92] that careful drivers typically avoid road anomalies such as potholes which makes automated RPCM challenging. This can result in inaccurate road condition assessment and hinder the ability to prioritize repair and maintenance.

### C. FUTURE RESEARCH DIRECTIONS

Crowdsensing has emerged as a promising approach for RPCM due to its cost-effectiveness and the ability to collect data using devices equipped with sensors like accelerometers and gyroscopes [21], [56], [71]. However, the accuracy of this data can be affected by several factors as discussed in Section IV-B. These factors include GPS updates, vehicle speed, vehicle parameters, and sensor platform placement. To address the resulting limitations and improve the accuracy of crowdsensing-based RPCM, it is important to collect data from a large number of vehicles with different speeds, types, and sensing platforms. By aggregating data from multiple vehicles, it is possible to extract information on road conditions that is largely independent of an individual vehicle and thus provide a more comprehensive and accurate assessment of road conditions.

To mitigate the formation of costly and dangerous road anomalies like potholes, a shift in focus is needed from merely detecting specific anomalies to implementing preventive maintenance strategies. This involves detecting and addressing the underlying factors contributing to anomalies such as cracks and depressions. Environmental factors like rain, humidity, and water seepage in road cracks can worsen deformities and accelerate pothole formation. Therefore, it is crucial to prioritize the detection and monitoring of minor road anomalies such as cracks.

Future research should consider developing road pavement condition indexing methods, specifically based on the IRI and PCI. The IRI measures the smoothness of a road, with lower values indicating better road quality. On the other hand, the PCI provides an overall assessment of a road section on a scale from 0 to 100, with higher values indicating better road quality. Accurately determining road quality requires considering surface anomalies such as cracks, swelling, rutting, potholes, and depressions. The PCI incorporates the type, severity, and number of anomalies present on the road surface. Understanding and monitoring these factors makes it possible to predict and prevent potholes and other surface defects, leading to improved road maintenance practices.

In summary, future research in crowdsensing-based RPCM should focus on preventive maintenance strategies. By detecting and addressing minor road anomalies, considering environmental factors, and leveraging crowdsensing, authorities can enhance road safety, reduce repair costs, and improve the overall quality and longevity of road networks.

## V. CONCLUSION

The increase in vehicle traffic and its adverse impact on road quality has created a need for more effective and timely road maintenance. Conventional road monitoring approaches suffer from problems such as a lack of real-time capabilities, often resulting in delayed critical maintenance. Despite substantial government funding allocated to road maintenance, the absence of efficient road quality monitoring limits the utilization of these resources. Furthermore, reliance solely on pothole detection means most monitoring techniques provide incomplete and potentially inefficient assessments of overall road quality. To address this challenge, a comprehensive systematic literature review was conducted to identify and evaluate existing road quality monitoring solutions. This resulted in the selection of 75 research papers. The evaluation criteria included sensory platforms, algorithms, detected road anomalies, and performance. Numerous approaches to Road Pavement Condition Monitoring (RPCM) were examined, each with merits and limitations. It was determined that smartphone-based RPCM solutions that incorporate Machine Learning (ML) techniques and enhanced data acquisition strategies provided superior performance.

Several issues were identified related to GPS and accelerometer data synchronization, vehicle speed, and vehicle parameters. Crowdsensing-based approaches can provide solutions, particularly when combined with indexes such as the International Roughness Index (IRI) and Pavement Condition Index (PCI). They can provide comprehensive insights into overall road quality, moving beyond surface anomalies to deliver accurate and effective real-time monitoring. In conclusion, existing RPCM methodologies were examined with an emphasis on pavement quality monitoring in terms of performance and cost-effectiveness. This work underscores the potential of an integrated, technology-driven approach to road monitoring for safer and more sustainable road infrastructure.

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