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Detection of Road Condition Defects Using Multiple Sensors and IoT Technology: A Review

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ABSTRACT The transportation efficiency and driving safety of road networks, which play an essential role in economic prosperity, are impacted significantly by damage and defects on the road surface. In current practice, it can take weeks or even months before related government departments repair such road conditions, mainly due to lack of awareness of any damage. This paper reviews the current status and limitation of a framework for sensors devices and assessment of road surface conditions. The review also incorporates the most relevant machine learning-based methods, challenges, and future trends to underpin large-scale deployment of road defects automation identification. It is expected that the technology can provide both qualitative and quantitative information about the road surface condition and thus enable timely maintenance to improve transportation efficiency and driving safety.

INDEX TERMS Internet of Things, road surface condition, networked sensor, transportation, machine learning.

I. INTRODUCTION

As ROADS serve as a main connection between residential, commercial, and industrial areas, they are essential for allowing people to travel between their homes and work. The risks along the roads depend on multiple factors, such as human error, weather conditions, transport mode, vehicle type, and road conditions. It may cause car accidents, which affect human lives and influence surrounding areas. On one hand, roads need to be maintained in good condition to prevent car accidents. All phases of road repair take time and effort in the search for defects and fix the issues. Thus, it is essential for roads to have continuous maintenance schedule to reduce the risk of accidents. On the other hand, some methods are promoted to prevent accidents, such as driver safety education, development of safer vehicles, and enhancement of infrastructure maintenance rules, etc. [1]. In the U.S., a quarter of major metropolitan roads are classified as being in poor condition [2].

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Reference [3] claimed that potholes and bumps cause inconvenient trip experiences to road users, and strain people's mobility. In contrast to damaged roads, roads in good condition provide economic and social benefit. Consequently, effective, and efficient road maintenance is an important subject for the country's public assets. The road management includes monitoring, assessing, and decision- making for necessary maintenance, repairs, and replacement of roads. As stated by the American Society of Civil Engineers, the prognosis "in the coming decade, the economy will lose almost four trillion dollars as a result" of roadway damage and defects (ASCE, 2016). This caution indicates the significance of the Infrastructure Management (IM), and that road conditions should be improved [4]. The assessment of road conditions is crucial for designing, planning, and determining the proper road maintenance program. Ninety-nine percent of the current data collection and analysis are conducted manually [5], [6]. The collected data is insufficient for road networks due to the network's size and the frequency of monitoring. As a result, efficient road maintenance and accuracy are affected negatively. Thus, most recent studies focus on using automated detection sensor devices to observe

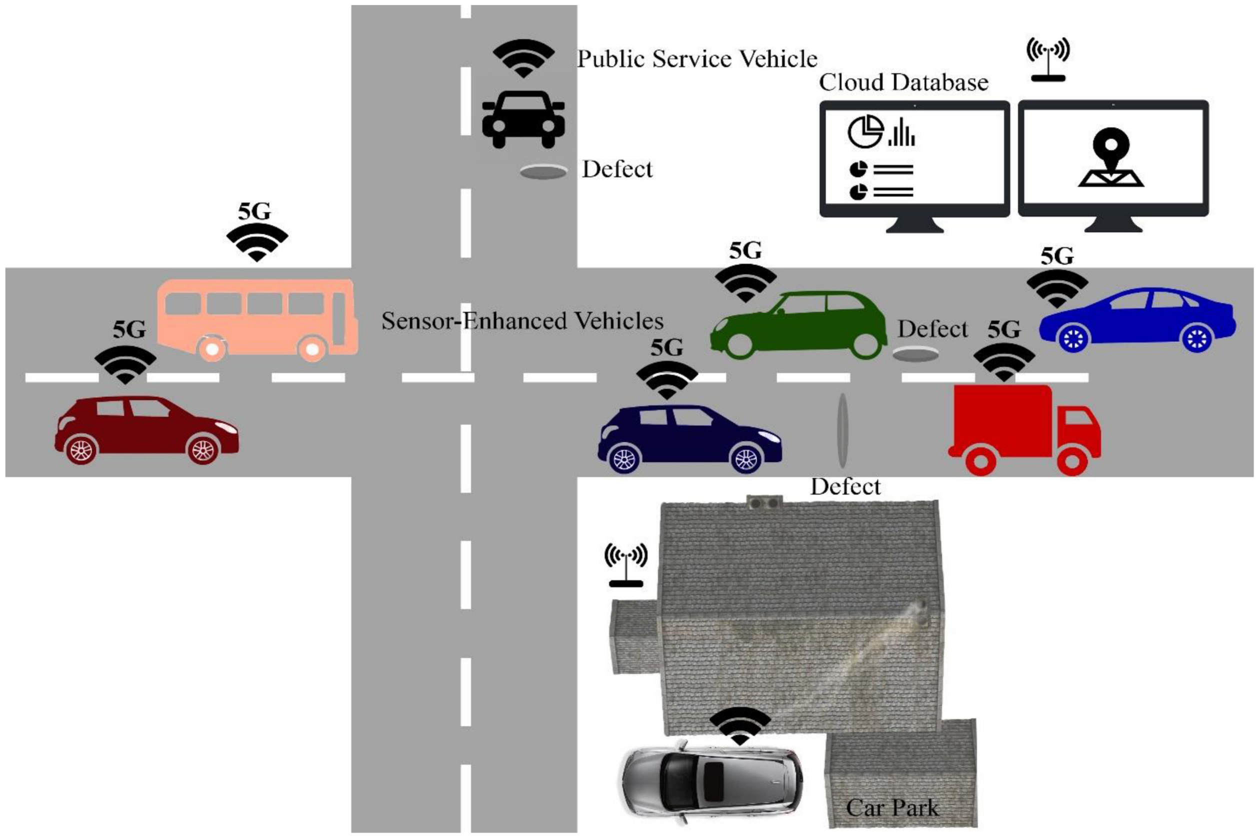

FIGURE 1. Overview of Methods of Communication for Automated Roadway Defect Detection.

and identify road defects to better support road maintenance department.

This paper efforts aim to the review and contrast of the current state of development in automated identification of road conditions. It leads to the problem of identifying road defects for automated monitoring and assessment of road asset conditions using networked vehicles with sensing capabilities and machine learning algorithms. The motivation of this paper is two-fold. There are two sets of stakeholders, the first is the transportation departments who want to maintain infrastructure to make the roads in good condition, and the drivers who want to use the roads for transportation. The earlier potholes are repaired the lower, the cost as the size increasing causes the cost to increase. The second set of stakeholders are drivers and businesses that use the roads for transportation goods who do not want unexpected damages or accidents because of poor road conditions. Researchers are working alongside the transportation department to provide developed instruments and avoid this issue. In the past, researchers used single ~~sensors~~ such as ~~cameras~~, GPS, lasers, and accelerometers, etc., as instruments to collect road defects data manually. Most recently, these single sensors can be integrated to one device to automatically collect data and find specific defect points.

Hence, this paper helps and provides the reader with the importance of road defects detection problem and its impacts on vehicle damage and human life. It is gradually showing the tools of finding road defects in past and present. For instance, how earlier single sensors devices were and become integrated into one sensor device to collect dataset automatically. As shows in Figure 1, transferring the dataset stored in the sensor device data to the cloud database center indicates to IoT usage and process of automated results. Moreover, it shows the treatment tools of processing algorithms using techniques such as sliding window, Machine Learning algorithms, frequency analysis and sensor fusion methods. Then, the limitation and challenges leading to the future trends of road condition. This comprehensive theory taking to understand the field and may also the gaps of this research zone. This paper distinguished from other papers due to general coverage of detect road defects beginning from the sensor device and ending in automation detection methods.

The organization of this review focuses on each major component for automated road defect detection. In Section II, the overview of various selected sensors and one integrated sensor platform are presented. Detailed review on processing algorithms for road pavement is explained in Section III. Section IV. shows how Cars are taking part in road surface

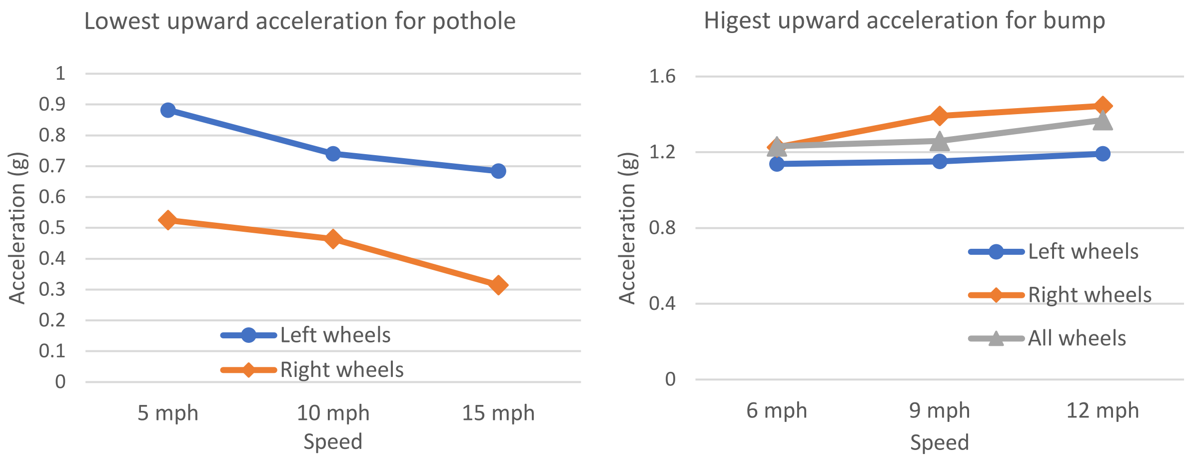

FIGURE 2. A Comparison of Accelerometer Response Due to (Left) a Pothole and (Right) a Bump.

damage detection experiments. Section V will show the limitations and challenges, which involve five parts. Section VI. Shows the future trends which include five types of review points. Finally, a conclusion is presented in Section VII.

II. OVERVIEW OF SENSOR TYPES FOR ROAD DEFECTS DETECTION

Sensors are considering a main instrument in the road defects identification field. This instrument is key to finding the road defects and starting point for treatment. There are various kinds of sensors, which can be used to detect road defects based on a case-by-case basis. Moreover, there are integrated sensors used as advanced identification of manual or automated data collection. These sensors measure the vehicle response to the defects, such as potholes, bumps, and cracks. The following parts explain most common single sensors. Then, the last part is the integrated sensor platform part shows how single sensors grow gradually and become computed in one-sensor device. This sensor device can detect defects using simple automation to decrease the issue of road condition.

A. ACCELEROMETER

An accelerometer is an electromechanical device for measuring velocity change or range in a single or multiple directions. This scale led to physical acceleration due to gravitational force, which is a unit of acceleration that acts as an electrical signal. On a practical scale, an accelerometer measures the acceleration of a mass connected on a spring. Under motion, as the mass is accelerated, a force is applied to the spring, either extending or compressing the spring depending on the direction of the acceleration. Then, the displacement of the mass is proportional for the acceleration [7], [8]. There are multiple types of accelerometer sensors categorized based on the technology used for their outputs. Some of these types are the piezoelectric accelerometer, piezoresistive accelerometer, and capacitive accelerometer. The piezoelectric accelerometer transfers the output of a mass voltage to acceleration. The piezoresistive accelerometer uses the alteration in resistance for measuring acceleration, whereas those that use the alteration in capacitance for measuring acceleration are called a capacitive accelerometer.

Due to the alterations in sensed magnetic domain of accelerometer influence, which are transferred into an electrical signal. That signal is because of alterations in the resistivity of material of the magnetic field called the Magneto resistive accelerometer [7].

The accelerometer sensor considered as a transducer that converts a mechanical pressure or equivalent energy to an electrical signal. Each one of three- axes of the accelerometer is dedicated as specific monitoring activity of the vehicle. The X axis monitors the turning left and right of vehicle, the Y axis monitors the slope on the road while the upward and downward movement of vehicles are measured by the Z axis that is utilized primarily for road defects detection. The accelerometer sensor has found applications in engineering scopes such as vehicle airbag deployment and crash detection. Moreover, recently accelerometer sensors have been used for road defects detection, with a comparison of accelerometer data show in Figure 2. Based on the concentration of this review, it was used for road surface condition monitoring and anomaly detection as well. One of the important advantages of accelerometer sensor is working in constant and stable position to decrease the noise signal issued by the Accelerometer. On the other hand, one of the disadvantages of less resistance accelerometer sensor is the fixed time and internal constant domain, which limiting their usage in some applications [7].

B. LASER, LIDAR

Light Detection and Ranging (LiDAR) is a remote sensing technology that uses light radiation to collect information about subjects without making physical contact with those subjects. This type of sensor considers one of technology sensors used for road defects identification [9]. Lidar systems uses scanning system reflecting light beams off of subjects.

The light pulse emitted from the sensor bounces off the goal subject, then it is reflected again to the sensor. The time it takes for the reflection to take the space between the scanner and the scanned subject can be computed [10]. There are two types of lidar systems: one is scanning lidar and the second is non-scanning lidar. Scanning lidar has single line scanning lidar and multi-line scanning lidar, where single or multiple laser beams are used to create a contour map. Non-scanning lidar is used as a 3D-flash lidar, which supplies data over a given region rather than a single point. The components of each type of lidar are based on system structure, working principle, the improvement around the world, and other existing problems. Lidar has high resolution and distant 3-D data in the absence of light and dangerous weather. In contrast to make fusion of lidar data, camera, and millimeter, the plenty can cover all the driving conditions dependably and entirely. Lidar accuracy can distinguish a human status, as riding, walking, movement speed, or direction. Also, it can work under extremely weather normally, which is considered an important sensor of a Level 3 or higher-level driverless vehicle. Lidar is a developed sensor converting information through laser technology [10].

LiDAR data can be collected from airborne objects, using airplanes. Spaceborne is collected using satellites, and terrestrial is collected form the ground, which can be either static or mobile. This needs to be indented. Mobile Laser Scanning (MLS) is the most common path to collect data for transportation applications since road advantages could be captured with a high scale of detail. In MLS scanning the system is installed on vehicles, which travel along the highway of concern capturing 3600 images of the roadway. The advantage of laser sensors that the data collection of vehicles is mounted with Global Navigation Satellite System (GNSS) receivers and inertial measurement unit (IMU) that spread information about the specific status of the sensor [9]. In other words, that laser sensors do not have to be close to the thing being measured, unlike accelerometer sensors which can only record defects that the vehicle as run across. The main disadvantages are Lidar systems can expensive and inability to measure distance in case of heavy rain, snow, or foggy weather, due to interference with the light beam path.

C. CAMERA TYPES

1) SINGLE CAMERA

Single still image, digital cameras are used for detecting a variety of distresses based on two- dimensional (2-D) photos. These cameras come in several types. The single mounted, high-speed charge coupled device (CCD) camera is considered one of the most applicable equipment for a 2-D result, which has been used for previously for distress detection in specific potholes and cracks. With the development of new camera technologies, there is another option, which is called the metal-oxide-semiconductor (CMOS) sensor. CMOS cameras are advantageous when a lower resolution is adequate and sensor speed does not require high speeds. Also, it has various advantages commonly used in digital imaging such as, an easy-to-use output, reasonable price, accessibility, and a high maturity of CMOS technique. In current years, the CMOS sensors have become widespread, as their disadvantages, such as low resolution has been overcome. However, recent sensor devices in high-speed vehicles does not seem to be used due to cost and technically related issues [4].

2) VIDEO CAMERA

The video camera is one of instruments used for collecting data from which 2-D images are extracted. In order of that, the video application was comparable to the line-scan and area-scan cameras. These are to be used for patches identification, among cracks and potholes, as these three kinds of defects have clear 2-D characteristics. Some researchers conducted video imaging for finding road defects. A comparable approach was developed by Radopoulou and Brilakis (2016) who used the video images from previously installed parking cameras on passenger vehicles. Furthermore, pothole detection based on video cameras has been researched [11], which resulted in the patch detection as described before and rear-view parking cameras, integrated in modern passenger vehicles, are used for data collection. A fisheye lens is installed to spread the angle of the camera. Dash cameras called Blackbox cameras have also been studied [4]. The advantages of video cameras that cameras can monitor scenarios of road defects and activities of vehicle damage, provide time resolution of defect development, and collect evidence of defects. In contrast, it can be costly and vulnerable.

3) LINE-SCAN CAMERA

The regular area scan cameras as described before have some disadvantages in output, such as a relative difference because of the angle and struggles in lighting, which is covered by using a line scan camera. Two cameras were used in the study of [12] with a resolution of 2000 $\times$ 1 pixel, including a pavement width of 4000 $\times$ 1 mm. A high-frame range such as 28 kHz, gives the ability for the vehicle to drive up to 90 km/h, while still collecting usable data. Another lower frame rate appoints the same resolution but can be less expensive and still provide data due to financial aspects. The commercial Laser Road Imaging System (LRIS) used in this content and merges the linear camera with laser lighting for obvious crack view. Also, line scanning can be conducted without the lighting, but this raises the challenges in the image processing level, equivalent to area-scan imaging. The Line scan approach is appointed only for pavement distresses, which are visible without depth as used by companies such as NEXCO and International Cybernetics. Furthermore, the line scan is proper for cracks, patches, and pothole detection. The advantage of Line scan cameras is high resolution, high-speed, and image large objects [4].

D. MICROPHONE

The microphone sensor can be used to measure pothole-induced signals, which can be analyzed to figure out road quality. Reference [13] noted that road features, especially potholes, could be detect by mobile vehicles fitted with shelf microphones and global positioning devices. Therefore, the microphones record pothole sound signals as the vehicles pass over defects. The microphones use a distributed vehicular sensing system to record sounds, which supply data needed to create urban noise maps. Microphone sensors are based on Nericell, a platform used in mobile phones by cyclists for detecting potholes, braking, and honking. It detects spikes in sound frequencies to estimate honking. Reference [13] set up an experiment in a controlled surrounding to determine the use of a microphone in detecting self-made irregularities on the road. The advantage is that they found out that the microphone accurately detects the irregularities. More powerful pothole patrol is conducted by a vehicular sensor network platform that uses superior microphones to estimate road quality.

Also, [14] observed that acoustic array sensors, comprised of a set of microphones, are use in detecting the increasing sound energy produced by vehicles passing by areas where they are installed. Therefore, based on the sound energy of approaching and leaving vehicles, the acoustic sensors can be used to determine the quality of the road. Reference [15] assumed further that the acoustic sensors fitted with directional microphones are embedded normally in the roadside and configured to receive sound that is categorized into a heavy vehicle, light vehicle with speed, high-speed light vehicle, and no vehicle classes. The disadvantage of microphone sensor may be that is extremely sensitive for any noise sound issued by the vehicle, which means it may not be defect or abnormal noise. The study used Mel-frequency Cepstrum Coefficients (MFCC) and Linear Predictive Coefficients (LPC) algorithms to accurately extract road features, and signals sent to smartphones.

E. GPS

Rapid innovations in GPS technology have increased its application due to its geo-positioning and tracking capabilities. One of the main applications of GPS technology is monitoring road transport routes [44]. GPS technology supports imaging satellite sensing to aid in gathering geo-position information and is applicable in extracting road features for instant updates to systems such as Google Earth [17]. When using GPS sensors to explore spatial positions, in this case, road features, the portable GPS device will need unimpeded sight to at least four satellites [18]. More accurate tracking data can be achieved by increasing the frequency of the receivers, using advanced chipsets in the GPS device, and augmentation-supported carrier-phase measurements.

Extracting road features uses remote sensing imagery based on exploring distinct characteristics of road features. If extracted successfully and correctly, the road features could help model a road [17]. However, road modeling is complex because roads have different sections with properties that affect the path shape. Consequently, knowledge-based, morphological-based, classification-based, and dynamic programming methods are used in extracting road features. GPS sensors, fitted at the center of gravity of vehicles, can help in autonomously supplying data input for these methods [17]. GPS sensors advantage is to provide vibrations and dynamics of the vehicles that machine learning algorithms and statistics can use to classify road infrastructure features, and thus, determine the condition of the road [45]. Also, GPS is easy to navigate and cost less compared to other types of sensors.

Barriers to the application of GPS technology in exploring road features include track dynamics and environment, which are preventable through matching geo-locations and tracks to the road through a digital map of the road network [20]. This approach solves the challenges of precision and accuracy of tracking data. Also, the map-matching algorithms offer the differential between GPS match and GPS positions of locations devices on the map. The disadvantages are lack of immediate updates of locations and battery failure.

F. INTEGRATED SENSOR PLATFORM (E.G., MOBILE PHONE)

Mobile phones are one of the devices included various sensors integrated into one device. In the past, sensors are used separately to detect and find road defects. Currently, advanced technologies are integrating sophisticated sensors to develop and improve road defects conditions identification. Modern integrated devices, such as smartphones are equipped with several sensors along with on-board storage, communication capabilities, and computing. Due to these characteristics, integrated sensors could be scalable, an intelligent, distinguished, and with no additional cost component of coming generation civil infrastructure monitoring systems in future smart cities. Over the past few years, there has been a growing focus on the spread of smartphone-based monitoring technologies inside the civil engineering track. The smartphone sensing model overall is still in its infancy, with encouragement for researchers to quickly expand its several applications [21].

The sensors included in the smartphones such as a barometer, gyroscope, accelerometer, proximity sensor, camera, touch screen, microphone, ambient light sensor, magnetometer, all have an important on-board computing capability. Researchers are considering the usage of smartphones with batteries that are charge by the users and have storage in gigabytes. Furthermore, smartphones are support by mobile operating systems and wireless communication hardware which can be used for field of data collection and uploading real-time data to server by Bluetooth, Wi-Fi, 3G, 4G, and 5G networks. Significantly, the smartphone-based monitoring method creates a cyber–physical system (CPS) via mobile crowdsourcing. The CPS platform empowered to connect the cyber, physical, and sensor system objects to a multilayered information processing domain [21].

All these features show that smartphones can become the primary sensing unit for the future civil infrastructure of monitoring systems. There has been a surge of research in

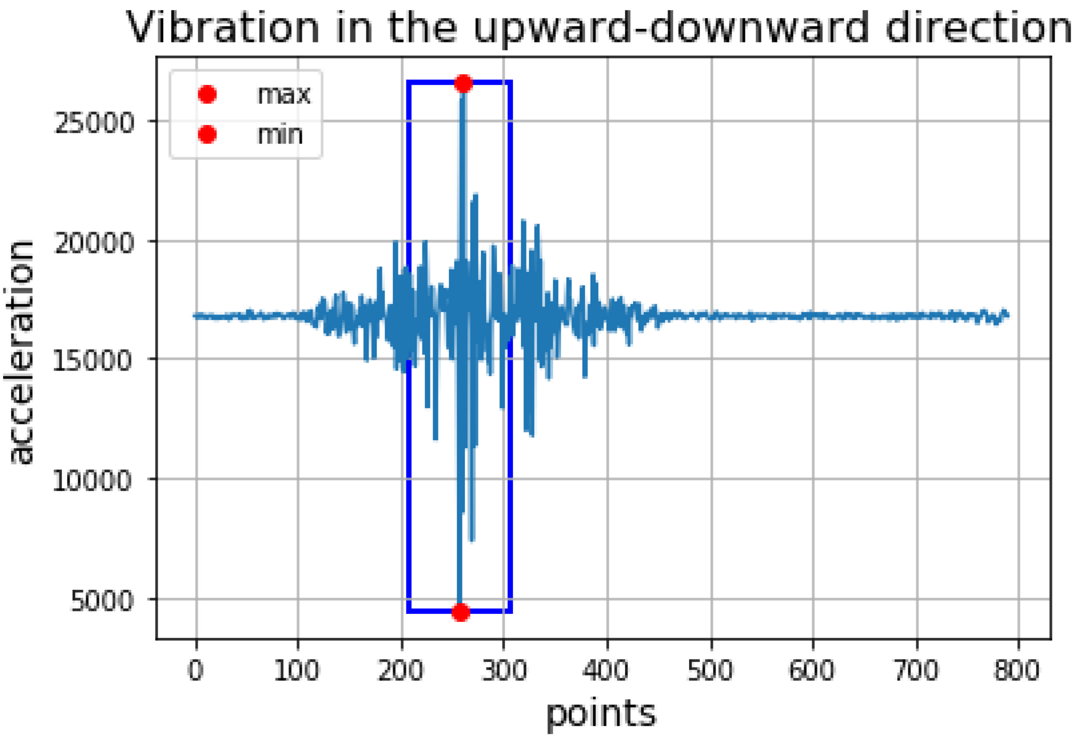

FIGURE 3. Sliding Window Approach Applied to Accelerometer Data from Road Defect Oscillations.

the last few years of mobile sensing for data collection, signal processing, and data visualization in real-world applications [21]. Lately, smartphones are helpful instruments for pavement condition assessment in a cost-efficient direction with comprehensive spatial coverage. Moreover, they provide a chance for frequent, comprehensive, and quantitative monitoring of pavement infrastructure. In the last few years, several studies have been conducted to explore the feasibility of using smartphone to assess pavement condition. Overall, pavement status could be categorized by the defects in the pavement surface, which affects the ride quality of vehicles. These defects can be in the shape of surface roughness, unevenness, potholes, cracks, deterioration, or damages. Pavement roughness is accepted globally as the pavement status sign because of its impact on ride quality, additional vehicle delay costs, maintenance costs, and fuel consumption. Most of the current studies in this scope are concentrating on detecting road bumps and defects instead of expecting pavement roughness. The first major smartphone-based app for the monitoring of road and traffic conditions was "Traffic Sense," created by Microsoft Research in 2008. This project concentrated on using the accelerometer, microphone, GSM radio, and GPS sensors in smartphones to detect potholes, bumps, braking, and honking [21]. The advantages of integrated sensors are the accuracy and flexibility to collect road defects based on computed sensors abilities in one sensor device. In contrast, some road defects in difficult zones do not need integrated sensors device due to difficulty of its road condition and reaching out using a vehicle. For example, a camera sensor device to detect road defects in mountains.

III. PROCESSING ALGORITHMS

A. SLIDING WINDOWS

A Sliding Windows processing algorithm is an adaptive road-distress detection method that is based on finding both non-crack features and the proper road feature classification steps to reduce the number of false-positives during monitoring. Road surface classification is a key step in finding different road features. Also, the sliding window approach is an important in detecting road defects because it provides a standard approach of minimal false positives.

Due to the pre-processing, which facilitates the process of defect detection not only reducing the noise, or enhancing cracks, but also referring to as dark linear features of the road. Pre-processing uses methods such as gray-scale morphological filters, image equalization, median filters, and amalgamation of segmentation methods, and morphological tools. Reference [22] implemented the sliding window technique by assuming that the intensity of the crack pixels was darker than the intensity of the pixel around the road defect. The size of the region of interest (ROI) around a crack area determines the position or location of the peak as shown in Figure 4. Therefore, according to the sliding technique, square ROIs with pre-determined size, ($Size_{pre}$) are created around the image. A pre-defined and specific step ($Step_{pre}$) are used in shifting the window. In this case, the size of the pre-processing image is determined by $Size_{pre}$ because every ROI is represented by one pixel. On the other hand, regions are likely to overlap based on $Step_{pre.}$ Based on this, cracks on the road will appear darker than the surrounding pixel.

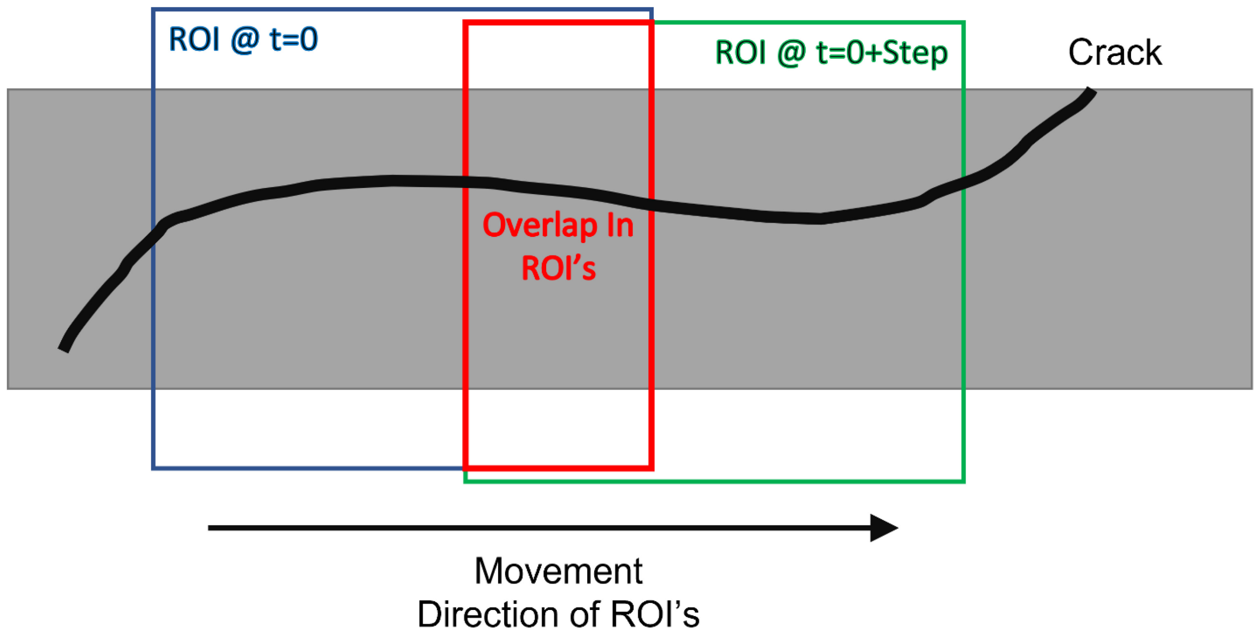

FIGURE 4. Region of Interest Movement in the Sliding Window Algorithm.

On the other hand, [22] applied the sliding window technique by densely sampling windows from detected road features and finds the Scale Invariant Feature Transform SIFTS descriptors in the windows. They used Fisher Vector formulation to decode the descriptors and then used a classifier to categorize the encoded features as damaged or good-quality roads. Lastly, they used a window-by-window voting system through the Gaussian Windows to create a segmentation responsible for detecting damaged features of the road. The strength of sliding window processing algorithm aims to decrease the use of nested loop and exchange it with a single loop, hence reducing the time complexity. For example, in the following Figure 5, the first sliding window move from left to right direction has three nested loops became a single loop. This approach limited the overlapping and shows the major defect that need maintenance.

B. MACHINE LEARNING

Reference [23] described machine learning as an application of Artificial Intelligence through which computer systems can learn and improve without being programmed. After a computer algorithm is trained, it applies the relationship learned to offer a solution to similar problems. This considers the main strength of using Machine Learning algorithms in automated identification of road defects. Moreover, these variety algorithms support and facilitate the study as related studies in Table 1, which we can assess and try multiple algorithms to show the accurate results. Machine Learning can be used with automated detection systems, especially those based on sound vibrations recorded through sensors [24]. Once these systems collect vibration signals and locations, the data is upload, processed, and divided into sliding windows as shown in Figure 3. Road defect segments are find using threshold techniques and learning classifiers. Potholes found from different sensors' data are clustered to find the exact location of the potholes, which are saved for addressing by maintenance. The machine learning aspect in this process takes place by filtering thresholds used in tuning parameters such as speed, speed vs. z-ratio, high-pass, xz-ration, and z-ration to optimize the accuracy of the system used in detecting potholes. Clustering results based on location helps the detection system increase the accuracy in determining the final location of the pothole by 92.4% for labeled data. Reference [25] observed that, unlike other pothole detection methods, for instance, vision-based methods and vibration-based methods, machine learning is advanced and comprehensive in extracting critical information from features.

Machine learning has affected pothole detection through machine learning classification [25]. The core competence of machine learning used in pothole detection is machine classification, which involves using a constructed model with a trained dataset to make predictions based on a set of variables in the testing test. Also, [24] postulated that besides breaching the limitations of traditional pothole detection method including a focus on specific types of road damages, for instance, cracks and potholes, and the incapability to work in dire situations, machine learning offers vision-based road defect detection and classification systems that are both cheaper and cost-effective compared to traditional AI methods.

1) SUPERVISED ALGORITHM

Supervised algorithms, including Artificial Neural Network (ANN), Support Vector Machine, Logistic Regression, Random Forest, and Naïve Bayesian, are used in training labeled training data to make predictions [40]. For instance, supervised learning is used in training an Artificial Neural Network (ANN) model to make predictions through artificial neurons, hence capable of solving pattern recognition

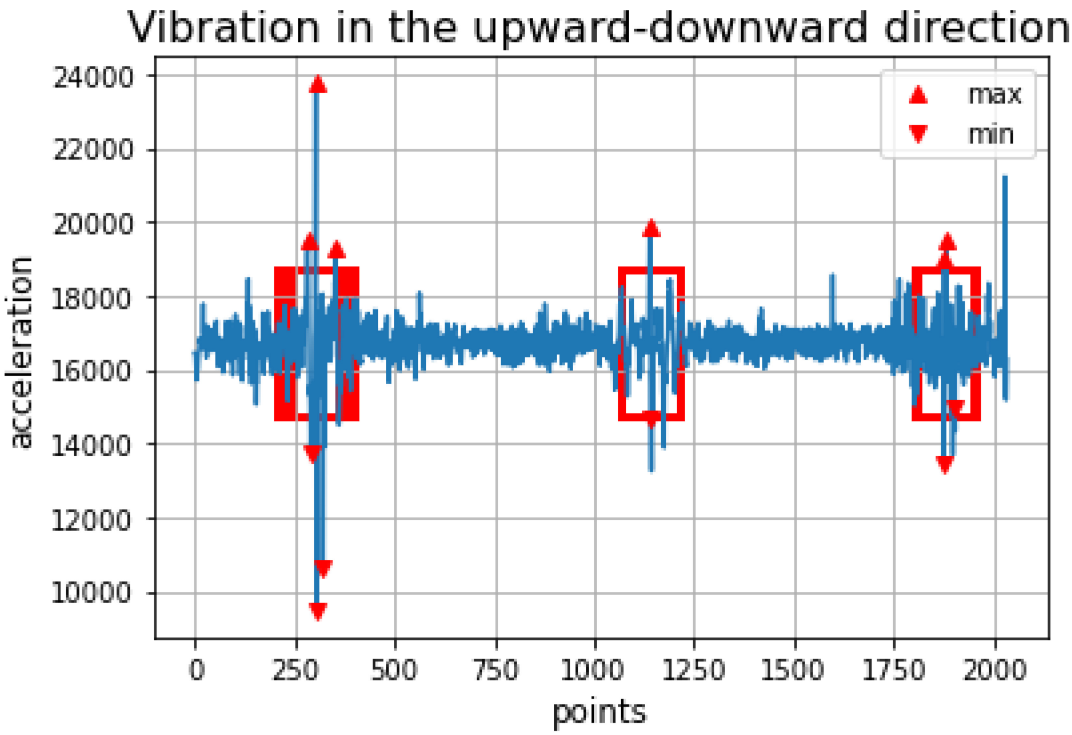

FIGURE 5. Sliding Window Algorithm with Nested Loops for Detection.

problems [23]. Therefore, the neuron can learn by adopting values of weights, which is used in determining the hidden value and weight based on provided input, which is the foundation of supervised learning identifying road defects. Also, [27] described supervised learning as the training of models by using datasets that join input data with labeled data. Like ANN, the convolutional neural network (CNN) leverages image information as input data. When using supervised algorithms, a data set of road images with potholes and without potholes are used for model training and validation, also known as the ground truth [23].

Also, Support Vector Machine (SVM) is a supervised machine-learning model that once a date set is putting into the system, it evaluates the data-seeking patterns for both classification (classes or groups) and regression (continuous relationship between data variables) analysis [11]. SVM algorithm classifies data sets by finding a hyperplane that optimizes the difference between data point clusters of different classes. The advantage of SVMs, is their ability to classify data with different labels besides their effectiveness in high-dimension space and memory efficiency. Reference [41] adopted crack forest, a framework that uses random structure forests, to detect uneven road cracks along the edges and cracks that were presented with complex topological structures. To achieve this, [41] extracted road features from various levels and directions, which they used in training the random forest model to detect similar defects along the edges and on the round surfaces.

One of the widest applications of a supervised algorithm is the automatic pavement crack detection, which requires preprocessing of the crack image to smooth the texture and increase the feasibility of existing cracks [20]. After preprocessing, the image is segmented into multiple non-overlapping blocks with unique feature vectors. This process is supported with SVM in detecting cracks.

2) UNSUPERVISED ALGORITHM

Unsupervised learning is described as a machine learning algorithm used in generating new input data or finding hidden features from datasets with input data but lacking labeled responses (Goodfellow, Bengio, & Courville, 2016). Therefore, the difference between supervised and unsupervised algorithms is the absence of data labels during the training of models. In other words, unsupervised algorithms used in training models neither have labeled samples or definite results for output, which means they help the computer in learning the relationship between the samples and classify them by themselves. The fact that unsupervised algorithms do not need to label datasets, it is considered more accurate because it reduced the impact of human subjective factors on the results. Another study by [42] postulated that unsupervised algorithms offer better training to datasets used in developing a training model, because their accuracy in detecting and quantifying road defects is not dependent on the model parameters. For instance, the algorithm does not require advanced lighting and can perform under any lighting conditions except under direct sunlight.

Earlier literature has adopted an unsupervised algorithm to train models to detect road damages. For instance, [40]

TABLE 1. Machine learning studies used for automated identification of road defects.

Authors	Type/Classifier	Dataset Used	Performance	Limitation
Akanksh Basavaraju, Jing Du, Fujie Zhou, and Jim Ji (2019)	Supervised Algorithms SVM, Decision Tree and Neural Network	Smartphone accelerometer, gyroscope, and GPS sensors (three axes)	Find the potentials and challenges of multiple machine learning techniques for road damage recognition. ML models trained with features extracted from all three axes give significantly higher accuracy, precision and recall rates as compared to models trained with features from only one axis perpendicular to ground.	A small of training dataset can cause loss of accuracy and precision. The inappropriate distribution of cracks, potholes and smooth road conditions results a bias and may affected the individual precision and recall rates. As in general neural networks require a large data set to accurately train itself using direct data, results can be improved by addressing shortage of data
Abbas Ahmadi a, Sadjad Khalesi and Amir Golroob (2021)	Supervised Algorithms Neural Network, SVM, decision tree, KNN, Bagged Trees.	Multiple cracks images using smartphone	Evaluate the efficiency of image processing and ML algorithms in automatic road crack detection and classification. The main feature of this model is its compatibility with images captured by smartphones, and it achieved accuracy equal to 93.86%	The challenge in using these images is that cameras are designed for limited purposes, and completely different from what the study needs. So, as they have features and side filters that are mostly not applicable to the requirements, and this issue significantly increase the size of output images. This can have negative effects on the pre-processing algorithm and as a result can reduce the efficiency of .the system

used an innovative unsupervised method that involved a gray histogram and Otsu method to detect road cracks under a low signal-to-noise ratio. Similarly, [5] leveraged minimum path selection to modify the unsupervised learning method of detecting road cracks. The improved algorithm reduced the loop and peak artifacts used in road crack

TABLE 1. *(Continued)* **Machine learning studies used for automated identification of road defects.**

Charalambos Kyriakou, Symeon E. Christodoulou, and Loukas Dimitriou (2021)	Supervised Algorithms Robust Regression, ANN, and bagged trees	High spatial resolution relates to both uni-dimensional (e.g., X, Y, Z accelerations, speed, etc.) and two-dimensional indicators (e.g., the smartphone's roll and pitch values)	Investigate and discuss the use of smartphones for the detection and classification of common pavement surface anomalies by using robust regression analysis, ANN, and bagged trees classification models. It results in high detection rates in the case of patches, potholes/manholes, and bumps (of about 95%–98% per run).	The collected raw data exposes the difficulty of the detection problem as variables, such as the vehicle pitch assumed to identify roadway anomalies. The vertical variability is random even at a point of known pavement surface anomaly. Also, these plots indicate areas of suspicion (highs and lows, away from the running average values), they are not reliable indicators. Additionally, the plots fail to provide information on other running parameters which influence the accuracy of the data
Cao, M. T., Chang, K. T., Nguyen, N. M., Tran, V. D., Tran, X. L., & Hoang, N. D. (2021)	Supervised Algorithms Least Squares Support Vector Classification (LSSVC)	Two thousand pavement images	Achieve the most desired rutting detection performance with classification accuracy rate, precision, recall, and F1 result measurement of 98.9%, 0.994, 0.984 and 0.989, respectively	The model construction is based on the FBI metaheuristic optimization process. As the FBI is a population-based stochastic search, the computational cost of the FBI-LSSVC-FS model construction phase can be high, especially when the number of the data instances is large. Also, the capability of the LSSVC in treating with noisy data samples or outliers has not been investigated in this work

(*Continued*)

detection. Another research by [35] integrated an unsupervised algorithm with the minimum intensity path of the window to obtain cracks at every scale in the image. The improved algorithm compares various cracks and develops a model for evaluating cracks using multivariate statistical hypotheses.

TABLE 1. ***(Continued)*** **Machine learning studies used for automated identification of road defects.**

Hani Alzraiee, Andrea Leal Ruiz; and Robert Sprotte (2021)	Supervised Algorithms Faster Region Convolutional Neural Networks (R-CNN)	Google Maps photogrammetry data set	Identify the pavement marking defects with a confidence level ranging from 43% to 99%. using deep learning algorithm called faster region convolutional neural networks (R-CNN) to predict a solution of marking defects.	Many studies mentioned the reasons that contribute to pavement defects also contribute to pavement marking defects, so the study is not address the relationship between them. However, this framework can be expressed into a thorough inspection tool for both road defects and pavement marking defects.
Jonpaul Nnamdi Opara, Aunt Bo Thein, Shota Izumi, Hideaki Yasuhara, and Pang-Jo Chun (2021)	Supervised Algorithms- A deep learning technique-YOLOv3	Survey data were taken by a survey vehicle called RIM (Road space Information Management system)	Detect cracks in pavements automatically. In addition, the pavement of the National Road was photographed using RIM and analyzed by YOLOv3 to examine the crack detection performance. A deep learning technique YOLOv3 makes use only features learned by a deep convolutional neural network. it was found that the precision value is 0.7 and the average IoU is 50.39%. From the visualization of the analysis results.	One issue is described that there are multiple types of cracks in one image, there is a case in which the exact answer cannot always be obtained. If this issue been solved, it would be added value.

(*Continued*)

3) SEMI SUPERVISED ALGORITHM

Semi-supervised is blends between supervised and unsupervised algorithms by integrating the right mix of both labeled and unlabeled datasets [43]. Research has showed that many of the unlabeled datasets used in the semi-supervised algorithm are pseudo-labeled so that a large dataset is achieved.

TABLE 1. ***(Continued)*** **Machine learning studies used for automated identification of road defects.**

Todkar, S. S., Baltazart, V., Ihamouten, A., Dérobert, X., & Le Bastard, C. (2021)	Supervised Algorithms One-class Support Vector Machines (OCSVM)	A pavement model generated using GprMax, and experimental data at university of Gustave Eiffel, Nantes Campus, Accelerated Pavement Test (APT) site. Both datasets are acquired/generated using the two configurations: ground-coupled and air-launched GPR	Detect millimeter interlayer debondings from Ground Penetrating Radar (GPR) B-scan images. Simulation tests allow to conduct sensitivity analysis to figure out the robustness of the detection method at various signal-to-noise ratios (10 dB to 60 dB).	A known non-debonding dataset is used to train the OCSVM model. The existence of debonding data (outliers) in this learning dataset could skew the classification model resulting to false detection (False Negative and/or False Positive). OCSVM is also limited by the number of classes for classification (inliers or outliers); However, this track cannot be used for multi-class classification
Syed Ibrahim Hassan a, Dympna O'Sullivan b, and Susan Mckeever c (2021).	Supervised Algorithms Faster Region Convolutional Neural Networks (R-CNN)	The Kaggle pothole dataset, one positive class (pothole present) 618 images	Find road conditions automatically by building a generalized learning model for pothole detection. The study promoted Tiny-YOLOv4 as the befitted model for real-time pothole detection with 90% detection accuracy and 31.76 FPS. Hence, it is proving the strength of the proposed approach for pothole detection and deployed on OAK-D for real-time detection.	The work is limited to detecting a single pavement defect- potholes. However, this can be extended to detect multiple pavement defects such as cracks, patches, and ruts. The trained model could be deployed in a number of ways- for offline detection on batches of images or on a smartphone or other hardware such as Nvidia Jetson Nano for real time pothole .detection

(*Continued*)

Although having a large, labeled dataset would be ideal in road damage detection. The process of using a semi-supervised algorithm in detecting road damage starts with training a model to detect damages on a road surface using labeled data. The algorithm uses an unlabeled image dataset of the trained models to get predicted output image

TABLE 1. ***(Continued)*** **Machine learning studies used for automated identification of road defects.**

Praticò, F. G., Fedele, R., Naumov, V., & Sauer, T. (2020)	Supervised Algorithms ANNs, random forest, SVM	Signatures (using acoustic sensors, located at the roadside)	Find and classify the structural health status (SHS) of a different cracked road pavement based on its vibro-acoustic signature. ANNs, random forest classifiers, and a set of support vector machine models were implemented to compare the efficiency of the developed ANN models and Results show great accuracy (i.e., MLP = 91.8%, CNN = 95.6%, RFC = 91.0%, and SVC = 99.1%).	The methods that are commonly used to carry out this assignment have become unsustainable (i.e., destructive, spatially limited, and expensive), and obsolete (e.g., do not allow continuous monitoring, or are not able to provide real-time information).
Kyriakou, C., Christodoulou, S. E., & Dimitriou, L. (2021)	Supervised Algorithms RUS-Boosted trees	2124 points for training, 1453 points for validating and 1625 for predicting, of which 25% was held out for cross validation purposes	Detect roadway speed bumps and it is based on the analysis of accelerometer and gyroscope readings (robust regression results). It uses a RUS-Boosted trees classification model to detect speed bumps and field experimentation has been conducted using a smartphone placed inside a traveling vehicle at specific mount positions. The average detection rate of speed bumps was found to be 99% which consider higher in comparison to all other existing techniques.	The method used are limited to the range of defects detected, which only the ones causing a vibration of the vehicle) and the missing of defects not on the vehicle's wheel path. This could be solved by participatory sensing.

(*Continued*)

dataset, which is considered semi-labeled image datasets. To improve the efficiency of the trained image model, an ensemble method, which is comprised of multiple models, is created so that the detection does not merely depend on a single trained model with the best performance but instead an integration of results from multiple trained models.

TABLE 1. ***(Continued)*** **Machine learning studies used for automated identification of road defects.**

Guo, J., Wang, Q., & Li, Y. (2021)	Semi-Supervised Algorithm	7,994 raw façade images	Develop a classifier to find the defects from façade images. For the academia, the algorithm is improved by the uncertainty filter to obtain a better performance. For the industry, the developed model can achieve a higher accuracy with the same labeled dataset, which reduces the time and cost of labeling work	The limited effect of unlabeled data to enhance the accuracy. However, one expression for this limit that it might be the model has reached a ceiling of learning new features from the unlabeled data. Hence, the semi-supervised learning method has a limited capacity to enhance the accuracy.
Liu, C., Wu, D., Li, Y., & Du, Y. (2021)	Semi-Supervised Algorithm	crowdsourced data of multiple vehicles	A self-training SSL algorithm was devised that used both labeled and unlabeled data to comprehensively evaluate the IRIs	The combining method of the SSL and MAE algorithms to solve the problem of IRI estimation for road sections with the later iterations is also an important direction for more research.
Amila Akagic, Emir Buza, Samir Omanovic, Almir Karabegovic(2018)	Unsupervised Algorithm	photometric information of 50 images	Achieve the case of low signal to noise ratio images. The method can be used for rough estimation of cracks on asphalt surface pavement. It is unsupervised method; hence it does not require existence of great amount of data needed for training. The method is simple and efficient.	One defect after applying is unwanted noise in the resulting images for some cases. However, the noise can be removed by applying simple noise removal filter in the added post-processing step.
Haifeng Li, Dezhen Song, Yu Liu, and Binbin Li(2018)	Unsupervised Algorithm	-AigleRN Dataset has 38 images. -CFDdataset has 118images -APRdataset contains33images	Develop a new MFCD method for detecting the cracks from pavement images	A crack evaluation model was built; however, the crack was selected as the detected crack if it passed statistical hypothesis test.

(*Continued*)

Therefore, these datasets are combined with a labeled dataset to train an algorithm used in detecting damages on a road surface.

Research has showed that despite semi-supervised learning's capacity to produce more sophisticated results through an ensemble, it is hardly preferred or used alone because these datasets require long time of training [43]. Therefore, during road damage detection, both supervised and semi-supervised learning are used. Supervised algorithm leverage estimation without pseudo-labeled datasets while semi-supervised algorithm uses labeled and semi-labeled datasets. A combination of both supervised and unsupervised learning helps in reducing false positives and hence better performance in the detection of road defects, as opposed to depending only on datasets trained from a supervised algorithm.

C. FREQUENCY ANALYSIS

The frequency of the sampling camera mounted on vehicles to collect datasets for the training model is a principal factor influencing the accuracy of detecting road damage. Earlier literature has shown that high-acquisition frequencies are responsible for reducing missing defects to the minimum [44]. The sampling frequency is a function of traffic flow, experimental environment, and the number of vehicles. A high-frequency sampling camera mounted on a low-speed traveling vehicle expected to result in better detection of road defects. Also, mounting a low-frequency camera on a high-speed vehicle is likely to result in less collection of images.

Reference [4] used ground-penetrating radar (GPR) to determine cracking and claimed that choosing a high frequency of 5GHz or more was ideal in achieving the purpose of the experiment. This is the strength of selecting high frequency rate and to be more accurate. Similarly, [1] studied how high frequencies could be use in determining cracking and based his research on 2GHz GPR. The results of the experiment based on GPR could be couple with images collected by a camera to develop a 3-D model of the road. The rationale for adopting high frequencies could be based on [46] assertions that when a camera running at 30Hz is used in collecting images to detect potholes, it has been done at a low speed to avoid misdetection. Nevertheless, [26] recommended using an extra high-speed, charge-coupled device camera to compensate for high driving speed.

D. SENSOR FUSION METHODS

Reference [47] proposed that different sensors could be fused to form multi-dimensional information on the structure of the pavement. The authors observed that sensor fusion is based on spatial registration and synchronization of data collected using navigational sensors such as GPS, DMI, and INS sensors. The rationale for sensor fusion is increases the quality of the signal, and image information relied upon for the extraction and classification of features, thereby improving the detection of damages or defects on road surfaces [47]. When sensors fitted on mobile vehicles and along the road collect raw data, the features and parameters are preprocessed. They used in determining the quality of the road including defects, artefacts, and deterioration areas are extracted and classified. Data from various sensors are registered and matched with a GPS receiver to map detected defects on a 2D road. The sensor output data to establish the relationship between the detected surface and the surface defects based on their presence, extent, and severity. The sensor data fusion becomes a decision-support output that operators rely on to diagnose the condition of road surfaces.

Distributed vehicular sensing is one of the most predominant methods of sensor fusion, which is based on people and mobile sensing. It uses onboard computers that have been integrated with accelerometers, Wi-Fi access, and GPS to detect features on the road. Vehicular sensing integrates various application-specific sensors including microphones sensors for sound analysis and GPS sensors for localization [34]. The two sensors are used with a generic algorithm for location and time-oriented detection of potholes from sound recorded by the microphone.

IV. HOW CARS ARE PARTICIPATING

Earlier literature has used vehicles as participants of road surface damage detection experiments. The vehicles are fitted with sensors that are used in collecting training datasets. For instance, [1] used one vehicle, which was fitted with cameras to collect training datasets while driving on a road in South Korea. The vehicle traveled on expressways and through city roads at 100km/h to train the neural works model, so it automatically detects defects and damages on road surfaces. A smartphone was installed where the black box is usually located, which enabled the cameras to take photographs of 1920 X 1080 resolution. A total of 6756 labeled datasets were collected, segmented, and categorized into six classes based on images obtained from driving on the roads. The accuracy of the experiment was reported as 0.8728 and 0.9387 when supervised and unsupervised algorithms were used in training the neural networks model.

Also, [48] used one vehicle moving at 27.8 FPS (approximately 30km/hr.), through two imaging lenses fitted with different fields of view (Fives) of 30°and 70°. The collected dataset was trained through deep learning, particularly deep YOLOv3 (you only look once, version 3) to train a model for automatic detection of potholes, cracks, and other road defects. The images lenses were fitted on the dashboard of the vehicle with a 30° FoV lens was responsible for detecting road defects from a distance while the 70° FoV lens compensated for detecting road defects from close and medium distances. The detection of road defects reached 71%, with a 29% miss rate. Likewise, [5] used one vehicle, moving at 10-15 km/h, with a camera mounted on the rear, below the number plate, to collect a dataset for training an SFT model to automatically detect potholes, cracks, and patches. The reported accuracy in the identification of potholes using the cameras and STF algorithm was approximately 74%.

Despite the above trend in literature, [16] observed that the use of multiple cars is recommended because it is difficult for a single car to detect all the distress characteristics of a road surface. Therefore, using a single car predisposes the outcome to inconsistencies attributed to misdetections.

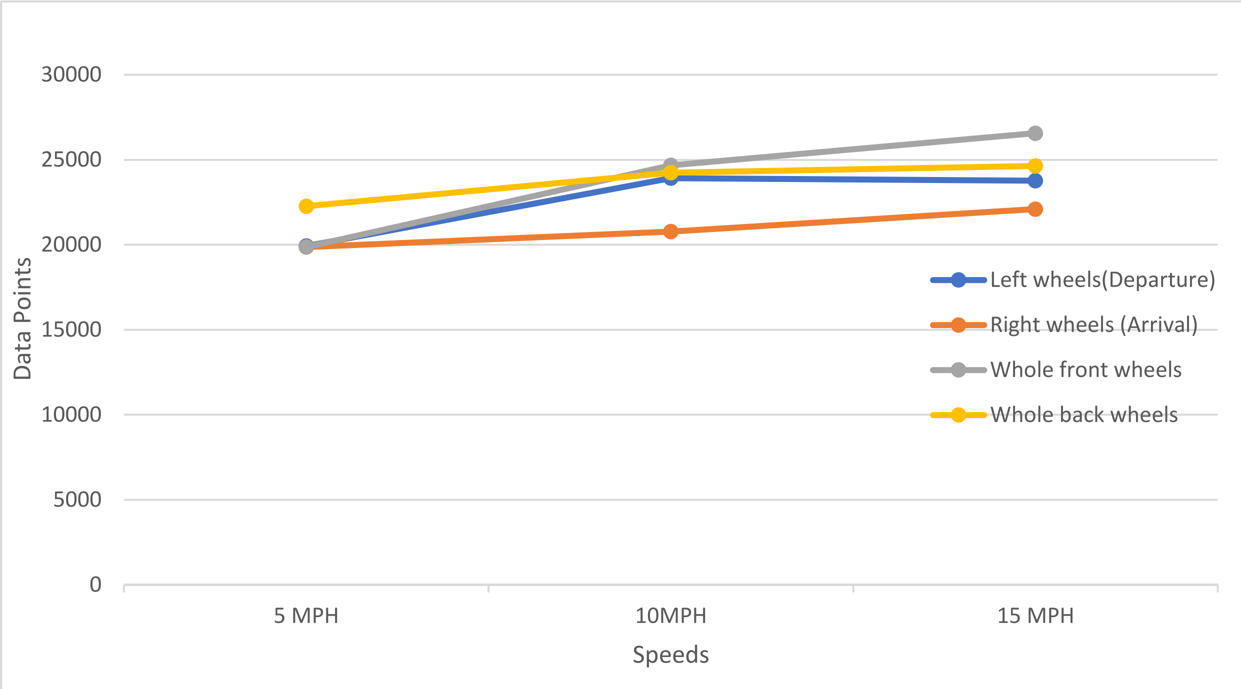

FIGURE 6. An Example of the Senor Response at Different Vehicle Speeds.

Using multiple vehicles (at least five) provides room for superimposition by multiple detections, and the matching of data gives a wider perspective on the condition of the road.

V. LIMITATIONS AND CHALLENGES

A. AXIS

Most studies used less than three sensors in detecting potholes and cracks because they mostly rely on car vibrations in determining the quality of the road. Using less than three sensors hinders the accuracy of collected data, because it does not account for all aspects of the features detected. Although there might be some slight variations in the time taken in extracting features when using more axes, the entire process is fast enough to be complete in real time and offers more variables of features, hence providing a more accurate representation of road quality [8]. This is because when features from at least three axes are used in training a machine language classifier, it results in less loss and enhances performance compared to using features from a single axis (perpendicular to the ground). Each axis is dedicated to measuring a particular activity and improving precision and recall rates for cracks.

Therefore, the challenge while multiple studies used the Y-axis, which focused on collecting vibration-oriented features, it is possible to use more axes to increase the precision and recall rate such that results are not depended on pothole detection but also other features like cracks and roughness of road's surface. For instance, in a study using three axes, the X, Y, Z-axes are used in measuring 3-dimensional vertical acceleration, which involves monitoring the upward and downward movement of vehicle vibration, making it easier to detect anomalies [7].

B. SPEED

Reference [49] studied the effect of vehicle acceleration on the quality of detecting road roughness. To achieve this, the author used probe vehicle body acceleration measurements, which involved comparing probe vehicle measurement with profiler measures using probe vehicle roughness index (PVRI) and vehicle vertical acceleration. The authors used PVRI in the study not only because it approximates the international roughness index (IRI), which determines the quality of the road, but also because the acceleration measurements that a probe car obtains are a representation of the acceleration response of a normal car as shown in Figure 6. Based on the calculations of the probe vehicle, the study observed that with a sampling frequency of 10Mz, at 2200mm intervals, the traveling speed was 80km/h. However, they associated the interval with high conflicts in results because the distance was too large to capture all variables for calculations. The author recommended that future experiments using probe cars should consider using a frequency of 1000 Hz because the calculated PVRI is based on the sampling rate.

Therefore, the accuracy of detecting road defects depends not only on the speed of vehicles but also on the frequency of the camera used in detecting the defects [16]. As a result, the probability of collecting an image at a specific location of the road surface through detection of a vehicle on an expressway depends on the traveling speed of the vehicle and the frequency of the sampling camera. Hence, a high-traveling speed car with a low-frequency camera could miss some information on the road surface and show low detection of road defects. On the other hand, a vehicle traveling at a slow speed with a frequency sampling camera is likely to detect the road surface better but risks duplication of detected features. The study recommended a traveling speed of 50km/h, with camera frequencies of 2 Hz for better detection of road defects using five vehicles. Hence, the speed can be increased gradually to be able detecting road defects in highways. The highways detection needs a high speed and high frequency of the sensor device collected by five vehicles. In this challenge, it can be comparison of each vehicle results and reach out the goal of road defects detection.

As highlighted above, [5] experimented using a vehicle traveling at speed of between 10 and 15 km/h to collect images that were used in training STFs model on how to find cracks on the road surface. According to the authors, a low speed was preferred to high-speed because they wanted to mitigate the effects of unexpected vibrations of the car as it traveled on roads across the cities which could have affected the quality of collected data. On the other hand, the dynamics of individual vehicles such as suspension and tiers have a high performance of the vehicle such as a BMW M3 experiencing potholes differently than off-road vehicle such as a Range Rover.

C. COST

To accurately detect road defects, one needs robust strategies to monitor the quality of the road surface [50]. Nevertheless, earlier literature has pointed out that methods for manually detecting and evaluating the challenge of road quality are expensive and time-consuming [50], [51]. However, there are more affordable and simple technologies that could be used to automatically detect road defects but there are concerns about their accuracy. A simple cost-effective experiment could be used to determine pavement distress. For instance, a real-time, low-cost road quality inspection system-based high-speed 3D transverse scanning technique fitted with an infrared laser-line projector and digital camera could be used to detect pavement distress like cracks, potholes, and shoving [23]. However, it suffers from low detection accuracy that is mostly due to its limited calibration procedure, which accepts few samples of collected images.

Also, the Kinect sensor has been used in detecting potholes and it proved cost-effective. Reference [52] adopted this technique to collect images of pavement depth from concrete and asphalt roads. Based on the results of the collected images, they used the images to determine the volume of the potholes using the area of the pothole and corresponding depth. They applied the trapezoidal rule on obtained area-depth curves and were able to determine the volume of the potholes. Although cost-effective, in comparison to the cost of using industrial cameras and sensors, it uses a small sample and hence might not affect its accuracy in automatically detecting potholes if the results from the experiments were used in building a training model. In summary, vision-based experiments or methods offer cost-effective strategies of detecting and finding road defects but suffer from inaccuracy caused by distortion and noise in collected imaged and video data. Therefore, [50] recommended adopting a more efficient technology capable of detecting various features from 2D images to improve the probability of accurately detecting and finding various road distress.

D. MOBILE PHONE

Mobile phones, particularly smartphones have been used in implementing vibration-based automated pothole detection systems [10]. An application is installed on the phone and sends vibration signals and location data to a server or computer. The application preprocesses the collected data through resampling, filtering, and reorientation. Then, it leverages a sliding window to divide the continuous signal into segments. On the other hand, the mobile communication network sends information about the segments of the pothole acquired through a simple threshold. The server uses a pre-trained machine learning classifier to find real potholes based on features extracted from the uploaded data. Data collected from multiple vehicles are used in finding the potholes, which the algorithm clusters to find the reallocation of the potholes.

As highlighted, these challenges are expensive but could be cheaper, for instance, if the mobile phones were not used. Since vibration-based automated pothole detection systems are based on mobile sensors, namely, accelerometer and GPS and not mobile phones, these sensors can be installed on vehicles making mobile phones redundant. Also, it is arguable that substituting the car's accelerometer with an application to measure the velocity of the traveling vehicle and send it to the server for pre-processing, exposes the pothole detection system to trade-offs such as phone or application malfunction or incompatibility of the technologies besides other concerns of battery-life and data corruption. Therefore, between extra costs of purchasing the mobile phone, setting up all the devices that make up the technology, the risk of incompatibility of devices, concerns over the mobile phone's battery life, and corruption of signal data makes for a lot of avoidable exchanges.

E. ALGORITHM

A wide range of algorithms has been adopted by earlier literature to achieve train models to automatically detect defects of the road surface. The rationale and the challenge for the existence of multiple algorithms is that there is no unique optimal algorithm that can be used in each case and thus, the best algorithm always depends on the nature of the problem. For instance, [23] used semantic texton forest (STF), a supervised algorithm on a labeled region of interest on the pavement to train a dataset model to automatically detect longitudinal and transverse cracks from data collected from roads across the streets of Cambridge. STF was preferred because its use of kernel features instead of point features during classifier/model training randomized decisions allowed for use of multiple features in segmentation including color, texture, and context. This promoted accuracy of detecting multiple longitudinal and transverse cracks on pavements there.

Likewise, [25] leveraged a pothole-detection algorithm, which was an arrangement of filters including speed, speed vs. z-ratio, z-peak, xz-ratio, and high-pass to dismiss a non-pothole event type based on data collected by mobile sensors (accelerometer, GPS) installed. The algorithm treated the threshold of each of the filters as tuning parameters to enhance the accuracy of the system in detecting potholes, which is the essence of machine learning. The algorithm helped in clustering the results based on location and hence achieving the location of the pothole with an accuracy of 92.4%.

Also, [9] adopted a pothole detection method that used traveling vehicles as virtual sensors to assess vibrations. The vehicles were fitted with a sensor, smartphone, and Internal Measurement Unit. The accelerometer collected data, which was normalized and used by the pothole detection algorithm to achieve information through interpolation of a GPS. The authors used the pothole detection algorithm because of its capacity to deal with fusion data techniques used in virtual sensors. Therefore, the module trained by the algorithm collected data from sensors mounted on the vehicle, processed the large dataset, and sent the results for detailed discussion. Therefore, the experiment followed three steps including collecting and normalization of data by the accelerometer, training module to detect potholes using the algorithm, and using the GPS to locate the pothole.

VI. FUTURE TRENDS

A. MULTI-SENSOR TYPE PROCESSING

Researchers are exploring the possibility of achieving real-time monitoring of the conditions of the roads and processing for potential automatic detection of road distress [1], [5], [40], [53]. Recent literature has examined how different accelerometer sensors, not merely those related or used with smartphones, computers, tablets, and other servers, could be adopted in road defect detection, and provide real-time notifications about road crack, potholes, and humps among other road defects [19], [45], [48]. The studies have projected that GPS technologies could be coupled with sensors to achieve a strategy-oriented solution to collect and use information about the condition of the road to enhance road maintenance.

On the other hand, the scope of the application of sensors is expanding. Earlier literature shows that automotive manufactures have leveraged the auto-detect capability of sensors to expand their application in safety and traffic management among others [45]. Therefore, automobiles have integrated in-vehicle sensors with vehicles to increase sensing and communication capabilities to offer smart and intelligent transportation systems. Also, government institutions are installing cameras and sensors along the road to monitor raw data about the environment and traffic conditions

Despite the success achieved in using sensors in collecting datasets, which are preprocessed and used in training models, there is a need for further development. For instance, the focus should be on optimizing the signal and image processing solutions for enhanced and effective handling of raw sensor data streams to enhance detection of defect features while minimizing the effect of environmental factors and devices used [47]. Also, the knowledge-based systems used in extracting features from collected datasets need to be improved to adopt more sophisticated pattern-recognition techniques for better segmentation of features and identification of road defect features. Furthermore, one of the major challenges addressed in the reviewed literature is the excessive cost of industrial cameras, sensors, and assembly of the system for accurate detection and identification of road distress. Therefore, future work should explore the possibility of cheaper sensors and technology that could be adopted without compromising the accuracy and reliability of road distress monitoring.

B. MASS PARTICIPATION (LARGE CAR FLEET)

Rental car companies have adopted sensors and sensing technology by seamlessly integrating sensing devices within their car fleets. Reference [54] noted that car rental companies are beneficiaries of the rapid development of online Web-based applications, which they have integrated with GPS-based content alerts, to enhance the accessibility of cars to every person at a minimum cost. Therefore, implementing (IoT) sensing devices in rentals is helping the customer achieve comfort and privacy in their rides. The seamlessness of these systems is transforming traveling in cabs or rental cars since rental cars can access a wider pool of customers requesting services around cities. The technology is helping cabs and rental car agencies increase their market shares and people getting easy access to cars, especially in cities where traveling by cab is part of city life.

Also, [55] noted that the IoT technology, implemented through sensors and GPS, is enhancing mobile-based vehicle fuel activities including monitoring of fueling in real time. Car rental companies might consider fitting ultrasonic fuel sensors in their car fleets to help management and drivers keep track of the fuel gauge. The ultrasonic fuel sensors are designed to send notifications through mobile applications when fuel is below a certain level. The sensors are integrated with GPS tracking that helps the system find the nearest pump locations. Therefore, drivers can depend on the system to manage their fuel-reloading patterns, especially when in route and ensure that the passenger enjoys uninterrupted rides because the driver forgot to fill up the tank with fuel before launching the trip.

Literature has shown that the rapid technological innovations in blockchain and IoT are being integrated to promote the efficiency, effectiveness, and reliability of car rental agencies in providing readily available cars to customers [56]. Therefore, blockchain allows for mass registration of cars by agencies or individuals pooling their cars together not only for the sake of providing a significant resource to customers who need them, but also as a means of enhancing the sustainability of resources to minimize carbon emissions. The authors noted that car rentals or owners can register their cars and users of the blockchain can choose the readily available car and acquire services through a peer-to-peer transaction governed by an automated system. The system monitors car usage in real time using sensors. The collected information helps making car service and maintenance schedules besides making the availability and usage more dependable for car rental agencies and customers.

C. ROAD MAINTENANCE DEVELOPING PLAN

After successfully collecting, analyzing, processing, and updating the status of the conditions of the roads, the personnel responsible for road maintenance should develop sustainable strategies to rehabilitate and keep the roads based on an accurate and efficient pavement management system [57]. Therefore, the process that succeeds analysis of the structural conditions in the area of interest includes geo-referencing to determine critical parts of the road, and simulations to highlight the impact of previous maintenance work. The authors observed that this plan improved highway performance because it gives room for both planning and distributing of resources based on need. Therefore, it helps in making proper maintenance and rehabilitation decisions.

Results of a trained model used in detecting road distress form part of the decision support concept (DSC) and decision in planning activities for maintaining and rehabilitating urban roads and support [58]. The authors recommended the adoption of the decision-support concept to improve planning for improving the urban roads using multicriteria methods and artificial neural networks. As a result, proper interaction between DSC promotes better decision making during the planning process. Planning happens on three decision levels including database, model base, and dialogue module but all relevant interactions between the three levels are achieved during the decision-making process. Therefore, decision makers, stakeholders, and experts can interact in the process when tackling various problems, whether structured or unstructured. The first management level includes the integration of data and information and is responsible for defining and structuring problems as well as it is feed of information to the higher decision levels. The second level is the tactical management level, responsible for delivering tactical decisions and creating solutions based on gathered information. Depending on the nature of the identified problem, different methods could be deployed. The third management level depends on the deliverables of experts from the preceding level to formulate strategies and frameworks for road maintenance.

Reference [59] noted one of the common strategies that most third-world countries and emerging economies give priority to roads in good condition that require minimal work and budget to keep and achieve a steady state of 100%. The authors argued that this plan of road maintenance assumes that road preservation offers maximum results in keeping road distress with more efficient maintenance costs. In most cases, planning is guided by a two-level, decision-making process, namely prioritization and optimization because road maintenance is expensive, and Department of Transportation hardly has enough resources to ensure roads are in a satisfactory condition [60]. As a result, road administrators rely on prioritization in coping with insufficient funding. Road administrators establish priorities based on collected information about road conditions. These priorities include blackspots, cost-effectiveness, functional types of road communications, the severity of road distress, and extreme traffic volume roads. Nevertheless, optimization is a crucial factor in planning because maintenance is to be done on optimal time and cost.

D. SLIDING WINDOWS

Sliding window is supportive technique of automated road defects identification. It considers one of the future solutions of road defects detection problems. However, there is an event window technique, which consider helpful technique beside the sliding window overlapping. One feature is that sliding windows may obtain an overlapping based on the sequence road defects findings. This overlapping may combine to an event window, which corresponds to possible real defects. For example, instead if there are four sliding windows overlapping, it can be one mean window. This technique is not used much in recent research and could be developed to mitigate the overlapping and may be a solution to categories the highest or lowest road defect vibration point. This category will help transportation maintenance team to find an obvious road defect need urgent maintenance intervention.

E. THE RISE OF AUTONOMOUS VEHICLES

The development and use of autonomous vehicles (AVs) can be described based on the respective level of automation (SAE levels) and the operational design domains (ODD) through which these vehicles provide automation features [61]. ODDs comprise weather conditions, roadway type, and speed. Also, unlike generic vehicles, their use is influenced by the SAE level of driving and various autonomous use cases that have been designed for specific ODDs, which interact with road features differently. In other words, AVs affect infrastructure owner–operators differently, and thus, road distress. For instance, depending on how AVs are implemented, platooned, and positioned, they will affect the condition of pavement and bridges.

From a stakeholder's point of view, AVs require a high maintenance of sensors that support its deployment for fleet use but could challenge proofing infrastructure [61]. Nevertheless, its adoption is rapidly increasing, especially for commercial fleets, and might lead to a partnership between fleet operators and infrastructure owner-operators, which would increase reliability in maintenance because of shared interests. However, the [61] noted that increasing the adoption of AVs will influence the quality and uniformity of road features. For instance, road marking signage will have to be consistent and well maintained. Also, since AVs rely on digital information, for instance, work zones will have to be standardized, concise, and secure enough to ensure the AVs are dependable.

More research into the potential increase of autonomous vehicles in city roads has projected that this technology will result in increased productivity in the transport sector, decreased costs, and increased safety [62]. However, the authors noted that the magnitude of the expected positive or negative consequences is undetermined. Preliminary findings states that the effect of truck loadings positioning on transportation infrastructure project is declining life of pavement structures. However, the use of AVs could benefit the infrastructure, especially pavement design, if they are deployed appropriately where their numbers increase to occupy 505 vehicles of the traffic. Therefore, their effect on the road infrastructure will depend on deployment. Appropriate deployment will benefit road pavement while inappropriate deployment will result in detrimental damage to the road infrastructure, especially pavement smoothness, fatigue cracks, and rutting.

VII. CONCLUSION

Road maintenance and rehabilitation is an expensive process that requires multiple resources to collect, the analysis of processes, the update status of roads, and draft maintenance. Nevertheless, road administrators, department of public asset management, and other stakeholders have limited resources to perform their tasks but are required to ensure road conditions are satisfactory. However, the rapid innovations in mobile sensing technologies coupled with machine learning have provided glimpses of hope as systems could be trained to automatically collect data through in-vehicle sensors, which are used in training models to automatically detect road distress features. Diverse types of algorithms, divided into unsupervised, supervised, and semi-supervised algorithms, have been adapted depending on the goal of the researchers to implement automatic detection of road features as stated in Table 1.

The reviewed literature has also shown that the accuracy of various pavement detections systems trained by algorithm depends not only on the traveling speed of the vehicle but also the frequency of cameras used in data images collection. Although the quality of the sensor's device can be change such as cameras, the reviewed literature highlights that using industrial cameras and other standard devices affects the financial feasibility of the application. As a result, the use of alternative and cheaper set-ups was explored. It was shown that less expensive set-ups provided cost-effectiveness at the expense of accuracy of detecting road features and cab be used in public transportation such as ambulances, fire vehicles, and postal vehicles. Also, the machine learning algorithms accuracy is automated and improved when multiple vehicles are used in the detection of road features because it mitigates the risk of misidentification.

Besides road maintenance, sensors applications have benefited car rental services. They have led to better and more reliable fuel management, and increased reliability in determining the availability of cars, hence helping the transportation department by updated reports of defects dataset and providing customers with satisfactory services. Hence, focusing on inexpensive sensors device, using an algorithm to automate the process of identification, and spread group of vehicles with installed sensors devices are valuable factors to reduce road defects issue and make the future of roads are smooth. On the other hand, mobile sensing has led to AVs, which according to reviewed literature, will transform the transportation sector. Nevertheless, the extent of their effect on transportation infrastructure is not yet fully understood.

REFERENCES

[1] F. D'Amico, A. Calvi, L. B. Ciampoli, M. G. Brancadoro, and F. Tosti, "Evaluation of the impact of pavement degradation on driving comfort and safety using a dynamic simulation model," in *Proc. Road Safety Simulat. Int. Conf.*, 2017, pp. 1–9.

[2] G. Xue, H. Zhu, Z. Hu, J. Yu, Y. Zhu, and Y. Luo, "Pothole in the dark: Perceiving pothole profiles with participatory urban vehicles," *IEEE Trans. Mobile Comput.*, vol. 16, no. 5, pp. 1408–1419, May 2017.

[3] H. Song, K. Baek, and Y. Byun, "Pothole detection using machine learning," in *Proc. Adv. Sci. Technol.*, 2018, pp. 151–155.

[4] T. B. J. Coenen and A. Golroo, "A review on automated pavement distress detection methods," *Cogent Eng.*, vol. 4, no. 1, 2017, Art. no. 1374822, doi: 10.1080/23311916.2017.1374822.

[5] S. C. Radopoulou and L. Brilaki, "Automated detection of multiple pavement defects," *J. Comput. Civil*, vol. 31, no. 2, 2016, Art. no. 4016057.

[6] Y. Cai and J. Derouin, "A low-cost on-board sensing device for road surface condition," in *Proc. IISE Annu. Conf.*, May 2019, pp. 1048–1053.

[7] I. H. B. Salau, A. J. Onumanyi, A. M. Aibinu, E. N. Onwuka, J. J. Dukiya, and H. Ohize, "A survey of accelerometer-based techniques for road anomalies detection and characterization," *Int. J. Eng. Sci. Appl.*, vol. 3, no. 1, pp. 8–20, 2019.

[8] M. Barriera, S. Pouget, B. Lebental, and J. V. Rompu, "In situ pavement monitoring: A review," *Infrastructures*, vol. 5, no. 2, p. 18, 2020.

[9] S. Gargoum and K. El-Basyouny, "Automated extraction of road features using LiDAR data: A review of LiDAR applications in transportation," in *Proc. 4th Int. Conf. Transp. Inf. Safety (ICTIS)*, 2017, pp. 563–574, doi: 10.1109/ICTIS.2017.8047822.

[10] J. Liu, Q. Sun, Z. Fan, and Y. Jia, "TOF Lidar development in autonomous vehicle," in *Proc. IEEE 3rd Optoelectron. Global Conf. (OGC)*, 2018, pp. 185–190, doi: 10.1109/OGC.2018.8529992.

[11] S. C. Radopoulou and I. Brilakis, "Improving road asset condition monitoring," *Transp. Res. Procedia*, vol. 14, pp. 3004–3012, Jun. 2016.

[12] M. Gavilán et al., "Adaptive road crack detection system by pavement classification," *Sensors*, vol. 11, no. 10, pp. 9628–9657, 2011. [Online]. Available: https://doi.org/10.3390/s111009628

[13] C. Kyriakou, S. E. Christodoulou, and L. Dimitriou, "Do vehicles sense, detect, and locate speed bumps," *Transp. Res. Procedia*, vol. 52, pp. 203–210, Feb. 2021.

[14] J. Guerrero-Ibáñez, S. Zeadally, and J. Contreras-Castillo, "Sensor technologies for intelligent transportation systems," *Sensors*, vol. 18, no. 4, p. 1212, 2018, doi: 10.3390/s18041212.

[15] M. Khalili, M. Ghatee, M. Teimouri, and M. M. Bejani, "Roadside acoustic sensors to support vulnerable pedestrians via their smartphone," 2018, *arXiv:1812.02752*.

[16] W. Yang, T. Ai, and W. Lu, "A method for extracting road boundary information from crowdsourcing vehicle GPS trajectories," *Sensors*, vol. 18, no. 4, p. 1261, 2018.

[17] I. Kahraman, I. R. Karas, and A. E. Akay, "Road extraction techniques from remote sensing images: A review," in *Proc. Int. Conf. Geomat. Geospatial Technol. Geospatial Disaster Risk Manag.*, 2018, pp. 339–342.

[18] X. Zhao, K. Carling, and J. Håkansson, "Reliability of GPS based traffic data: An experimental evaluation," Högskolan Dalarna, Borlänge, Sweden, Working Papers, 2014.

[19] H. Maeda, Y. Sekimoto, T. Seto, T. Kashiyama, and H. Omata, "Road damage detection and classification using deep neural networks with smartphone images," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 33, no. 12, pp. 1127–1141, 2018, doi: 10.1111/mice.12387.

[20] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
[21] A. H. Alavi and W. G. Buttlar, "An overview of smartphone technology for citizen-centered, real-time and scalable civil infrastructure monitoring," *Future Gener. Comput. Syst.*, vol. 93, pp. 651–672, Apr. 2019.
[22] D. A. Chacra and J. Zelek, "Municipal infrastructure anomaly and defect detection," in *Proc. 26th Eur. Signal Process. Conf. (EUSIPCO)*, 2018, pp. 2125–2129, doi: 10.23919/eusipco.2018.8553322.
[23] R. Amhaz, S. Chambon, J. Idier, and V. Baltazart, "Automatic crack detection on two-dimensional pavement images: An algorithm based on minimal path selection," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 10, pp. 2718–2729, Oct. 2016.
[24] A. A. Angulo, J. A. Vega-Fernández, L. M. Aguilar-Lobo, S. Natraj, and G. Ochoa-Ruiz, "Road damage detection acquisition system based on deep neural networks for physical asset management," in *Proc. Mexican Int. Conf. Artif. Intell.*, 2019, pp. 3–14.
[25] C. Wu et al., "An automated machine-learning approach for road pothole detection using smartphone sensor data," *Sensors*, vol. 20, no. 19, p. 5564, 2020. [Online]. Available: https://doi.org/10.3390/s20195564
[26] A. Basavaraju, J. Du, F. Zhou, and J. Ji, "A machine learning approach to road surface anomaly assessment using smartphone sensors," *IEEE Sensors J.*, vol. 20, no. 5, pp. 2635–2647, Mar. 2020.
[27] A. Ahmadi, A. Khalesi, and A. Golroo, "An integrated machine learning model for automatic road crack detection and classification in urban areas," *Int. J. Pavement Eng.*, vol. 23, no. 10, pp. 1–17, 2021.
[28] C. Kyriakou, S. E. Christodoulou, and L. Dimitriou, "Do vehicles sense, detect, and locate speed bumps," *Transp. Res. Procedia*, vol. 52, pp. 203–210, Feb. 2021.
[29] M. T. Cao et al., "Image processing-based automatic detection of asphalt pavement rutting using a novel metaheuristic optimized machine learning approach," *Soft Comput.*, vol. 25, pp. 12839–12855, Aug. 2021.
[30] H. Alzraiee, A. L. Ruiz, and R. Sprotte, "Detecting of pavement marking defects using faster R-CNN," *J. Perform. Constr. Facilities*, vol. 35, no. 4, 2021, Art. no. 4021035.
[31] J. N. Opara, A. B. B. Thein, S. Izumi, H. Yasuhara, and P. J. Chun, "Defect detection on asphalt pavement by deep learning," *Int. J.*, vol. 21, no. 83, pp. 87–94, 2021.
[32] S. S. Todkar, V. Baltazart, A. Ihamouten, X. Dérobert, and C. Le Bastard, "One-class SVM based outlier detection strategy to detect thin interlayer debondings within pavement structures using ground penetrating radar data," *J. Appl. Geophys.*, vol. 192, Sep. 2021, Art. no. 104392.
[33] S. I. Hassan, D. O'Sullivan, and S. McKeever, "Pothole detection under diverse conditions using object detection models," in *Proc. IMPROVE*, 2021, pp. 128–136.
[34] F. G. Praticò, R. Fedele, V. Naumov, and T. Sauer, "Detection and monitoring of bottom-up cracks in road pavement using a machine-learning approach," *Algorithms*, vol. 13, no. 4, p. 81, 2020.
[35] C. Kyriakou, S. E. Christodoulou, and L. Dimitriou, "Spatial roadway condition-assessment mapping utilizing smartphones and machine learning algorithms," *J. Transp. Res. Rec.*, vol. 2675, no. 9, 2021, Art. no. 3611981211006105.
[36] J. Guo, Q. Wang, and Y. Li, "Semi-supervised learning based on convolutional neural network and uncertainty filter for façade defects classification," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 36, no. 3, pp. 302–317, 2021.
[37] C. Liu, D. Wu, Y. Li, and Y. Du, "Large-scale pavement roughness measurements with vehicle crowdsourced data using semi-supervised learning," *Transp. Res. C, Emerg. Technol.*, vol. 125, Apr. 2021, Art. no. 103048.
[38] A. Akagic, E. Buza, S. Omanovic, and A. Karabegovic, "Pavement crack detection using Otsu thresholding for image segmentation," in *Proc. 41st Int. Convent. Inf. Commun. Technol. Electron. Microelectron. (MIPRO)*, 2018, pp. 1092–1097.
[39] H. Li, D. Song, Y. Liu, and B. Li, "Automatic pavement crack detection by multi-scale image fusion," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 6, pp. 2025–2036, Jun. 2019.
[40] W. Cao, Q. Liu, and Z. He, "Review of pavement defect detection methods," *IEEE Access*, vol. 8, pp. 14531–14544, 2020, doi: 10.1109/ACCESS.2020.2966881.
[41] Y. Shi, L. Cui, Z. Qi, F. Meng, and Z. Chen, "Automatic road crack detection using random structured forests," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 12, pp. 3434–3445, Dec. 2016.
[42] D. P. Kumar, T. Amgoth, and C. S. R. Annavarapu, "Machine learning algorithms for wireless sensor networks: A survey," *Inf. Fusion*, vol. 49, pp. 1–25, Sep. 2019.
[43] A. Cholaquidis, R. Fraimand, and M. Sued, "On semi-supervised learning," 2018, *arXiv:1805.09180v2*.
[44] Y. Du, Z. Weng, C. Liu, and D. Wu, "Dynamic pavement distress image stitching based on fine-grained feature matching," *J. Adv. Transp.*, vol. 2020, Feb. 2020, Art. no. 5804835. [Online]. Available: https://doi.org/10.1155/2020/5804835
[45] J. Guerrero-Ibáñez, S. Zeadally, and J. Contreras-Castillo, "Sensor technologies for intelligent transportation systems," *Sensors*, vol. 18, no. 4, p. 1212, 2018, doi: 10.3390/s18041212.
[46] D. Joubert, A. Tyatyantsi, J. Mphahlehle, and V. Manchidi, "Pothole tagging system," in *Proc. 4th Robot. Mechatronics Conf.*, Nov. 2011, pp. 1–4. [Online]. Available: https://hdl.handle.net/10204/5384
[47] A. Uus et al., *NDT Sensor Fusion: Optimization of NDT Sensor Data Processing Strategies for Road Infrastructure Inspection*, UTSG, Bristol, U.K., 2016.
[48] Y.-C. Lin, W. H. Chen, and C. H. Kuo, "Implementation of pavement defect detection system on edge computing platform," *Appl. Sci.*, vol. 11, no. 8, p. 3725, 2021. [Online]. Available: https://doi.org/10.3390/app11083725
[49] S. W. Katicha, J. El Khoury, and G. W. Flintsch, "Assessing the effectiveness of probe vehicle acceleration measurements in estimating road roughness," *Int. J. Pavement Eng.*, vol. 17, no. 8, pp. 698–708, 2015, doi: 10.1080/10298436.2015.1014815.
[50] T. Kim and S. K. Ryu, "Review and analysis of pothole detection methods," *J. Emerg. Trends Comput. Inf. Sci.*, vol. 5, no. 8, pp. 603–608, 2014.
[51] P. Wang, Y. Hu, Y. Dai, and M. Tian, "Asphalt pavement pothole detection and segmentation based on wavelet energy field," *Math. Problems Eng.*, vol. 2017, Feb. 2017, Art. no. 1604130. [Online]. Available: https://doi.org/10.1155/2017/1604130
[52] I. Moazzam, K. Kamal, S. Mathavan, S. Usman, and M. Rahman, "Metrology and visualization of potholes using the Microsoft kinect sensor," in *Proc. 16th Int. IEEE Annu. Conf. Intell. Transp. Syst.*, 2013, pp. 1284–1291.
[53] I. Bosi, E. Ferrera, D. Brevi, and C. Pastrone, "In-vehicle IoT platform enabling the virtual sensor concept: A pothole detection use-case for cooperative safety," in *Proc. 4th Int. Conf. Internet Things, Big Data, Security (IoTBDS)*, 2019, pp. 232–240, doi: 10.5220/0007690602320240.
[54] C. Y. Sai, D. Saravanan, Y. V. Tej, and T. H. Vineesha, "Smart renting of vehicles using IoT," *Int. J. Innov. Technol. Exploring Eng.*, vol. 8, no. 6, pp. 1270–1273, 2019.
[55] R. Khatun, S. Antor, A. Ullah, and A. Hossain, "Vehicle fuel activities monitoring system using IoT," *Adv. Internet Things*, vol. 9, no. 4, pp. 63–71, 2019, doi: 10.4236/ait.2019.94005.
[56] A. Nair, N. Chacko, R. Kasim, and A. Sunny, "EtherRent: A cooperative car rental platform," *Int. Res. J. Eng. Technol.*, vol. 7, no. 4, pp. 1780–1785, 2020.
[57] M. Montoya-Alcaraz, A. Mungaray-Moctezuma, and L. García, "Sustainable road maintenance planning in developing countries based on pavement management systems: Case study in Baja California, México," *Sustainability*, vol. 12, no. 1, p. 36, 2020, doi: 10.3390/su12010036.
[58] I. Marović, I. Androjić, N. Jajac, and T. Hanák, "Urban road infrastructure maintenance planning with application of neural networks," *Complexity*, vol. 2018, May 2018, Art. no. 5160417. [Online]. Available: https://doi.org/10.1155/2018/5160417
[59] A. I. Setianingsih, S. Sangaji, and A. Setyawan, "Road maintenance and rehabilitation program using functional and structural assessment," in *Proc. IOP Conf. Series, Mater. Sci. Eng.*, vol. 176, 2017, Art. no. 12030, doi: 10.1088/1757-899x/176/1/012030.
[60] J. Mikolaj and L. Remek, "Road network management: Repair action plans for self-governing regions," *Procedia Eng.*, vol. 153, pp. 577–583, Aug. 2016.
[61] "Impacts of automated vehicles on highway infrastructure," Res. Develop. Technol., Turner-Fairbank Highway Res. Center, U.S Dept. Transp., McLean, VA, USA, document FHWA-HRT-21-015, 2021.
[62] H. Noorvand, G. Karnati, and B. S. Underwood, "Autonomous vehicles: Assessment of the implications of truck positioning on flexible pavement performance and design," *J. Transp. Res. Board*, vol. 2640, no. 1, pp. 21–28, 2017, doi: 10.3141/2640-03.