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An Alternative System for Assessing Pavement Condition in the Event of an Epidemic: A Case of COVID-19

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Abstract: Maintaining the efficiency of road pavement is essential to achieving the highest road performance and comfort for road users. Pavement monitoring plays a significant role in maintaining the sustainability of road networks. Additionally, assessments have been performed using different equipment and devices or through visual inspections to determine the type and severity of pavement degradation. However, some obstacles may affect the sustainability of road networks by preventing the regular monitoring and maintenance of pavements, such as the COVID-19 pandemic. Due to the COVID-19 pandemic, the construction and management of transportation systems have been affected by economic shut-downs and imposed social restrictions. Road networks have also suffered from neglect and a lack of monitoring and maintenance due to the government's lockdowns in addition to strict regulations that limit movement on roads and any form of construction, monitoring, inspection, and evaluation to improve road pavement conditions. This research introduces a safe pavement monitoring system using an e-bike to evaluate and predict pavement degradation. An accelerometer sensor and line-scan camera were used to collect pavement vibration data during the e-bike's movement. The results of the proposed monitoring method showed reliable evaluation outcomes. Moreover, the SVM model showed a significant contribution to detecting and classifying pavement distress.

Keywords: pavement condition; vibration; prediction

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1. Introduction

The infrastructure and transportation sectors are the backbone of urban cities and significantly contribute to a city's economic income. Those sectors have faced many obstacles over the last few decades, including wars, natural disasters, and health pandemics, which have reduced their quality and usage while increasing their rehabilitation and reconstruction costs. Recently, the COVID-19 pandemic had a significant effect on business, decreasing the GDP percentage in most countries worldwide; additionally, many setbacks and disturbances were caused in those countries' institutions and work systems during and after the pandemic. Due to the COVID-19 pandemic, the construction and management of transportation systems have been changed and affected by economic shut-downs and imposed social restrictions. Road networks have also suffered from neglect and lack of monitoring and maintenance due to government lockdowns, in addition to strict regulations that limit movement on roads and any form of construction, monitoring, inspection, and evaluation to improve road pavement condition. Therefore, the need for an accurate pavement monitoring system that satisfies the needs of the COVID-19 pandemic restrictions, in terms of keeping a safe social distance and minimizing contact with other people, is a top priority, allowing for the inspection, evaluation, and prediction of road pavement conditions in order to ensure the continuation of appropriate maintenance and treatment processes.

Currently, governments focus on improving road network sustainability and pavement quality to provide a high level of service for roadway users. Road networks need to be inspected and evaluated frequently by transport agencies to maintain the condition of road pavement. The technologies and techniques used for road pavement assessment vary according to several factors, including the road classification, traffic condition, monitoring device, level of deterioration, and environmental condition [1].

Sustainability is maintained for any road pavement during any pandemic by applying different planning, monitoring, assessment, prediction, and maintenance strategies after considering all the applied restrictions. In the COVID-19 pandemic, the same strategies have to be applied to keep the pavement in perfect condition. Pavement monitoring is the first step in pavement management and evaluation systems, and the data from monitoring reflect the condition and health status of road pavement surfaces [2,3]. However, outdoor procedures such as monitoring and inspections need to be fast, accurate, and committed to the imposed restrictions, such as social distancing [4].

On the other hand, predicting the pavement condition has a significant role in identifying the pavement health status and detecting and classifying the distress type, severity, and quantity [5]. The accuracy of pavement condition predictions depends mainly on selecting appropriate prediction models and data sizes and types [6]. This study used a support vector machine (SVM) model to detect and classify pavement defects on local roads based on vibration signals conducted by an accelerometer sensor. The accuracy of the prediction model is a significant factor for future treatment and maintenance actions for pavement surfaces. Preprocessing steps must be applied to prepare the data for building the prediction models, and include filtering, labelling, and feature extraction [7,8]. All preprocessing methods are necessary for noise-cancelling raw data. This study applied a high-pass filter to raw vibration signals to ensure the data were smoothed.

This research introduces a safe pavement-monitoring system using an e-bike to evaluate and predict pavement degradation (see Figure 1). An accelerometer sensor and a line-scan camera were used to collect the pavement vibration data during the e-bike's movement. This paper is structured as follows: the next section presents the literature review; it is followed by the explanation of the data in Section 3; after that, the results are presented and discussed in Section 4; finally, in Section 5, the conclusion and future research direction are given.

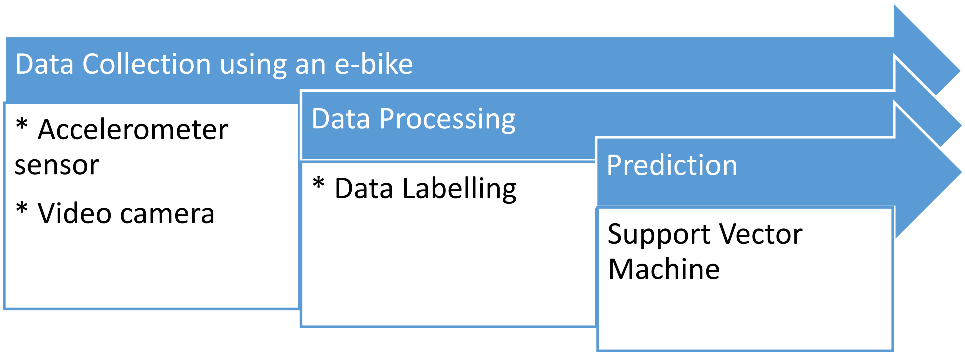


Figure 1. The research structure of the proposed system.

2. Literature Review

Levels of road service and pavement efficiency are among the most significant elements of transportation sustainability. Therefore, regular inspections and frequent monitoring are necessary to maintain high-quality road pavement to provide more comfort and safety for roadway users [9] while also reducing fuel consumption and vehicle maintenance costs [10]. However, some conditions may arise and affect the sustainability of road monitoring and, subsequently, periodic maintenance. Consequently, some deterioration and distress appear on the surface of pavements, such as cracking, patching, rutting, etc. Usually, the neglect of road maintenance and periodic monitoring causes damage to appear on the pavement surface [11]. Some unplanned cases of neglect, such as the COVID-19 pandemic, may cause postponements or delays to the monitoring and periodic maintenance of road pavements; thus, some types of deformations such as corrugation, cracking, and potholes may appear despite a decrease in road-use levels [12]. This happened at different road spots after around two years of lockdowns in most countries because of the COVID-19 pandemic [12].

During the COVID-19 pandemic, one of the obstacles that prevented fieldwork was the requirement of providing safe social distancing between the monitors themselves and other community members [13]. Hence, some field inspection requests faced rejection from governments or health organizations under the requirements of the pandemic restrictions in order to protect workers and prevent the widespread of coronavirus among the monitors [14]. Researchers have revealed that any epidemic could change the sustainability of the transportation system by increasing travel and operation costs, changing travel needs, and decreasing revenues [14].

In the past, precisely before the coronavirus pandemic, a significant revolution was produced in pavement monitoring systems by using high-quality devices to measure the condition of pavement surfaces [1,15]. To clarify, for the walk-and-look inspection method, at least two expert inspectors need to complete the rating of any local road surface, and the same monitor numbers are required when evaluating the pavement condition using a car or van [16,17]. Thus, working as a team is required to effectively complete the monitoring work.

Unfortunately, this method cannot be utilized in the presence of a severe epidemic that requires mandatory social distancing, such as COVID-19. Therefore, we needed to develop a safe pavement monitoring system that could satisfy the required social distancing requirements in accordance with the restrictions imposed by the World Health Organization [18].

The proposed method for monitoring local roads using electric bicycles provides an opportunity for transport agencies and governments to conduct periodic monitoring of road pavements and determine the type and severity of their deterioration [2]. An e-bike was used as a pavement-monitoring vehicle to evaluate the pavement condition while moving over a road section (Katto et al. [19], Shtayat et al. [20,21], and Cafiso et al. [9]). They used an accelerometer sensor or smartphones fixed on the handlebar or rear basket to measure the vibrations of the vehicle chassis during movement over the pavement. The measured vibration signals revealed the condition of the pavement's deterioration in terms of severity and location. The vibration signals' fluctuations indicate potential distress on the road pavement [22]. Shtayat et al. [20] revealed that the level of the fluctuations changed according to the severity of distress. Moreover, a camera or mobile camera was used during the vehicle's movement to match the vibration signals and record video regarding distress type, severity, quantity, and location. In this research, an accelerometer sensor and line-scan camera are used to identify the level of deterioration on a local road by measuring the vibration signals from an e-bike chassis. Additionally, a matching was made to confirm the conducted data with the observation results.

Predicting pavement performance is another way of measuring the efficiency of using the vibration-based method a pavement monitoring technique. To clarify, the accuracy of the prediction models depends mainly on the quality of the conducted data. Moreover, distress detection and classification are the main items in forecasting the pavement's health status [23]. Many previous studies developed different prediction models to correctly and accurately analyse the condition of road pavement, including support vector machines (SVMs) [23], linear regression (LR) [24], a decision tree (DT) [25], a random forest (RF) [26], and neural networks (NNs) [27]. Prediction models provide a clear vision of the road pavement's current and future health status. Moreover, by the prediction models, the researchers can detect distress and classify it according to its type and severity [28]. In this study, detection and classification processes were applied to identify the type, severity, and location of distress using the support vector machine model (SVM). SVM is a supervised machine learning algorithm that uses wide-range and dimensional data space for classification and regression analysis. It has been widely used for detecting, classifying, and forecasting the performance of vibrations [5]. Two main preprocessing steps must be applied to prepare the vibration data for building the prediction model, including data labelling and feature extraction [26]. Data labelling is a process focused on identifying the start and end points of the fluctuated signals that may represent potential distress [29]. The process aims to identify the possible anomalies on the pavement from signals and classify them into windows that include the entire length of distress. At the same time, feature extraction is a process that focuses on extracting the targeted spikes from labelled windows.

3. Data Section

In this study, we used an e-bike as a monitoring vehicle to measure the vibration data when moving over a road segment. The selected local road named "Argyle Street" is a one-way local road located in Fitzroy, Melbourne, Australia. We visually inspected about 150 m of the chosen road to identify the quantity and quality of pavement distress (see Figure 2). The visual inspection revealed many forms of pavement distress spread along the selected road segment, such as patches and alligator and longitudinal cracks (see Figure 3). These defects cause discomfort for roadway users during their daily activities (Shtayat et al., 2020) [1]. We performed the data collection of this study in 2021 during the COVID-19 pandemic restrictions. We considered all health precautions and requirements, such as social distancing, wearing a mask, and sterilizing the devices. We started the data collection procedure by calibrating the devices by moving on an ideal pavement to identify the engine noise and normal vehicle chassis vibration. Figure 2 shows the site location of the study.

Figure 2. The site location of the study (Google Maps).

(**a**) (**b**) (**c**)

Figure 3. The inspected pavement distresses: (**a**) alligator cracks, (**b**) patches, and (**c**) longitudinal cracks.

3.1. Data Collection Using E-Bike

In this study, we used an electric bicycle model delivery bike as a monitoring vehicle. Additionally, we used a triaxial acceleration sensor (model PCB 356B18) to collect the three axes' vibration signals (x, y, and z) at a frequency of 5000 Hz from the e-bike while it was moving on the selected local road segment. We fixed the sensor on the top handlebar using double-sided tape. At the same time, we set the line-scan camera (model Basler racer—raL4096-24gm) on the back basket with a 45 angle toward the ground for clear and wide vision. We used the recorded video to match the distress type, severity, and location. Moreover, we selected the travel speed of the e-bike to be 10 km/h (the speed limit of the road is 40 km/h). The selected travel speed allowed the driver to drive over the distress spots without the need to perform sudden braking or deceleration. Figure 4 shows the measured vibration data using the accelerometer sensor.

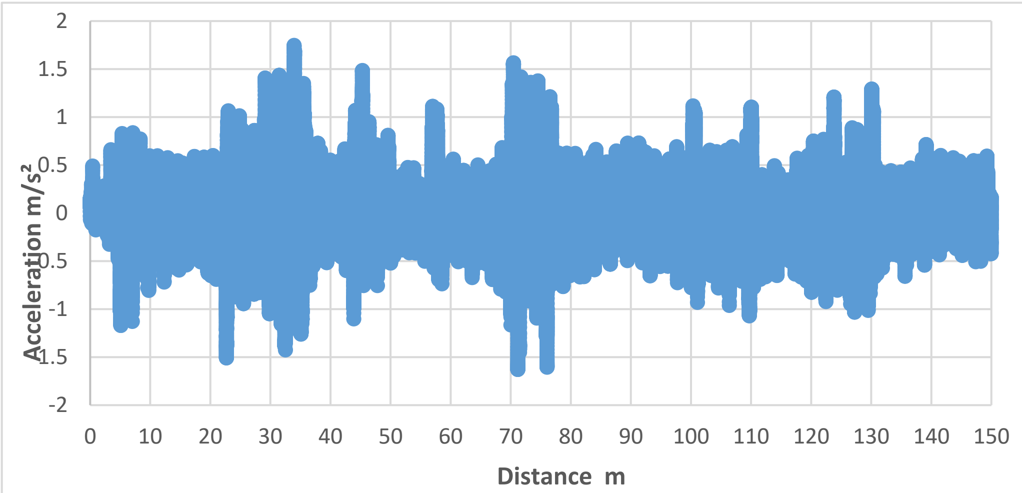
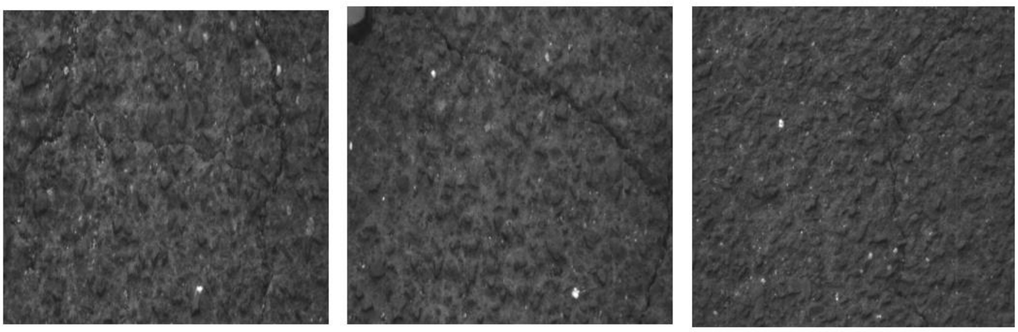


Figure 4. Vibration signals recorded from an e-bike using an accelerometer sensor.

Figure 4 shows the results of the recorded vibrations displayed fluctuations in the signals along the selected road segment. The unsteady spikes showed that the movement of the e-bike was not completely comfortable due to defects and anomalies on the road surface. Figure 4 shows the most significant fluctuation thresholds were more than -1.0 m/s^2 and 1.0 m/s^2, located at stations 20–25 m, 30–37 m, 43–47 m, 55–60 m, 70–76 m, 100–103 m, 105–108 m, and 128–133 m. After reviewing the recorded video and visual inspection reports, we concluded these spots have high-severity pavement distress, including patches and alligator cracks, while the other medium-level fluctuations between -0.5 m/s^2 to 0.5 m/s^2 represented minor pavement distress, such as longitudinal cracks. The data also showed a few incompatible spikes due to the orientation axis of the accelerometer sensor being a bit far from the centre axis of the e-bike. Figure 5 shows the captured images of the distresses on the road pavement during the e-bike movement.



(**a**) (**b**) (**c**)

Figure 5. The camera-captured distress: (**a**) alligator crack, (**b**) patches, (**c**) and longitudinal cracks.

3.2. Data Preprocessing Using Labelling Technique

Data labelling is a process used to match the recorded vibration signals with the inspected distress in terms of the location, type, and severity. To clarify, the process aims to manually compare and confirm the fluctuated signals with each distress location and then identify the type and severity according to the recorded video and visual inspection. After the matching, we established manual windows for each potential distress. Each window consists of the start and end point of each possible distress. Moreover, we identified the length of each distress from the spikes on the signals. In this study, we labelled various pavement defects in separate windows, including patches and alligator and longitudinal cracks.

More simply, the process aims to determine the guaranteed start and end point from unusual peaks representing the defects' dimensions. In predicting pavement performance, data labelling significantly advances the detection and classification process for pavement distresses from a massive raw dataset. Table 1 shows the labelled data from vibration signals. The table presents the boundaries of each pavement distress as identified by the number of spikes and root mean squared error (RMSE). The low RMSE values indicate that the proposed extraction method was reliable and accurate.

Table 1. A sample of the labelled data.

Distress (m)	RMSE (m)	Distress Length (m)	Number of Spikes	Distress Type
5.1–7.22	0.11	2.12	22	Patch
9.76–12.34	0.13	2.58	27	Patch
22.69–24.85	0.1	2.16	23	Alligator crack
29.85–31.47	0.08	1.62	16	Alligator crack
33.96–35.11	0.14	1.15	12	Longitudinal crack

3.3. Prediction the Pavement Condition Using SVM

We developed a machine learning model to present the detection and classification results of pavement distress based on the labelled vibration signals (training). Moreover, we used the unlabelled data for testing the developed model. The developed model was a binary model named support vector machine. The systematic of this binary prediction model depends mainly on using the 0, 1 (yes or no) datasets. This study used SVM to detect and classify pavement distress based on vibration data. The input of the prediction model was the vibration data, while the outputs of the model were the distress types.

In this study, we considered three distress types in the SVM model, including patches and alligator and longitudinal cracks. We identified all of the considered defects using labelling processing. Regarding the datasets, we divided the development process of the SVM into two main datasets, including 70% for training and 30 % for testing. Tables 2–4 show the developing results of the SVM model in detecting and classifying each type of pavement distress.

Table 2. The detection and classification of patches using SVM.

Label/Distress	Precision	Recall	F1-Score	Support
Normal	0.97	0.95	0.96	33,547
Patches	0.96	0.96	0.96	2889
Accuracy			0.96	
Weighted average	0.97	0.97	0.97	

Table 3. The detection and classification of alligator cracks using SVM.

Label/Distress	Precision	Recall	F1-Score	Support
Normal	0.97	0.99	0.98	33,547
Alligator cracks	0.95	0.94	0.94	1089
Accuracy			0.94	
Weighted average	0.95	0.96	0.95	

Table 4. The detection and classification of longitudinal cracks using SVM.

Label/Distress	Precision	Recall	F1-Score	Support
Normal	0.96	1.00	0.98	33,547
Longitudinal cracks	0.91	0.92	0.91	549
Accuracy			0.93	
Weighted average	0.96	0.96	0.96	

Tables 2–4 presented the worthiness of using the SVM model to detect and classify pavement distresses. The SVM model showed excellent values in the detection and classification of the patches and alligator and longitudinal cracks. Moreover, the values of precision for patches and alligator and longitudinal cracks showed acceptable values, with about 96%, 95%, and 91%, respectively. In contrast, the recall metrics values were 96%, 94%, and 92% for the predicted distress, respectively. The F1 score values showed excellent performance with about 96% for patches, 94% for alligator cracks, and 91% for longitudinal cracks. These metrics values indicated that the SVM was significantly detected and classified the distress types. The prediction of the patches provided higher accuracy with about 96%, while the accuracy of prediction of the alligator cracks was about 94%. At the same time, the lower detection and classification accuracy was 93% for longitudinal cracks. Additionally, according to the tables above, the ability of the SVM model to identify the no-distress state (normal) was high, with an average of about 97%.

4. Discussion

This study focused on introducing a safe pavement monitoring system that can be used by researchers, transport agencies, and governments to accurately monitor road network conditions under the highly imposed COVID-19 pandemic restrictions. The proposed monitoring method aimed to provide a clear indication of the current health status of pavement without the need for a fully prepared vehicle or using the traditional inspection process, which involves many inspectors. This method showed that using an e-bike was simple and provided reliable monitoring results. It also provided accurate outcomes (vibrations) conducted from an accelerometer sensor. The overall results of pavement monitoring showed that the accelerometer sensor has a significant contribution to successfully and accurately evaluating the road pavement conditions. Moreover, the recorded vibration signals reflected the actual level of pavement deterioration and explained the quality (severity) and quantity (number of distress spots and location) of pavement distress.

In Summary, using the SVM model to detect and classify the pavement distresses presented high-efficiency results. The significance of working as a binary model provided high-accuracy results in predicting three different distress types located at the selected local road, including patches and alligator and longitudinal cracks. The prediction results showed a significant contribution to predicting patches and alligator cracks; however, we observed lower accuracy when predicting longitudinal cracks due to limitations in data size. The fluctuation in the accuracy of the SVM to detect and classify the pavement distresses depended on several factors, including the speed of the monitoring vehicle, severity of pavement distress [2], the wheel width of the monitoring vehicle [30,31], and traffic conditions [1]. In the case of travel speed, the speed of 10 km/h is recommended by Lekshmipathy et al. [32] to be used by e-bikes in pavement monitoring. On the other hand, regarding the distress severity, medium and high severities provided more vibrations and clear boundaries on vibration signals and, therefore, can be detected as potential distress while labelling the data. Regarding the wheel width, the wider wheel provides a clear tire stamp over distress and thus achieves the required measurement of the entire defect size [33]. Moreover, traffic conditions significantly affect the accuracy of monitoring the pavement condition. More clearly, with ongoing traffic, the driver needs to accelerate, decelerate, and brake while driving, thus affecting the recorded vibration data. As a result, in this study, the impact of traffic may be neglected, which is considered effective when adopting the use of the e-bike as a health-safe monitoring vehicle under COVID-19 restrictions. Thus, the most accurate and significant measurement results are achieved on empty roads in the event of a lockdown.

5. Conclusions

This research presents a safe, healthy, and reliable pavement monitoring system to be used during the COVID-19 pandemic or any other health disaster under the highest standards of sterilization. The proposed monitoring system focused on measuring the vibrations of an e-bike chassis that reflected the comfort riding levels and pavement deformation conditions on local road pavements. Moreover, the vibration signals were conducted from a triaxial accelerometer sensor mounted on the middle of the e-bike handlebar. Furthermore, a video camera was installed on the back basket to record a video of the ground during the e-bike's movement. The monitoring results showed that the test speed was suitable to be used in further studies. The speed provided consistent vibration signals that reflected the actual distress quantity and quality. Moreover, the mounting location at the top handlebar was an appropriate position to mount the sensor; hence, the sensor can easily measure the vibrations without any obstacles. Furthermore, the accelerometer sensor showed a significant ability to measure a wide range of vibration data from the local road during vehicle movement. Lastly, using a video camera to monitor the pavement condition effectively matched and compared the signals with recorded video to ensure that each distress has been measured and determined by conducted signals.

A preprocessing step, including data labelling, was used to manually identify the potential windows from vibration signals that contained unusual fluctuation peaks. The labelled data was used for training the prediction model, while the unlabelled data was used for testing the prediction model. A machine learning model named SVM was used to detect and classify the pavement distresses based on high-frequency vibration data.

The results revealed that the SVM model successfully detected and classified three pavement distress types, including patches and alligator and longitudinal cracks, with high prediction accuracy. Moreover, the results of this research indicated that the proposed monitoring method could be used for further studies, such as monitoring side-walks, parking, and concrete track coverings. In addition, the study recommends using electric vehicles or hybrid vehicles to minimize engine noise and vehicle chassis vibrations.

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References

1. Shtayat, A.; Moridpour, S.; Best, B.; Shroff, A.; Raol, D. A review of monitoring systems of pavement condition in paved and unpaved roads. *J. Traffic Transp. Eng.* **2020**, *7*, 629–638. [CrossRef]
2. Shtayat, A.; Moridpour, S.; Best, B.; Shroff, A.; Raol, D. Dynamic monitoring of asphalt pavement using mobile application. In Proceedings of the 26th World Road Congress World Road Association (PIARC), Abu Dhabi, United Arab Emirates, 6–10 October 2019.
3. Soni, J.; Gujar, R.; Shah, D.; Parmar, P. A Review on Strategic Pavement Maintenance with Machine Learning Techniques. In *Intelligent Infrastructure in Transportation and Management*; Springer: Singapour, 2020; pp. 141–151. [CrossRef]
4. Haque, M.M.; Chin, H.C.; Debnath, A.K. Sustainable, safe, smart—Three key elements of Singapore's evolving transport policies. *Transp. Policy* **2013**, *27*, 20–31. [CrossRef]
5. Shtayat, A.; Moridpour, S.; Best, B.; Rumi, S. An Overview of Pavement Degradation Prediction Models. *J. Adv. Transp.* **2022**, *2022*, 7783588. [CrossRef]
6. Marcillo, P.; Caraguay, L.V.; Hernández-Álvarez, M. A Systematic Literature Review of Learning-Based Traffic Accident Prediction Models Based on Heterogeneous Sources. *Appl. Sci.* **2022**, *12*, 4529. [CrossRef]
7. Zhang, L.; Lan, M.; Zhang, J.; Tao, D. Stagewise Unsupervised Domain Adaptation With Adversarial Self-Training for Road Segmentation of Remote-Sensing Images. *IEEE Trans. Geosci. Remote Sens.* **2021**, *60*, 5609413. [CrossRef]
8. Zhu, Z.; Dong, Z.; Liu, Y. Detecting corrupted labels without training a model to predict. In Proceedings of the International Conference on Machine Learning, Baltimore, MD, USA, 17–23 June 2022; pp. 27412–27427.
9. Cafiso, S.; Di Graziano, A.; Marchetta, V.; Pappalardo, G. Urban road pavements monitoring and assessment using bike and e-scooter as probe vehicles. *Case Stud. Constr. Mater.* **2022**, *16*, e00889. [CrossRef]
10. Chen, L.; Fan, Z.; Liu, P.; Qian, Z. Optimization Model of Network-Level Pavement Maintenance Decision considering User Travel Time and Vehicle Fuel Consumption Costs. *Adv. Civ. Eng.* **2021**, *2021*, 4699838. [CrossRef]
11. Prakash, G.; Yuan, X.-X.; Hazra, B.; Mizutani, D. Toward a Big Data-Based Approach: A Review on Degradation Models for Prognosis of Critical Infrastructure. *J. Nondestruct. Eval. Diagn. Progn. Eng. Syst.* **2021**, *4*, 021005. [CrossRef]
12. Li, J.; Yin, G.; Wang, X.; Yan, W. Automated decision making in highway pavement preventive maintenance based on deep learning. *Autom. Constr.* **2022**, *135*, 104111. [CrossRef]
13. Miller-Rushing, A.J.; Athearn, N.; Blackford, T.; Brigham, C.; Cohen, L.; Cole-Will, R.; Edgar, T.; Ellwood, E.R.; Fisichelli, N.; Pritz, C.F.; et al. COVID-19 pandemic impacts on conservation research, management, and public engagement in US national parks. *Biol. Conserv.* **2021**, *257*, 109038. [CrossRef]
14. Mogaji, E.; Adekunle, I.; Aririguzoh, S.; Oginni, A. Dealing with impact of COVID-19 on transportation in a developing country: Insights and policy recommendations. *Transp. Policy* **2022**, *116*, 304–314. [CrossRef] [PubMed]
15. Cao, W.; Liu, Q.; He, Z. Review of Pavement Defect Detection Methods. *IEEE Access* **2022**, *8*, 14531–14544. [CrossRef]
16. Zhang, D.; Zou, Q.; Lin, H.; Xu, X.; He, L.; Gui, R.; Li, Q. Automatic pavement defect detection using 3D laser profiling technology. *Autom. Constr.* **2018**, *96*, 350–365. [CrossRef]
17. Ragnoli, A.; De Blasiis, M.R.; Di Benedetto, A. Pavement Distress Detection Methods: A Review. *Infrastructures* **2018**, *3*, 58. [CrossRef]
18. Sohrabi, C.; Alsafi, Z.; O'Neill, N.; Khan, M.; Kerwan, A.; Al-Jabir, A.; Iosifidis, C.; Agha, R. World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). *Int. J. Surg.* **2020**, *76*, 71–76. [CrossRef]
19. Katto, J.; Takeuchi, M.; Kanai, K.; Sun, H. Road infrastructure monitoring system using e-bikes and its extensions for smart community. In Proceedings of the 1st ACM Workshop on Emerging Smart Technologies and Infrastructures for Smart Mobility and Sustainability, Los Cabos, Mexico, 21 October 2019; pp. 43–44.
20. Shtayat, A.; Moridpour, S.; Best, B. Using e-bikes and private cars in dynamic road pavement monitoring. *Int. J. Transp. Sci. Technol.* **2021**, *11*, 132–143. [CrossRef]
21. Shtayat, A.; Abu Alfoul, M.; Moridpour, S.; Al-Hurr, N.; Magableh, K.; Harahsheh, I. Waiting Time of Public Transport Passengers in Jordan: Magnitude and Cost. *Open Transp. J.* **2019**, *13*, 227–235. [CrossRef]
22. Harikrishnan, P.M.; Gopi, V.P. Vehicle Vibration Signal Processing for Road Surface Monitoring. *IEEE Sens. J.* **2017**, *17*, 5192–5197. [CrossRef]
23. Roberts, R.; Giancontieri, G.; Inzerillo, L.; Di Mino, G. Towards Low-Cost Pavement Condition Health Monitoring and Analysis Using Deep Learning. *Appl. Sci.* **2020**, *10*, 319. [CrossRef]
24. Karballaeezadeh, N.; Mohammadzadeh, S.D.; Shamshirband, S.; Hajikhodaverdikhan, P.; Mosavi, A.; Chau, K.W. Prediction of remaining service life of pavement using an optimized support vector machine (case study of Semnan–Firuzkuh road). *Eng. Appl. Comput. Fluid Mech.* **2019**, *13*, 188–198. [CrossRef]
25. Piryonesi, S.M.; El-Diraby, T.E. Using Machine Learning to Examine Impact of Type of Performance Indicator on Flexible Pavement Deterioration Modeling. *J. Infrastruct. Syst.* **2021**, *27*, 04021005. [CrossRef]
26. Kaur, D.; Pulugurta, H. Comparative analysis of fuzzy decision tree and logistic regression methods for pavement treatment prediction. *WSEAS Trans. Inf. Sci. Appl.* **2008**, *5*, 979–990.
27. Guo, X.; Hao, P. Using a Random Forest Model to Predict the Location of Potential Damage on Asphalt Pavement. *Appl. Sci.* **2021**, *11*, 10396. [CrossRef]

28. Dan, H.-C.; Zeng, H.-F.; Zhu, Z.-H.; Bai, G.-W.; Cao, W. Methodology for Interactive Labeling of Patched Asphalt Pavement Images Based on U-Net Convolutional Neural Network. *Sustainability* **2022**, *14*, 861. [CrossRef]
29. Wen, T.; Ding, S.; Lang, H.; Lu, J.J.; Yuan, Y.; Peng, Y.; Chen, J.; Wang, A. Automated pavement distress segmentation on asphalt surfaces using a deep learning network. *Int. J. Pavement Eng.* **2022**, 1–14. [CrossRef]
30. Fan, Z.; Wu, Y.; Lu, J.; Li, W. Automatic pavement crack detection based on structured prediction with the convolutional neural network. *arXiv* **2018**, arXiv:1802.02208.
31. Di Mascio, P.; Ragnoli, A.; Portas, S.; Santoni, M. Monitor Activity for the Implementation of a Pavement—Management System at Cagliari Airport. *Sustainability* **2018**, *13*, 9837. [CrossRef]
32. Xue, W.; Wang, D.; Wang, L. Monitoring the Speed, Configurations, and Weight of Vehicles Using an In-Situ Wireless Sensing Network. *IEEE Trans. Intell. Transp. Syst.* **2014**, *16*, 1667–1675. [CrossRef]
33. Lekshmipathy, J.; Samuel, N.M.; Velayudhan, S. Vibration vs. vision: Best approach for automated pavement distress detection. *Int. J. Pavement Res. Technol.* **2020**, *13*, 402–410. [CrossRef]