CHEMICAL ENGINEERING TRANSACTIONS
VOL. 109, 2024
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it
Guest Editors: Leonardo Tognotti, Rubens Maciel Filho, Viatcheslav Kafarov

ISBN 979-12-81206-09-0; **ISSN** 2283-9216
DOI: 10.3303/CET24109101

Digital Twin: Challenge Road Damage Detection on Edge Device

Haniah Mahmudah[a,b], Ali Musyafa[b], Aulia Siti Aisjah[b], Syamsul Arifin[b], Catur Arif Prastyanto[c]

[a] Electrical Engineering Department, Politeknik Elektronika Negeri Surabaya, Indonesia
[b] Engineering Physics Department, Institut Teknologi Sepuluh Nopember, Indonesia
[c] Civil Engineering Department, Institut Teknologi Sepuluh Nopember, Indonesia
aulia.sa@ep.its.ac.id

The development of digital twins as a new technology aligns with the main strategic objectives of some of the world's top manufacturing countries. Several studies on digital twin cities have been performed, including the interaction of the Internet of Things (IoT) with smart cities, smart city traffic disaster risk management, and smart road inspection. The purpose of the research is to offer a survey of digital twin cities that includes road damage inspection as support for smart roads. The deployment of IoT technology and artificial intelligence (AI) to construct road defect detection systems on edge devices. This is the most recent breakthrough and an open challenge to creating a road defect detection system using edge AI on digital twins. As a result, edge AI devices are required to perform automatic and real-time road inspections. However, edge AI devices for detecting road damage have limited computing and storage capacities. Much of the physical system modeling has been completed in the construction of digital twin cities for road damage detection. In order to deploy CNN models on devices, some require physical system development. The stages involved in the development and implementation of a CNN model for an edge AI device road damage detection system are hardware selection, software development, developing the road damage detection application, edge device optimization, security and connectivity, testing and validation, and deployment. To improve system performance and reduce inference time, the CNN model must be optimized before being deployed on edge devices as edge AI.

1. Introduction

The digital twin is the development and application of Cyber-Physical Systems (CPS), which aim to develop intelligent control systems, industrial application software, fault diagnosis software, and related tools, as well as sensor protocols and communication systems to realize real-time connectivity, accurate identification, efficient interaction, and intelligent control of manufacturing equipment and products (Hu et al., 2021). The Digital Twin is at the forefront of the industry 4.0 revolution, which is enabled by enhanced data analytics and IoT connectivity. The IoT has enhanced the amount of data available in industry, healthcare, and smart city contexts. Through the establishment of a connected physical and virtual twin as the digital twin. The digital twin can address the difficulty of seamless integration between IoT and data analytics. The digital twin environment enables quick analysis and real-time decisions based on reliable data (Fuller et al., 2020).
Technological advancements, such as the creation of powerful semiconductor chips at an extremely competitive rate, are growing the IoT. One of the technical advancements is the growing popularity of IoT, which is linked to other technologies and has functions in a variety of everyday applications. Autonomous linked cars, flying robots, and smart houses are some examples of IoT that are integrated into existing systems or that allow the construction of wholly new concepts. The IoT, big data, cloud computing, and AI are all rapidly developing technologies and industries that will form the foundation for smart city design. All smart cities are increasingly progressing from static 3D modelling to digital twins. It combines dynamic digital technology and static 3D modelling to create a novel concept of a digital twin city. The wide adoption of the digital twin concept at the city level, as well as smart city development, contributes to the creation of digital twin cities. Several studies have

Paper Received: 13 January 2024; Revised: 2 February 2024; Accepted: 6 April 2024
Please cite this article as: Mahmudah H., Musyafa A., Siti Aisjah A., Arifin S., Arif Prastyanto C., 2024, Digital Twin: Challenge Road Damage Detection on Edge Device, Chemical Engineering Transactions, 109, 601-606 DOI:10.3303/CET24109101

been conducted on digital twins cities (Traoré & Ducq, 2022), such as the interaction between IoT and smart cities (Alahi et al., 2023), disaster risk management (Ariyachandra & Wedawatta, 2023), intelligent road inspection (Fan et al., 2022). According to previous research, there has been no investigation into road damage detection systems on edge devices that can support digital twins. That it can monitor road damage in real time. To close the gap, collaboration among IoT, AI, and robotics is required to support digital twin cities in road damage inspection as a smart road damage detection system on edge devices as edge AI. That edge AI detects road damage in real time and automatically, with visualization in the form of smartphone applications and websites. As a result, this research offers a road damage detection system on an edge device that can operate in real time and autonomously. The purpose of this research is to depict a current survey of digital twin cities with road damage inspection as a support for smart roads. The IoT, AI, and hardware-based road damage inspection system with trends and prospective participation, with the newest breakthroughs, real-world involvement, and open challenges. Therefore, there is a demand for real-time road damage survey devices that utilize AI and CNN models. Hence, there is a need for a road inspection device that works in real time and automatically using edge devices. Using edge AI devices to acquire and evaluate real-time data on road damage. However, edge AI devices capture mobile, real-time, and automatic road defect data. Edge AI devices that identify road concerns have limited computation and storage capabilities, but they use less power, considerably improving energy efficiency. Edge AI can process data on-device rather than transferring it to a faraway data center for analysis. Furthermore, there are critical features that may pose challenges to the adoption and integration of road damage inspection as a smart road. This comprehensive analysis gives a good summary of significant themes as well as essential recommendations for future research. In the near future, this study will also serve as a resource for practitioners and researchers.

2. Road damage inspection in digital twin cities

A digital twin is a constantly updated digital replica of a physical system or component. Its goal is to monitor the system's performance, experiment with various scenarios, predict defeats, and uncover opportunities for system operation. A physical system or component that performs a given duty is represented by a physical entity. It is made up of sensors and actuators that allow information to be exchanged and orchestrated between the physical object and its digital representation. Sensors such as cameras, GPS, and data communication devices are connected to hardware as an edge device to build a road damage detection system (Dimd et al., 2023). Creating a digital twin of a city, including smart roads with an integrated road defect inspection system. This is a forward-thinking approach that utilizes advanced technologies, i.e., AI and IoT, to improve urban infrastructure and boost economic sectors. The digital twin technology can be used in conjunction with road defect inspection using AI and IoT for smart roads, as follows:

2.1 Creating a digital twin

There are several stages to developing a digital twin. Data must be gathered from a variety of sensor sources, including IoT devices. Several studies on road damage inspection have been conducted utilizing 3-axis accelerometer sensors (Eriksson et al., 2019), accelerometer sensors on smartphones (Mednis et al., 2011), lidar sensors arranged in an array (Nuzula et al., 2023), and laser sensors utilized for stereo vision (Shen et al., 2014). Camera sensors have been utilized to identify road damage as technology has advanced and camera sensor prices have grown increasingly competitive.

Application for inspecting road damage utilizing camera sensors and smartphone camera sensors (Maeda et al., 2018). In addition, data on road damage was gathered via satellite photos, GIS databases, and city records. The data is in the form of the type, level, and location of road damage, and it is all merged to construct a system with the purpose of each component, resulting in a comprehensive digital picture of the city and its roads (Sudibyo & Alimudin, 2023). Data about cities is utilized to create detailed 3D models of cities and road networks, allowing visualizations of virtual assets as digital twins. This image aids in system modeling and accurate analysis.

2.2 Road damage inspection and IoT integration

Based on the usage of sensors in the road damage inspection system, represent a road damage inspection system by integrating IoT sensors. Several research on the use of sensors in road damage inspection systems have been conducted, and these sensors include accelerometers (Rana & Asaduzzaman, 2021), array LiDAR (Nuzula et al., 2023), stereo vison using laser (Shen et al., 2014) and cameras using image processing technique (Sai Ganesh Naik & Nirmalrani, 2021). GPS module can provide exact location data for geographically mapping road damage. The research camera and GPS on a smartphone are being used to develop an integrated road damage inspection systems (Maeda et al., 2018). Many studies on road damage inspection have combined numerous sensors, mainly cameras and GPS, to create an integrated road damage inspection

system.GPS modules can provide exact location data for geographically mapping road damage. Several sensor devices and GPS modules are linked to a control module that detects road damage using edge AI device technology such as smartphones (Maeda et al., 2018), the NVIDIA Jetson Nano (Pratama et al., 2021), the Raspberry Pi on UAVs (Qurishee, 2019), and pothole detection using the Raspberry Pi (Asad et al., 2022).
It is utilized for continuous monitoring due to the integration of IoT sensors in the road damage inspection system. An automatic continuous monitoring system is implemented in this continuous monitoring, which is represented in a system. This is used to detect and assess road damage automatically, allowing for more efficient road monitoring. Data integration is used in digital twin cities, which means connecting data from IoT sensors with digital twins to provide real-time updates and analysis of road conditions in a virtual environment.

2.3 Smart data analytics: AI and ML

A variety of systems for identifying road damage autonomously have been developed. There are three primary methodologies: (1) Sensor-based methods, including accelerometers based on vibration sensors. (2) laser scanning-based 3D reconstruction methods based on lasers and stereo vision. (3) Methods for processing images and video frames, as well as machine learning (ML) and deep learning (DL). The vibration sensor-based technique typically employs sensors that can measure the magnitude of the vibration, such as acceleration sensors. Many studies have been conducted; however, the application of accelerometer sensors necessitates specific attention in terms of installation techniques during data collection and setting the accelerometer sensor threshold for declaring road damage. Because the degree of vehicle engine vibration has a significant impact on data gathering using accelerometer sensors, the computation of the accelerometer sensor threshold to declare road damage varies.
Although laser scanning-based technology detects road damage more accurately than earlier methods, the equipment is huge and costly. The availability of cost-effective camera sensors and advances in image processing techniques have sped up the development of road damage identification models. Camera sensors employ image processing with contour identification as well as image data processing. Pothole identification image processing techniques using classic machine learning (ML) algorithms produce a high level of accuracy while needing large computer resources and high electricity.
DL and ML techniques are utilized in system modeling to analyze sensor data, forecast future road damage, and estimate the degree of existing damage using the CNN model. Several studies on road damage inspection systems, for example, use the CNN model as an edge AI. Detection and classification of road damage utilizing CNN models and smartphones, employing the InceptionV2 and MobileNet model architectures (Maeda et al., 2018), and Yolo model (Zhen Liu et al., 2022). Several road damage detection researchers used the CNN model on various edge devices, such as the Raspberry Pi (Qurishee, 2019). To improve system performance through tuning the hyperparameter MobileNetV1 model (Aqsa et al., 2022) and MobileNetV2 model on the NVIDIA Jetson Nano (Hernanda et al., 2022). Table 1 shows details on the CNN model, system performance, and edge AI devices employed. The CNN model research results reveal that the system performs effectively, but there is still an opportunity for improvement in system performance and inference time on edge AI devices (Mahmudah et al., 2023).

Table 1: The CNN model on edge devices

CNN Model	Performance system	Edge device	Reference
MobileNet	Recall 71%, precision 77%, inference time 1,5 s.	Smartphone	(Maeda et al., 2018)
MobileNetV2	Loss 0.4, frame per second 60.	NVDIA Jetson Nano	(Pratama et al., 2021)
MobileNetV1	Accuracy 60% frames per second 1.2	Raspberry-Pi	(Asad et al., 2022)
MobileNetV2	Mean average precision 0.22.	NVDIA Jetson Nano	(Sudibyo and Alimudin 2023)
MobileNetV2	Mean average precision 0.086, average recall 0.241.	NVDIA Jetson Nano	(Hernanda et al., 2022)

3. Hardware deployment for CNN models on an edge device

There are various processes involved developing and deploying a CNN model for an edge device road damage detection system. Figure 1 depicts the stages involved in developing and implementing a CNN model for an edge AI device road damage detection system. High performance, accuracy, and inference time must be considered when creating edge AI device. As a result, CNN models must evaluate a variety of parameters, including hardware selection. The considerations made to select the CNN model and hardware were such that the road damage detection system performed well. Considerations are made based on the demands and environment in order for the road damage detection system to function successfully.

3.1. Hardware selection

A mobile device must be used in conjunction with an edge device as edge AI. It selects a suitable edge device, such as the Raspberry Pi, the NVIDIA Jetson series, or the Intel Neural Compute Stick. Due to the restricted capacity of edge devices, aspects such as processing power, memory, and networking options should be addressed based on the complexity of the CNN model and the size of the CNN model deployment.

3.2. Software development

Software development entails installing an operating system, an edge AI framework, and sensor integration. To build a road damage system on edge devices by installing a lightweight Linux-based operating system, such as Raspbian for Raspberry Pi or NVIDIA JetPack for Jetson devices. Select a TensorFlow Lite, ONNX Runtime, or OpenVINO AI framework that is compatible with an edge device (Openja et al., 2022). Optimize the CNN model for inference based on the framework of choice. A road damage detection system contains sensors such as accelerometers or GPS, as well as sensor drivers and APIs that are integrated into the software stack. Create software to collect data from sensors and cameras. Integrate AI frameworks for model deployment and inference.

3.3. Develop The Road Damage Application

Road damage detection using a CNN model on an edge device. Ensure the CNN model is optimized for the hardware to achieve real-time or near-real-time performance. Write inference code that collects data from sensors or cameras, processes it through the CNN model, and interprets its results, such as recognizing the types and degree of road damage. The road damage system is part of a digital twin city initiative in which the edge device is integrated with the digital twin platform, allowing for seamless data transmission.

3.4. Edge Device Optimization

Once the CNN model is trained and evaluated, it integrates into the digital twin environment. The inference integration involves deploying the model on a server or edge device capable of real-time inference. Implement a mechanism to capture real-time images of roads within the digital twin. Pass these images through the deployed CNN model for inference, detecting road damage instances in real-time. Table 1 explains the CNN model's use of edge devices. The deployment of the CNN model on devices requires additional research. The CNN model research results show that the system performs effectively, but there is still potential to increase its performance on edge devices. When using edge AI devices, it is crucial to optimize the CNN model for system performance. Methods post-training include quantization or pruning, which improve inference time (Mahmudah et al, 2023). Hardware acceleration using GPUs or specialized AI accelerators, which can drastically shorten inference time, makes it critical to deploy CNN models on edge devices. As part of power management, implement power-saving capabilities, especially if the edge device is battery-powered.

3.5. Security and Connectivity

A wireless connection is used to send the CNN model to the edge device for road damage detection purposes. Wireless communication necessitates connectivity and data security. The data for the detection of road damage is transmitted to the server via a wireless connection over the internet. IoT devices with wireless connectivity can communicate data to centralized servers using various wireless technologies such as 4G/5G (Alahi et al., 2023), Long Range (LoRa), or Narrowband Internet of Things (NB-IoT). Edge computing, which uses edge devices to process data locally on IoT devices, reduces latency and reduces the quantity of data transferred over networks (Ketu & Mishra, 2022). Encryption and secure communication protocols are used in data security to protect the data being transmitted. Cloud-based AI services for model training, optimization, and analysis. Cloud-to-edge data synchronization is used to update models and configurations on edge devices. Implement data encryption algorithms to provide secure data transmission between edge devices and other systems. Network configuration options, such as Wi-Fi or cellular connectivity, are used to ensure that edge AI devices can safely transmit data to central servers or cloud platforms.

3.6. Testing and Validation

Edge AI devices should be thoroughly tested in a variety of scenarios to provide accurate and dependable road damage detection. Test the device's performance under various lighting, weather, and road surface conditions. To ensure that road damage identification is accurate, the CNN model requires system findings to be validated against ground truth data. Analyses the CNN model outputs for decision-making and future action.

3.7. Deployment

Road damage detection utilizing the CNN implementation model on edge devices involves field implementation, monitoring, and maintenance. Field deployment involves deploying the edge device in the desired location on the vehicle, ensuring that it is installed safely and protected from environmental conditions. It applies an optimized CNN model to edge devices based on a CNN model that performs effectively in systems. CNN models are integrated and deployed in software stacks to provide real-time inference. Monitoring and maintenance Enable remote monitoring to track the performance of deployed edge devices. Update the software and firmware on a regular basis to eliminate issues and improve system performance.

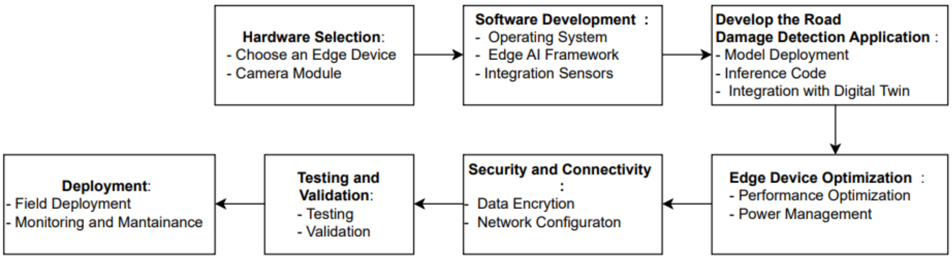

Figure 1: The stages involved developing and implementing a CNN model for an edge AI device road damage detection system.

The various stages involved the development and use of CNN models for edge AI device road defect detection systems. The selection of edge devices is based on the demands and intended outcomes. Finally, select a CNN model that can be employed on edge devices. The issue in developing and deploying CNN models on edge devices is to focus on high system performance and efficiency in terms of inference time when detecting road damage objects. Several approaches to optimization, including quantization and pruning, are used to minimize inference time. This procedure is concerned with the efficient utilization of energy in devices with limited power in order to maximize efficiency. Data connectivity and security are determined by the availability of wireless connections in the surroundings. If there is no wireless internet connection available at the road damage data collection point, the data can be saved on a data storage device. Data can be sent wirelessly or via Wi-Fi, which is cheaper.

4. Conclusion

Much of the physical system modeling has been completed in the construction of digital twin cities for road damage detection. In order to deploy CNN models on edge devices, some require physical system development. The stages involved in the development and implementation of a CNN model for an edge device road damage detection system are hardware selection, software development, developing the road damage detection application, edge device optimization, security and connectivity, testing and validation, and deployment. Several studies have been conducted, but more work is needed to optimize the inference time for the CNN model on the edge device for the road damage system. The CNN model for road damage systems is optimized for inference time using quantization and pruning. More research is needed to optimize inference time for the utilization of sensors, and CNN models on mobile edge devices are required to detect road damage.

Acknowledgments

The authors would like to thank Politeknik Elektronika Negeri Surabaya and Institut Teknologi Sepuluh Nopember for financial support, laboratory equipment and facilities for this work.

References

Alahi, M. E. E., Sukkuea, A., Tina, F. W., Nag, A., Kurdthongmee, W., Suwannarat, K., & Mukhopadhyay, S. C., 2023, Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends, *Sensors*, *23*(11). https://doi.org/10.3390/s23115206.

Ariyachandra, M. R. M. F., & Wedawatta, G., 2023, Digital Twin Smart Cities for Disaster Risk Management: A Review of Evolving Concepts, *Sustainability (Switzerland)*, *15*(15). https://doi.org/10.3390/su151511910.

Asad, M. H., Khaliq, S., Yousaf, M. H., Ullah, M. O., & Ahmad, A., 2022, Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective, *Advances in Civil Engineering*, *2022*. https://doi.org/10.1155/2022/9221211.

Dimd, B. D., Cali, U., Hajialigol, P., Moazami, A., Gourisetti, S. N. G., Lobaccaro, G., & Aghaei, M., 2023, Digital Twins: Shaping the Future of Energy Systems and Smart Cities through Cybersecurity, Efficiency, and Sustainability. https://doi.org/10.36227/techrxiv.22731911.v1.

Eriksson J., Girod L., Hull B., Newton R., Madden S., H. B., 2019, The Pothole Patrol:Using a Mobile Sensor Network for Road Surface Monitoring, *Conference on Engineering Innovations*, *70*(9), 499–509.

Fan, R., Zhang, Y., Guo, S., Li, J., Feng, Y., Su, S., Zhang, Y., Wang, W., Jiang, Y., Junaid Bocus, M., Zhu, X., & Chen, Q., 2022, Urban Digital Twins for Intelligent Road Inspection, *IEEE International Conference on Big Data, Big Data 2022*, *January 2023*, 5110–5114.. https://doi.org/10.1109/BigData55660.2022.10021042.

Fuller, A., Fan, Z., Day, C., & Barlow, C., 2020,Digital Twin: Enabling Technologies, Challenges and Open Research, *IEEE Access*, *8*, 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

Hu, W., Zhang, T., Deng, X., Liu, Z., & Tan, J., 2021, Digital twin: a state-of-the-art review of its enabling technologies, applications and challenges, *Journal of Intelligent Manufacturing and Special Equipment*, *2*(1), 1–34. https://doi.org/10.1108/jimse-12-2020-010.

Hernanda Z. S., Mahmudah H., and Sudibyo R. W., CNN-Based Hyperparameter Optimization Approach for Road Pothole and Crack Detection Systems, 2022 IEEE World AI IoT Congress, AIIoT 2022, pp. 538–543, 2022.

Ketu, S., & Mishra, P. K., 2022, A Contemporary Survey on IoT Based Smart Cities: Architecture, Applications, and Open Issues, *Wireless Personal Communications*, Vol. 125, Issue 3, Springer US. https://doi.org/10.1007/s11277-022-09658-2.

Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., & Omata, H., 2018, Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images, *Computer-Aided Civil and Infrastructure Engineering*, *33*(12), 1127–1141. https://doi.org/10.1111/mice.12387.

Mednis, A., Strazdins, G., & Zviedris, R., 2011, Real Time Pothole Detection using Android Smartphones with Accelerometers, *International Conference on Distributed Computing in Sensor Systems and Workshops (DCOSS)*. https://ieeexplore.ieee.org/document/5982206.

Mahmudah, H.; Arifin S; Aisjah S.A., 2023, A Survey of the Optimization System Road Damage Detection on CNN Model for Edge Device, *ICITCOM*. https://icitcom.umy.ac.id/

Nuzula, N. Z., Sudibyo, R. W., Mahmudah, H., & Sa'Adah, N., 2023, Implementation of LiDAR Array System for Damaged Road Characteristic Identification on Moving Vehicle, *International Electronics Symposium*, 244–249. https://doi.org/10.1109/ies59143.2023.10242498.

Openja, M., Nikanjam, A., Yahmed, A. H., Khomh, F., Ming, Z., & Jiang, J., 2022, An Empirical Study of Challenges in Converting Deep Learning Models, *2022 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. https://ieeexplore.ieee.org/document/9978197.

Pratama, I. D., Mahmudah, H., & Sudibyo, R. W., 2021, Design and Implementation of Real-time Pothole Detection using Convolutional Neural Network for IoT Smart Environment, *International Electronics Symposium 2021,* 675–679. https://doi.org/10.1109/IES53407.2021.9594038.

Qurishee, M. A., 2019, Low-cost deep learning UAV and Raspberry Pi solution to real time pavement condition assessment, Scholar. https://scholar.utc.edu/theses/601/.

Rana, S., & Asaduzzaman., 2021, Vibration based pavement roughness monitoring system using vehicle dynamics and smartphone with estimated vehicle parameters, *Results in Engineering*, *12*, 100294. https://doi.org/10.1016/j.rineng.2021.100294.

Sai Ganesh Naik, M. B., & Nirmalrani, V., 2021, Detecting Potholes Using Image Processing Techniques and Real-World Footage, *Proceedings of the 34th Southern African Transport Conference (SATC 2015)*, *Satc*, 893–902. https://doi.org/10.1007/978-981-16-1056-1_72.

Shen, T., Schamp, G., & Haddad, M., 2014, Stereo vision based road surface preview, *2014 17th IEEE International Conference on Intelligent Transportation Systems, ITSC 2014*, 1843–1849. https://doi.org/10.1109/ITSC.2014.6957961

Sudibyo, R. W., & Alimudin, A., 2023, Design and Implementation of Artificial Intelligence-based Real-time Pothole Detection for IoT Smart Infrastructure, *Inform: Jurnal Ilmiah Bidang Teknologi Informasi Dan Komunikasi*, *8*, 125–131. https://ejournal.unitomo.ac.id/index.php/inform/article/view/6221

Traoré, M. K., & Ducq, Y., 2022, Digital Twin for Smart Cities: An Enabler for Large-Scale Enterprise Interoperability, *CEUR Workshop Proceedings*, *3214*.

Zhen Liu, Hailu Yang, Xingyu gu and Lutai Wang, 2022, Novel YOLOv3 Model With Structure and Hyperparameter Optimization for Detection of Pavement Concealed Cracks in GPR Images, IEEE Transactions on Intelligent Transportation Systems .