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Pavement health 4.0: a novel AI-enabled PavementVision approach for pavement health monitoring and classification

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ABSTRACT

To determine the extent of pavement damage and forms of pavement distress, road pavement conditions must be precisely assessed. As a result, monitoring systems are regarded as an important stage in the maintenance procedure. In recent times, numerous investigations have been carried out to track the condition of pavement and monitor road surfaces. In the undertaken study, we have proposed a novel artificial intelligent (AI) and computer vision-enabled PavementCarevision 4.0 approach to detect and classify pavement health conditions i.e., defects. In this study, a customized pavement-2000 dataset has been designed which contains more than 2,000 images of a variety of pavement defects. In the initial phase, we pre-processed and enhanced pavement images using the customized adjustable linear contrast enhancement methodology. The enhanced pavement image samples were fed to the proposed customized YOLOV8 enabled PavementHealth 4.0 framework for pavement condition detection of a variety of pavement defects such as longitudinal cracks, alligator cracks, transverse cracks, and potholes. The proposed customized YOLOV8 enabled PavementHealth 4.0 framework has achieved an accuracy of 99.20 percent; an receiver operating characteristic (ROC) value of 0.98 and outperformed existing AI-based state-of-the-art methodologies such as pose NET, YOLOv7, YOLOv5, long short-term memory network (LSTM), Mask region-based convolutional neural network (R-CNN), and decision tree.

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1. INTRODUCTION

Highways have undergone significant expansion over the course of more than a century, becoming prominent worldwide transportation routes [1]. Given the rapid population expansion and economic development, maintenance issues are of utmost importance, as they contribute to a rise in the number of vehicles and traffic accidents [2]. Pavement maintenance refers to the efforts made to preserve or prolong the lifespan of pavement until significant restoration or total reconstruction is carried out [3]. An initial assessment of the pavement condition is crucial in the planning of pavement maintenance [4]. Assessing the state of the road pavement and figuring out how well it performs in terms of offering road users a safe and comfortable experience begins with pavement condition monitoring which is a part of pavement maintenance [5]. Preventive maintenance is a useful technique to extend the functional life of a pavement [6]. Monitoring and detecting defects in pavement surfaces are crucial measures in maintaining the road infrastructure [7]. Conventionally, manual pavement monitoring has been carried out by trained professionals, which is an approach that is susceptible to errors, hazards and inefficiencies [8], [9]. Numerous investigations have been carried out to track the condition of pavement and monitor road surfaces. Manual detection, sensor-based, smartphone-based, and remote sensing technologies can identify pavement distress. Each approach has drawbacks, though [10]. Smartphone and sensor-based methodologies, as previously indicated, have constraints in precisely identifying various types of defects. Remote sensing technologies, while very accurate, are accompanied by several constraints, including higher costs for data collection and less adaptability [11]. To help choose the best maintenance procedures, a variety of monitoring systems have been employed to assess both paved and unpaved road surfaces and identify the kind and degree of pavement degradation [5]. Depending on the type of equipment and measuring technique utilized, there are two ways to monitor the status of the pavement: i) static monitoring and ii) dynamic monitoring. Static monitoring requires fixed detecting equipment [12]. In dynamic monitoring, equipment can be installed on or inside a vehicle to gather data when the vehicle is moving through selected road segments in specific spots for a predetermined amount of time [10]. Dynamic monitoring shows the condition of the pavement at several road sites. The asphalt pavement surface deteriorates and the asset value decreases as a result of improper and delayed maintenance. Therefore, it is necessary to schedule precise and consistent pavement condition monitoring, in part based on pavement distress evaluations, to maintain the quality of the current asphalt pavement surface. Since the middle of the 20th century, pavement health monitoring which is crucial to pavement management systems has been a focus of transportation research [13]. The majority of pavement distresses must be repaired as soon as possible because they usually start out as cracks in the road surface and could endanger traffic safety. Repetitive environmental or human influences will cause faults in this damaged pavement to worsen if it is not corrected in a timely way [14]. The most crucial elements to take into account when assessing the condition of asphalt pavements are the kind, severity, and degree of cracks in the pavement surface [15], [16]. Figure 1 represents a classification of variety of cracks such as pipe crack, bridge crack, pavement crack, road crack, and tunnel crack.

Ranyal *et al.* [17] have developed an attention-based approach to monitor pavement health, detect cracks, and measure them. However, they did not explore any concepts related to artificial intelligent (AI)-enabled pavement monitoring, crack detection, and classification. A machine learning-based approach for the development of distress and sustainability monitoring has been proposed by Jung *et al.* [18]. However, they did not discuss anything related to pavement health monitoring based on the classification. Ranieri *et al.* [19] have proposed an AI-based approach for the road surface monitoring. However, they did not discuss any ideas related to AI-enabled pavement monitoring, crack detection and classification. Mishra *et al.* [20] have proposed an internet of things (IoT)-based approach for structural road monitoring. However, they did not explore any concepts related to AI-based pavement monitoring and classification. Obaidat *et al.* [21] proposed a geographic information system (GIS) based approach to map road conditions. However, they did not propose any ideas related to pavement health monitoring, crack detection and measurement. Xu *et al.* [22] have discussed various methods related to dynamic pavement health and service quality. However, they did not propose or discuss any ideas related to pavement health monitoring, crack detection and classification. Kargah-Ostadi *et al.* [23] have proposed an IoT-based approach to monitor pavement conditions using the concept of connected vehicles. They did not discuss any ideas related to AI-enabled pavement monitoring, crack detection and classification. Safaei *et al.* [24] have proposed a pixel-based approach for pavement crack detection. However, they have not discussed any ideas related to AI-based pavement crack detection and classification. Bao *et al.* [25] have proposed a computer vision and AI-based approach to perform structural monitoring of roads. However, they did not discuss any ideas related to pavement crack classification and detection. They did not propose a complete framework to monitor pavement health and classify a variety of cracks such as alligator cracks, longitudinal, transverse cracks, and potholes. Kypris and Markham [26] have proposed a magnetic field-based approach to perform structural monitoring of pavements. However, they did not discuss any ideas related to AI-enabled pavement monitoring, crack detection and classification. Spencer *et al.* [27] have proposed an advanced computer vision-based methodology to perform inspection and monitoring of pavements. However, the proposed methodology was a very basic computer vision approach which did not discuss any ideas related to AI-enabled pavement health monitoring, crack detection and classification. Mondal and Jahanshahi [28] have proposed a vision-based approach for road structure monitoring and condition assessment. However, they did not discuss anything related to pavement health monitoring, crack detection and classification. In one of the researches conducted by [29] mentioned the cross-validation of machine learning algorithms with consideration of feature ranking techniques. Wang *et al.* [30] discussed a YOLOv8-based approach for pavement health monitoring and condition assessment during the transport research board meeting. However, they did not propose a complete framework to monitor pavement health and classify a variety of cracks such as longitudinal cracks, transverse cracks, alligator cracks and potholes.

In recent times, fellow researchers have made a few attempts to design a complete AI and computer vision-based framework to detect and classify a variety of pavement defects. Still, designing a complete AI and computer vision-enabled framework has remained an open research problem. This study offers significant contributions to the field of pavement health monitoring and classification, laying the groundwork for further advancements in infrastructure maintenance. In the proposed study, we have proposed a novel AI and computer vision-enabled PavementHealth 4.0 approach to detect and classify pavement defects which surpasses existing methodologies in accuracy and efficiency. The key contributions of this work include the creation of a customized dataset, Pavement2000, comprising over 2,000 images of various pavement health conditions i.e., longitudinal cracks, transverse cracks, alligator cracks and potholes; and the development of a customized adjustable linear contrast enhancement methodology to pre-process and enhance pavement images. Furthermore, the proposed YOLOv8-enabled PavementHealth 4.0 framework demonstrates remarkable performance in detecting and classifying pavement defects, achieving an accuracy of 99.20 percent and a receiver operating characteristic (ROC) value of 0.98. The subsequent sections of this paper will delve into the necessity of the proposed PavementHealth 4.0 framework, its architecture and methodology, the results obtained, and concluding remarks, providing a comprehensive overview of our research findings and their relevance in advancing pavement health monitoring practices.

Figure 1. Classification of crack conditions

2. THE PROPOSED METHOD: PAVEMENTHEALTH 4.0 FRAMEWORK

The contributions that this study makes are: creation of a customized dataset termed ”Pavement2000” [1], which contains more than 2,000 images of a variety of pavement health conditions (defects) such as longitudinal cracks, transverse cracks, alligator cracks and potholes, design of a customized adjustable linear contrast pavement enhancement methodology [2], design and development of the proposed YOLOv8-enabled PavementHealth 4.0 framework for detection and classification of a variety of pavement defect conditions such as longitudinal cracks, transverse cracks, alligator cracks and potholes [3], testing of a proposed YOLOv8-enabled PavementHealth 4.0 framework as shown in Figure 2 [4]; for detection and classification of a variety of pavement defect conditions such as longitudinal cracks, transverse cracks, alligator cracks and potholes.

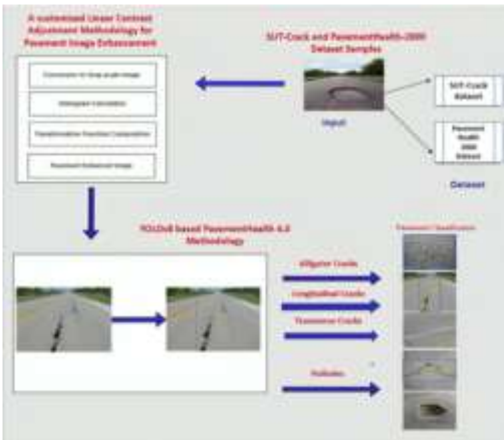


Figure 2. The architecture design of the proposed PavementHealth 4.0 framework

3. METHOD

The research was conducted in a sequential manner as shown in Figure 3, following a series of stages; i) data collection, ii) data pre-processing, iii) design of customized pavement enhancement framework, and v) testing of proposed YOLOv8 model.

Figure 3. Stages for adopted research methodology

3.1. The architecture design of a proposed PavementHealth 4.0 framework

Data collection: in the undertaken study, we have proposed a novel AI and computer vision-enabled PavementCarevision 4.0 approach to detect and classify pavement health conditions and cracks. In this study, a customized pavement-2000 dataset has been designed which contains more than 2,000 images of a variety of pavement health conditions such as alligator cracks, longitudinal cracks, transverse cracks and potholes. The dataset contains 511 samples for alligator cracks, 510 samples for longitudinal cracks, 512 samples for transverse cracks and 520 samples for potholes defects. Table 1 describes SUT-Crack and PavementHealth-2,000 pavement samples.

Table 1. Pavement dataset (SUT-Crack and PavementHealth-2000)

Pavement defect classification	No. of samples
Alligator cracks	511
Longitudinal cracks	510
Transverse cracks	512
Potholes	520
Total	2,053

3.2. A customized linear contrast enhancement methodology

In the initial process, the pavement defect samples are converted into grey-scale images for pre-processing and image enhancement process. Figure 2 represents the architecture design of the proposed PavementHealth 4.0 Framework. As shown in Figure 2, the SUT-Crack and PavementHealth-2000 samples are given as input to the customized linear contrast enhancement methodology. Algorithm 1 represents a customized adjustable linear contrast pavement enhancement methodology.

3.3. A customized YOLOv8 enabled PavementHealth 4.0 framework

Deep learning models perform exceptionally well in a variety of tasks, but they are sometimes viewed as “black-box” models since it is difficult to understand how they make decisions and reason. For critical applications such as pavement detection, financial prediction, autonomous driving, and medical diagnostics, an understanding of the interpretability of deep learning models is essential. Investigating deep learning models’ interpretability in-depth is crucial for gaining a sense of intuition about their performance. The customized YOLOv8 Pavement model is chosen as the models for verification in the undertaken study. Mosaic augmentation is one of the novel training approaches used by YOLOv8 to improve model performance. To encourage the model to learn item contexts in various settings and against varied backdrops, YOLOv8 blends four pavement samples during the training phase. However, to avoid any potential performance loss, this augmentation is turned off for the last ten training epochs. A deep neural network is the foundation of the YOLOv8 architecture. The input pavement image is divided into a grid, and for each grid cell’s items, bounding boxes and class probabilities are predicted. Typically, the network design consists of detection, down sampling, and convolutional layers. A backbone network is utilised by YOLOv8 to extract hierarchical information from the SUT-Crack and PavementHealth-2000 image samples. Backbone networks with a good balance between speed and accuracy, such as CSPDarknet53, are frequently utilised. Developed by Ultralytics, the creators of YOLOv5, YOLOv8 is a cutting-edge computer vision model. This new model offers built-in functionality for object recognition, classification, and segmentation tasks. It can be accessed through both a command line interface and a Python package. Using transfer learning, we trained a YOLOv8 model on the SUT-Crack and PavementHealth-2000 datasets. First, we initialised the model with pre-trained weights from the SUT-Crack dataset, and then we refined it into a customized PavementHeath-2000 dataset. The model was trained for 300 epochs with an initial learning rate of 0.01 using a batch size of 16. Using the GPU platform, the customized YOLOv8 Pavement model has been put into practice, trained, and validated on the Google Colab platform. As shown in Figure 2, The pavement image samples, collected from the SUTCrack and the customized PavementHealth-2000 dataset, will be input into the customized YOLOv8-enabled PavementHealth 4.0 Framework as detailed in Algorithm 1. The extracted enhanced pavement samples will be sent to the proposed customized YOLOv8-enabled PavementHealth 4.0 Framework for pavement detection and classification. If a Pavement defect is detected, it will be sent to the corresponding customized YOLOv8-enabled PavementHealth 4.0 framework to classify: i) alligator cracks, ii) longitudinal cracks, iii) transverse cracks, and iv) potholes. Algorithm 2 describes in detail about the complete YOLOv8 enabled pavement defect classification process.

3.3.1. Algorithm 1: the customized adjustable linear contrast enhancement methodology

Step 1: in the initial process, the pavement samples are converted into grey-scale images for the pre-processing and image enhancement process. Let a pavement sample can be represented by P= $\{P\ (a,\ b)\}$. Where, an input pavement image where $p(a,b)$ denotes the level of intensity of pavements at $(a,\ b)$. The number of pixels present in a pavement sample is N, and the grey pavement sample has M digitized levels. The digitised levels can be represented as $\{P_0, P_1, ..., P_{N-1}\}$ and therefore, $\forall P\ (a,\ b) \in \{P_0, P_1, ..., P_{N-1}\}$. The frequency of p_m is achieved by,

$$f(P_m) = \frac{x_m}{T}, x = 0,1, \dots, (N-1) \tag{1}$$

where x_m is the pavement total no. of pixels, and the level of intensity of P_m is the pavement image. Based on the frequencies, the relative cumulative frequency can be given by (2).

$$f(P_m) = \sum_{x=0}^{m} f(P_x), x = 0,1, \dots, (N-1) \tag{2}$$

The enhanced pavement image can be represented by P=$\{p(a,b)\}$ and Q=$\{q(a,b)\}$ to be the pavement enhanced image. The transformation from the initial pavement sample from input P to enhanced pavement image Q can be shown as,

$$Q = h(P) = \{f(p(a,b)) | \forall p(a,b) \in P\} \tag{3}$$

Step 2: initialize pavement nodes (2^{N-1}+1) on the spectrum pavement enhanced sample image. These pavement nodes initialize histogram reference nodes $P_Q = [P_0^Q, P_1^Q, \dots, N_M^Y]$ that is placed on the pavement histogram spectrum of the pavement enhanced image as:

$$P_N^Q = Q_{min} + n\frac{Q_{max}-Q_{min}}{2^{N-1}}, x = 0, \dots, 2^{d-1} \tag{4}$$

Step 3: The enhanced pavement sample image can be given by,

$$X_y^X = P_n\ if\ f(P_n) \geq \frac{P}{2^{n-1}}, X = 0, \dots, 2^{N-1} \tag{5}$$

Algorithm 2. The customized YOLOv8 enabled PavementHealth 4.0 framework

```
Step 1: input: pavement sample images of SUT-Crack and PavementHealth-2000 dataset.
Step 2: output: pavement sample detection (AlligatorCracks) or
Pavement sample detection (LongitudinalCracks) or
Pavement sample detection (TransverseCracks) or
Pavement sample detection (Potholes)
Function pavement classfication (PavementImages[SUT-Crack, PavementHealth-2000]) {
Step 1. Capture the processed pavementimage samples
Step 2. Build customized YOLOv8 enabled PavementHealth 4.0 model
Step 3. Initiate YOLOv8 enabled PavementHealth 4.0 model training using pavement image
samples for X = Pavement[Y ]
Step 4. PavementDetection(X) = input pre-processed and enhanced pavement sample images
Compile YOLOv8 enabled PavementHealth 4.0 model
PavementDetectMetric ←= accuracy
PavementModel ← optimizer = Adam
TrainYOLOv8 - PavementHealth 4.0 model ← SUT-Crack and PavementHealth-2000 dataset
PavementDetectResults = pavement sample detection (AlligatorCracks) or
Pavement sample detection (LongitudinalCracks) or
Pavement sample detection (TransverseCracks) or
Pavement sample detection (Potholes)
}
```

4. RESULTS AND DISCUSSION

In this study, we have applied pavement sample images collected from SUT-Crack and the customized PavementHealth-2000 dataset. In the initial phase, we pre-processed and enhanced pavement images using the customized adjustable linear contrast enhancement methodology. The enhanced pavement image samples were fed to the proposed customized YOLOV8 enabled PavementHealth 4.0 framework for pavement condition detection of a variety of pavement health defect conditions such as alligator cracks, longitudinal cracks, transverse cracks and potholes as described in section above. The proposed customized YOLOV8 enabled PavementHealth 4.0 framework is compared with existing deep learning and machine learning approaches, such as PoseNET, YOLOv7, YOLOv5, long short-term memory network (LSTM), and Mask R-CNN, and decision tree which have received corresponding accuracy of 84, 83.79, 82, 76.82, 76.39, and 71. Table 2 describes the accuracy metric comparison of the proposed customized YOLOV8 Enabled PavementHealth 4.0 Framework with customized machine learning and deep learning methodologies such as Pose NET, YOLOv7, YOLOv5, Decision Tree, long short-term memory network (LSTM), and Mask region-based convolutional neural network (R-CNN), and decision tree.

Table 2. Pavement dataset (SUT-Crack and PavementHealth-2000)

List of methodologies	No. of samples
The proposed customized YOLOV8 enabled PavementHealth 4.0	99.20
POSE NET	84
YOLOV7	83.79
YOLOv5	82
LSTM	76.82
Mask R-CNN	76.39
Decision tree	71

The custom YOLOV8 enabled PavementHealth 4.0 framework has attained an impressive accuracy of 99.20 percent and a ROC value of 0.98, exceeding the performance of existing state-of-the-art AI-based methods. Figures 4 and 5 depict the accuracy and the loss comparison results of the proposed customized YOLOV8 enabled PavementHealth 4.0 framework. Figure 6 shows the ROC curve for the customized YOLOV8 enabled PavementHealth 4.0 framework, along with other customized machine learning and deep learning methods including Pose NET, YOLOv7, YOLOv5, decision tree, LSTM, Mask R-CNN, and decision tree.

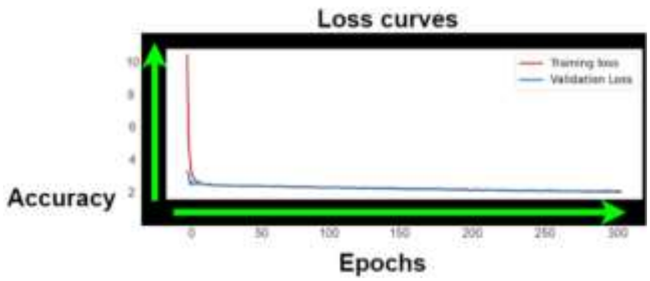


Figure 4. Training accuracy representation of the proposed PavementHealth 4.0 framework

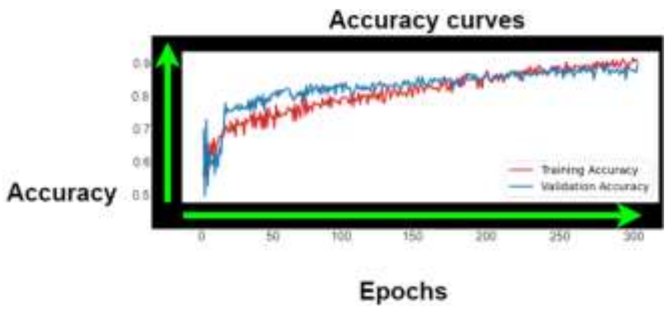


Figure 5. Testing Accuracy representation of the proposed PavementHealth 4.0 framework

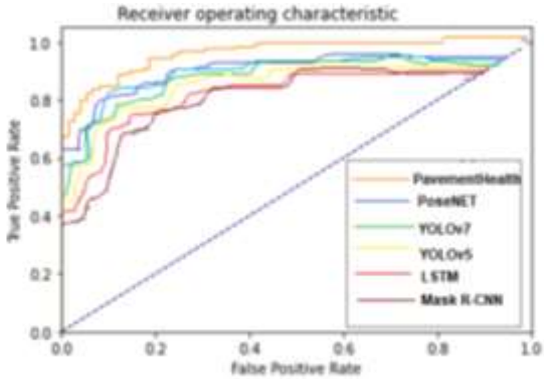
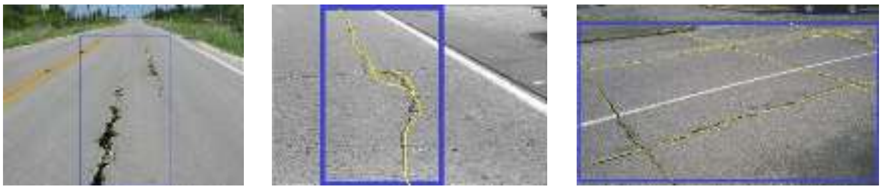


Figure 6. ROC representation of the proposed PavementHealth 4.0 framework

Figure 7 (Figures 7(a) to 7(c)) and Figure 8 (Figures 8(a) and 8(b)) represent the Pavement health condition detection and classification using the proposed customized YOLOV8 enabled PavementHealth 4.0 framework. Comparing the present study with previous researches, our approach stands out for its comprehensive nature and superior performance. While prior methodologies showed promise, they often lacked the accuracy and performance required for real-world applications. However, it's important to acknowledge the limitations of the current research, including reliance on a single dataset and the need for further validation in diverse real-world scenarios. Although, our framework surpassed expectations in terms of accuracy, indicating its potential for widespread adoption in pavement management systems



(a) (b) (c)

Figure 7. Classification representation of pavement health defect conditions such as: (a) longitudinal cracks, (b) longitudinal cracks, and (c) transverse cracks

(a) (b)

Figure 8. Classification representation of pavement health conditions such as (a) transverse cracks and (b) potholes using the proposed YOLOv8 enabled PavementHealth 4.0 framework

5. CONCLUSION

The timely and precise identification of pavement distress is essential for road safety, effective maintenance scheduling, and a thorough evaluation of pavement conditions. In conducted experiments, we have applied pavement sample images collected from SUT-Crack and the customized PavementHealth-2000 dataset. In the initial phase, we pre-processed and enhanced pavement images using the customized adjustable linear contrast enhancement methodology. The enhanced pavement image samples were fed to the proposed customized YOLOV8 enabled PavementHealth 4.0 framework for pavement condition detection of a variety of pavement health conditions such as alligator cracks, longitudinal cracks, transverse cracks and potholes. The dataset contains 511 samples for alligator cracks, 510 samples for longitudinal cracks, 512 samples for transverse cracks and 520 samples for potholes defect conditions. The extracted enhanced pavement samples will be sent to the proposed customized YOLOv8-enabled PavementHealth 4.0 framework for pavement detection and classification. If a pavement pose is detected, it will be sent to the corresponding customized YOLOv8-enabled PavementHealth 4.0 framework to classify: i) alligator cracks, ii) longitudinal cracks, iii) transverse cracks, and iv) potholes. The proposed customized YOLOV8 enabled PavementHealth 4.0 Framework is compared with existing deep learning and machine learning approaches, such as PoseNET, YOLOv7, YOLOv5, LSTM, and Mask R-CNN, and decision tree which have received corresponding accuracy of 84, 83.79, 82, 76.82, 76.39, and 71. The proposed customized YOLOV8 enabled PavementHealth 4.0 Framework has achieved an accuracy of 99.20 percent and a ROC value of 0.98 and outperformed existing AI-based state-of-the-art methodologies. In the future, the proposed customized YOLOV8 enabled PavementHealth 4.0 can be enhanced with explainable artificial intelligence (XAI)-based methodologies for achieving more accurate pavement health condition detection and classification.

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