Chapter 11
A Brief Review of Computer Vision Technology in Pavement Management

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Abstract The integration of computer vision technologies into pavement management represents a paradigm shift from traditional, manual inspection methods towards automated, efficient, and data-driven approaches. This paper presents a brief review on state-of-the-art computer vision methodologies, starting from the process of obtaining data through diverse data acquisition technologies such as 3D laser scanning, RGB-D sensors, ground-penetrating radar (GPR), and unmanned aerial vehicles (UAVs), reaching to developing advanced deep learning models (integration of YOLO object detectors or R-CNN with transformer-based networks). These technologies offer significant benefits, including high accuracy in object detection and segmentation, real-time processing capabilities, substantial reductions in inspection time and cost, improved worker safety by minimizing roadside exposure, and the generation of quantifiable data for precise maintenance planning. However, they face persistent challenges, including sensitivity to environmental conditions (e.g., poor lighting, shadows), difficulties in generalizing across diverse pavement types and complex defect morphologies, computational intensity, data imbalance in training datasets, and the high cost of some acquisition systems. Despite these hurdles, the continued evolution of computer vision holds immense potential for developing fully automated, robust, and comprehensive pavement condition.

Keywords Pavement Condition · Crack Segmentation · CNN.

Introduction

The application of computer vision technology to pavement management has grown dramatically in recent years, driven by the need for efficient automated inspection systems [1]. Manual visual inspection of pavement cracks is extremely labor-intensive and relies entirely on human judgment [2, 3]. Additionally, manual inspections require obstructing traffic and can be dangerous [4]. Computer vision approaches involve systematic acquisition and analysis of images to identify and classify distress regions [5].

The implementation of computer vision-based distress detection and evaluation systems represents a significant shift toward automated infrastructure evaluation [6]. These systems have become increasingly important for promoting data-driven road maintenance, offering continuous and timely monitoring capabilities that are less labor-intensive and more cost-effective than manual inspection methods [6]. Despite these contributions, computer vision-based systems face significant challenges with similarity in features between cracks and background noise in poor lighting, complex textures, blurred boundaries between tiny cracks and local noise, and low-quality, blurry images collected at high speeds [3].

Typical image processing methods for pavement crack detection primarily include edge detection [7, 8], threshold segmentation [9], and region growing techniques [10, 11]. Edge detection algorithms identify crack boundaries using mathematical operators such as Sobel, Prewitt, and Canny operators [7, 10]. The Canny edge detection operator has been particularly effective when combined with morphological operations for automating crack measurements of length, width, and area [12].

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On the other hand, threshold segmentation methods separate crack regions from pavement backgrounds by setting appropriate pixel intensity thresholds. These approaches assume that cracks have lower intensity values than the surrounding pavement surface [13]. Region growing methods complement these techniques by generating pixel-level labels and performing segmentation of neighboring pixels with similar properties such as grayscale [14]. Several specialized filtering and analysis methods have been developed for pavement crack detection. Gabor filters have proven effective for analyzing textures with specific orientation and frequency characteristics, making them suitable for identifying cracks of various orientations and types [15–17]. Wavelet transform-based methods have been proposed by adjusting the wave in scale (stretched or shrunk) to correspond with the form of a signal and translated along the entire signal to capture various locations of cracks [18]. Computer vision systems have also incorporated Hough transforms for region-of-interest detection and local binary patterns for texture analysis [19].

Data Acquisition Technologies

The performance of all these image processing techniques is directly tied to the dataset they're trained on. Datasets are usually obtained through these methods:

Three-dimensional (3D) Laser Scanning

3D laser scanning accounts for 95% of the reported efforts for acquiring high-resolution, full-coverage 3D pavement surface data, accounting for over 95% of the reported efforts in 2015 [20]. 3D laser scanners are particularly advantageous for their insensitivity to varying lighting conditions and poor intensity contrast, which often hamper 2D image-based methods [21]. Furthermore, 3D data provides crucial depth information for accurate crack detection and allows for precise measurements of defects like rutting and raveling [7, 21]. Although laser scanning is the predominant technology for pavement distress measurement, a wide range of other 3D imaging techniques (e.g., stereo vision, shape-from-focus, interferometry) offer viable and often superior alternatives for specific applications [20].

Kaartinen et al.'s [22] comprehensive review study demonstrated that Terrestrial Laser Scanning (TLS) and Mobile Laser Scanning (MLS) systems generate essential, high-resolution 3D point clouds for contactless detection and assessment of distresses manifesting in height and depth. However, LiDAR can be extremely costly, computationally intense, and vulnerable to surface properties, scanner position, and weather/light conditions [22].

To address the technical limitations of the technology, Yi et al. [23] proposed a framework integrating LiDAR, deep neural networks, and Building Information Modeling (BIM) to automatically detect and manage distresses. The framework localizes defects, including alligator cracks, a combined crack class, and potholes, by drawing 3D bounding boxes around them. The proposed model 'PointPillar' achieved a 3D mean average precision (3D mAP) of 62.7% and a recall of 78.5%, outperforming other 3D detection models in accuracy and inference time [23].

RGB-D Sensors

Inexpensive consumer-grade RGB-D sensors provide a unique combination of 2D visual and 3D depth data at a fraction of the cost of LiDAR or professional laser scanners. Asadi et al. [24] used an inexpensive RGB-D sensor mounted on a car and a Raspberry Pi 4 to run deep learning models for crack detection. The best-performing model (Faster R-CNN with ResNet 101 and reduced region proposals) achieved 97.6% accuracy and ran at 12 fps. However, the dataset lacked very small crack instances and other pavement distresses (e.g., potholes, rutting).

Huang et al. [25] developed an end-to-end road condition monitoring framework with feature-level fusion of RGB integrated with surface normal (SN) data. The dataset consisted of RGB-D image pairs manually annotated and including potholes and non-defective surfaces such as manholes. The proposed system yielded a mean IoU of 89.8%. The model also showed a substantial performance in detecting potholes even in poor lighting conditions.

Another study by Mahmoudzadeh et al. [26] used an affordable RGB-D sensor to perform fusion of color and depth data. This fusion enabled the researchers to reconstruct 3D pavement surfaces and estimate International Roughness Index (IRI) values. The results, which were validated against rod-and-level measurements on both a rough and a smooth road section, showed a strong correlation ($R^2 > 0.95$) and high accuracy (90%). While these findings are promising given the sensor's low cost, the study's limitations include its use of a static data collection method—which is less practical compared to collecting data at traffic speeds—and the small sample size of only two road sections. Furthermore, the impact of environmental variables was not thoroughly investigated.

Ground-Penetrating Radar (GPR)

The high-frequency electromagnetic waves emitted from ground-penetrating radar (GPR) have conventionally been used to identify layer thickness, delamination, and even measuring densities of pavements [27–29]. The usage of this technology in crack evaluation was limited; however, a study by Li et al. [30] integrated deep learning with GPR-based forward simulation using a 1 GHz air-coupled antenna and complex signal processing to improve detection of subgrade defects, such as looseness, voids, and cavities. The study simulated defect models, enhanced GPR images, and built a dataset to train YOLO v3 and SSD models. The findings showed that YOLO v3 achieved a higher mAP@0.5 (76.69%) compared to SSD (75.07%) on a combined dataset of standard samples and field samples. Field tests confirmed the practical applicability of the approach. The approach was successfully validated in a field test using a 450 MHz air-coupled antenna [30].

Unmanned Aerial Vehicles (UAVs) / Drones

The application of unmanned aerial vehicles (UAVs) in transportation has shown promising results in significantly improving road safety, traffic monitoring, and infrastructure management. Their effectiveness is driven by advanced computer vision and deep learning, which use the unique aerial perspective to enhance accident reconstruction, vehicle tracking, and the automated detection of infrastructure defects [31].

UAVs, combined with deep neural networks, can effectively locate major road distresses like potholes, rutting, and corrugations on unpaved roads [32]. In addition, UAV-captured video frames can be used to estimate the size of detected potholes [32]. Moreover, the substantial benefits of drone-based monitoring include reporting cost savings ranging from 13% to 94% and time savings from 37.5% to 90% compared to traditional methods [33]. However, widespread adoption faces regulatory (e.g., visual line-of-sight (VLOS) restrictions), technical (e.g., limited battery life), and social (e.g., privacy concerns) barriers [31].

Smartphones and Cameras

Smartphones can be used for collecting various images, enabling real-time capture of pavement conditions. While readily accessible and low-cost, their effectiveness can be limited by lighting and image quality without advanced processing. Mahdy et al. [34] developed deep network models for instance segmentation of six pavement distress types (longitudinal, transverse, block, and alligator cracks, bleeding, and potholes). The models were trained on a dataset of 1,040 images captured on Upper Egypt Road with a smartphone mounted on a vehicle bumper while driving. The study compared YOLOv5 to Mask R-CNN, in which the former demonstrated high object detection performance (86.8% mAP@0.5), while the latter achieved slightly better segmentation prediction. The findings suggest that YOLOv5 is more effective for object detection tasks with smaller datasets, whereas Mask R-CNN is better suited for image segmentation [34]. However, the dataset suffered from a class imbalance with a notably low number of pothole images, likely causing the models to underfit for that class. This is a typical manifestation of such an imbalance, leading to the observed performance where precision exceeded recall for potholes [34].

Another approach by Chen et al. [35] utilized smartphone accelerometer data, converting 1D vibration signals into 2D time-frequency-energy spectrograms using Wavelet Transform (WT) and Short-Time Fourier Transform (STFT) for classification with a VGG16 CNN. The WT-CNN model outperformed STFT-CNN, achieving 97.2% accuracy in distinguishing transverse cracks from manholes and normal road surfaces [35].

Object Detection Models

Popular one-stage object detection models like YOLOv3 (You Only Look Once), YOLOv5, and the latest version, YOLOv8, are widely recognized for their speed and real-time capabilities. Recent advancements have focused on enhancing their accuracy and robustness through architectural improvements. For instance, Shao et al. [36] demonstrated the YOLOv5 model's potential for crack detection and size estimation. The model was trained on images from PTZ cameras on China's Jingshi Highway. The model successfully detected and classified cracks with an 83% mAP@0.5 and estimated their size by converting pixel dimensions in low-distortion image regions into real-world measurements. Despite these promising results, the approach has notable drawbacks: its crack size estimation was validated against a very small sample of only 12 real measurements, and the method is best suited for preventive maintenance on already well-maintained roads.

Addressing common limitations like poor small-sized road defects, Sun et al. [37] integrated several key improvements to the more advanced model YOLOv8 model, such as the SPD-Conv layer and a more efficient neck structure. Their research used a subset composed of 2000 Chinese road damage images (collected using a camera mounted on a motorcycle and a drone) from the RDD2022 dataset annotated with five types of detection objects: vertical cracks, horizontal cracks, alligator cracks, potholes, and repair. The improved YOLOv8 model achieved a 2.8% increase in mAP@0.5 (from 74.6% to 77.4%) and a 22.6% reduction in parameters compared to the baseline, while maintaining a real-time detection speed of 43 FPS. However, the model's performance under poor lighting or extreme weather conditions remains unverified. Additionally, false positives are still an issue, and the model is yet to support real-time monitoring or continuous learning for adapting to new defect types or environmental changes.

Beyond model architecture, the quality of the training data itself is a decisive factor. Fan et al. [38] conducted a systematic study comparing image preprocessing techniques like grayscaling and binarization on the performance of the YOLOv8 algorithm on various imbalanced datasets. The distresses were longitudinal cracks, transverse cracks, alligator cracks, oblique cracks, and potholes. Their primary finding was that dataset balancing had a far greater impact on performance than any preprocessing method. In fact, imbalanced datasets caused models to be biased toward dominant crack classes, whereas a custom balanced dataset of 400 images ensured more stable and generalized detection across all distress types, highlighting that small, skewed datasets lead to poor performance.

The pursuit of robust, generalizable models has led to the development of sophisticated hybrid architectures. Xie et al. [39] combined YOLOv8 with a context anchor attention mechanism (Star-CAA) that enhances feature extraction and a task-aligned dynamic (TAD) detection head that aligns classification and localization tasks dynamically. Trained on the large, multinational RDD2022 dataset (47,420 images), the model achieved a 59.7% F1-score (2.3% higher than YOLOv8-N) and a 59.9% mAP@0.5 (3.2% boost over baseline YOLOv8-N), while also being lighter and faster. Additional validation on the UAV-PDD2023 dataset confirmed strong generalization capabilities, with notable performance gains in diverse and challenging environments captured via drone imagery.

Parallel to the development of sophisticated hybrid models, significant research efforts have been dedicated to optimizing fundamental detection and segmentation approaches. For instance, a study by Xu et al. [40] directly evaluated Faster R-CNN and Mask R-CNN for crack detection without including a separate classification of crack types. The authors used data augmentation and pre-trained weights from ImageNet to train the models on a small dataset. Their results showed that while both models outperformed YOLOv3 and generalized well when tested on another dataset, Faster R-CNN provided superior bounding boxes, whereas Mask R-CNN excelled at instance segmentation. A key limitation was that both struggled with complex cracks in bifurcated, curved, or low-light conditions.

Segmentation Models

To move beyond detecting a crack to quantification of crack geometry, specialized semantic segmentation models are essential; they trade the rough bounding box for a detailed, pixel-level outline of the distress. Zhao et al. [41] introduced HWCNet, a hybrid CNN-Transformer model that excelled at preserving crack continuity in low-contrast scenarios. The model featured a specialized backbone with MobileOne Blocks for efficient local feature extraction, GAMC Blocks with dilated convolution for multiscale context capture, and SPDConv for detail-preserving downsampling. In addition, the model used a focal dice loss function that emphasizes hard-to-segment regions to deal with class imbalance between crack pixels and background. The hybrid CNN-Transformer model outperformed classical models like U-Net by achieving mAP@0.5 ranging from 82.37% to 86.95% across four datasets (Asphalt3h, GAPs, Asphalt3k, and High Way) with varying characteristics, despite remaining computationally intensive and requiring high-quality annotations.

Similarly, Yadav et al. [42] developed HCTNet for pixel-level road crack segmentation, which uses a Vision Transformer (ViT) encoder to capture long-range dependencies and a CNN decoder with a gated-attention mechanism. Evaluated on Crack500, DeepCrack, and a custom Indian dataset (1532 images), HCTNet achieved exceptional mAP@0.5 scores, with the lowest still being 97.52% on the custom dataset, demonstrating high effectiveness against noise and varied crack patterns. The ablation study showed that the gated-attention mechanism and hybrid loss function were found to significantly improve segmentation accuracy, especially against noise and varying crack patterns. This model is highly effective for automated crack segmentation, reducing reliance on manual inspection.

Whereas most models in literature excel at only one type of detection and struggle with complex field conditions like shadows and varied distress characteristics, Zhong et al. [43] proposed a solution to simultaneously achieve region-level (classification/localization) and pixel-level (segmentation) pavement distress detection through developing an end-to-end multitask fusion for pavement distress detection (PDDNet). Using a ResNet-101 backbone with multiscale feature fusion and a combined loss function including Dice loss, PDDNet was trained on a UAV-collected dataset (UAPD) of 3,151 images labeled with seven distress types. It achieved an outstanding performance with a mAP@0.5 of 81% for region-level detection and 79.5% for pixel-level segmentation, outperforming models like Mask R-CNN and U-Net and showing robustness to environmental challenges. A remaining limitation was the infrequent misclassification of large potholes as patches and difficulty distinguishing composite alligator cracks.

Table 1 Comparative summary of deep learning models for pavement distress detection, segmentation, and evaluation

Article	Architecture	Dataset	Output & Metrics	Advantages	Limitations
Xu et al. (2022) [40]	Faster R-CNN / Mask R-CNN with RoIAlign	148 smartphone images with various crack types	Bounding boxes & masksHigh Accuracy vs. YOLOv3	Works well with very few images (∼130); Outperforms YOLOv3	Small dataset; Struggles detecting complex cracks, Sensitive to settings
Zhao et al. (2025) [41]	HWCNet (CNN-Transformer hybrid with ASFF, EMA)	Asphalt3h, GAPs, Asphalt3k, High Way (varying scales & contrasts)	Pixel-level segmentationmAP@0.5: 71.99%–91.39%F1-Score: 76.83–88.78%	Strong generalization; excels on fine, low-contrast cracks	Computationally expensive; requires high-quality data
Yadav et al. (2024) [42]	HCTNet (CNN+ViT for global context + Gated-attention decoder for local details)	Crack500, DeepCrack, & a new 1532-image set	Pixel-level segmentationmAP@0.5: 97.52%IoU: 98.76%, F1: 98.69%	SOTA performance; Combines global and local features	High computational cost; Hard for real-time use
Zhong et al. (2024) [43]	PDDNet (ResNet backbone) Multiscale fusion + U-Net/YOLO-like decoder	UAPD: 3,151 UAV images, 7 distress types	Bboxes + Masks mAP@0.5: 81%-79.5% (+10.7% over Mask R-CNN)	Outperformed Mask R-CNN & U-Net significantly	Class confusion (pothole vs. patch); Struggles with shadows/rare crack types
Wen et al. (2022) [44]	PCDNet (CNN classifies patches + automatic threshold seed algorithm to refine pixels)	10,000 3D images (1 mm resolution)	Pixel-level crack mapmAP@0.5: 88.5%	Fine crack detection; Resilience to issues like shadows and surface stains.	Misidentifies road markings and sealed edges as cracks.
Abohamer et al. (2021) [45]	AlexNet CNN with automatic features learning from 3D images	850 3D images; IRI: 0.79-5.40 m/km	IRI value regressionR^2: 0.985, RMSE: 0.059	No manual features needed; Superior to ANN models	Struggles with high IRI; Small and local dataset

The development of robust crack detection and segmentation models often involves a trade-off between performance and the practicality of data preparation. While Zhong et al. pursued a high-performance, multitask solution, Wen et al. [44] prioritized data efficiency with PCD-Net, a three-phase deep learning framework model designed to deliver pixel-level crack segmentation using only patch-level annotations. This patch-level training approach significantly reduces the labor and time required for dataset elevation. The model classifies patches, identifies crack seeds, and ensures continuity with a region-growing layer. By integrating 3D elevation data, it can perform well even in the presence of shadows and stains. The model achieves a mAP@0.5 of 88.5%, a recall of 90.2%, and an F1-score of 89.3% on a diverse test set. The model excels as well at detecting fine cracks and avoids false positives from non-crack features with varying elevations. However, PCDNet struggles with exhibiting false positive detection of non-crack features with crack-like elevation profiles, such as road markings and sealed crack edges. In addition, this model should be tested on another dataset for generalization to different pavement types and complex conditions.

Applications of deep learning extend beyond distress detection and segmentation to predicting overall pavement condition indicators. Abohamer et al. [45] employed a pre-trained AlexNet CNN to classify pavement sections into four IRI categories (poor, fair, good, and very good) using 850 3D images. For comparison, they also developed artificial neural networks (ANN) and multinomial logit (MNL) models using distress indices. The CNN significantly outperformed these traditional methods, achieving 85% accuracy (R^2 = 0.985, RMSE = 0.059) compared to approximately 58% for both ANN and MNL, confirming that distress-based predictors alone are insufficient for reliable IRI classification. Unlike preceding studies focused on detailed defect detection, Abohamer et al. [45] demonstrates CNNs' utility for high-level condition assessment. However, a key limitation emerged: the CNN's performance decreased for sections with IRI values exceeding 3.00 m/km, as high roughness variations increased prediction scatter. Notably, while the ANN and MNL models were less accurate overall, their performance remained stable across roughness levels. This contrast underscores a common challenge in deep learning applications to pavement assessment: maintaining accuracy under high-variability conditions of severely deteriorated roads.

Collectively, these studies illustrate the fundamental trade-offs between model complexity, data requirements, and task specialization in automated crack detection and segmentation. Table 1 summarizes the findings of deep learning models recently developed in literature.

Conclusion

Computer vision has firmly established itself as a cornerstone of modern pavement condition evaluation, offering transformative benefits over labor-intensive and subjective manual inspections. With innovative data acquisition methods, these systems facilitate rapid, large-scale, and non-destructive pavement assessment. The proliferation of sophisticated deep learning architectures, particularly one-stage detectors like YOLOv8 and its enhanced variants, alongside multi-task and segmentation networks, improved accuracy in detecting, classifying, and quantifying pavement distresses at both region and pixel levels.

The investment in computer vision technologies confers transformative benefits:

- *Improved Efficiency and Cost Reduction:* Automated systems drastically accelerate the inspection process, covering large road networks in a fraction of the time required for manual surveys, leading to substantial savings in labor and operational costs. Studies on UAVs report time savings of 37.5% to 90% [33].

  Objective and Quantifiable Assessment: Computer vision algorithms provide consistent, data-driven metrics for distress detection and measurement, eliminating the subjectivity and variability inherent in human visual inspection.

- *Data-Driven Maintenance Planning:* The precise, geo-referenced data generated enables predictive maintenance strategies, allowing agencies to prioritize repairs, optimize resource allocation, and extend pavement service life based on accurate condition maps.

- *Comprehensive and High-Resolution Data:* UAVs and mobile scanning systems facilitate frequent, network-level data collection, creating rich historical datasets for trend analysis and performance modeling.

Despite the remarkable progress, several critical challenges impede widespread and robust deployment:

- *Generalization and Data Limitations:* Many models struggle to generalize across different pavement types, geographic regions, or uncommon distress forms. This is often exacerbated by imbalanced training datasets, which lead to bias towards dominant classes.

- *Computational and Deployment Constraints:* The high computational cost of state-of-the-art models, particularly large CNNs and Transformers, creates a trade-off between accuracy and the feasibility of real-time processing on affordable, embedded hardware for in-vehicle systems.

- *High Cost of Data Annotation:* The supervised learning approach that dominates the field requires vast volumes of accurately labeled data. Pixel-level annotation for segmentation tasks is exceptionally time-consuming and expensive, creating a major bottleneck for model development.

- *Maintenance and Rehabilitation (M&R) Programming:* Applying AI to M&R programming is still a major research gap, requiring more effort in developing algorithms capable of solving constrained optimization problems for optimal treatment strategies.

The path forward involves creating more robust, lightweight, and environmentally resilient models. Key to this evolution will be the strategic fusion of multi-modal data, such as 2D RGB with 3D depth or GPR, and the curation of larger, more diverse datasets. Success in these areas will enable computer vision to become the central nervous system of fully autonomous, next-generation pavement management infrastructure.

References

1. Y. Xu, Z. Zhang, Review of Applications of Artificial Intelligence Algorithms in Pavement Management, Journal of Transportation Engineering, Part B: Pavements 148 (2022). https://doi.org/10.1061/jpeodx.0000373.
2. H.S. Munawar, A.W.A. Hammad, A. Haddad, C.A.P. Soares, S.T. Waller, Image-based crack detection methods: A review, Infrastructures (Basel) 6 (2021). https://doi.org/10.3390/infrastructures6080115.
3. W. Song, G. Jia, H. Zhu, D. Jia, L. Gao, Automated pavement crack damage detection using deep multiscale convolutional features, J Adv Transp 2020 (2020). https://doi.org/10.1155/2020/6412562.
4. G. Tang, C. Yin, X. Zhang, X. Liu, S. Li, Crack-Detection Method for Asphalt Pavement Based on the Improved YOLOv5, Journal of Performance of Constructed Facilities 38 (2024). https://doi.org/10.1061/jpcfev.cfeng-4615.
5. L. Ali, F.S.K. Alnajjar, W. Khan, M.A. Serhani, H. Al Jassmi, Bibliometric Analysis and Review of Deep Learning-Based Crack Detection Literature Published between 2010 and 2022, Buildings (2022). https://api.semanticscholar.org/CorpusID:247934892.
6. Y. Wang, Q. Qi, L. Sun, W. Xian, T. Ma, C. Lu, J. Zhang, An Intelligent Detection and Classification Model Based on Computer Vision for Pavement Cracks in Complicated Scenarios, Applied Sciences (2024). https://api.semanticscholar.org/CorpusID:268824673.
7. W. Li, J. Huyan, S.L. Tighe, Pavement Cracking Detection Based on Three-Dimensional Data Using Improved Active Contour Model, Journal of Transportation Engineering, Part B: Pavements 144 (2018). https://doi.org/10.1061/jpeodx.0000028.
8. X. Zhang, W. Yang, X. Tang, J. Liu, A fast learning method for accurate and robust lane detection using two-stage feature extraction with YOLO v3, Sensors (Switzerland) 18 (2018). https://doi.org/10.3390/s18124308.
9. N. Kheradmandi, V. Mehranfar, A critical review and comparative study on image segmentation-based techniques for pavement crack detection, Constr Build Mater 321 (2022). https://doi.org/10.1016/j.conbuildmat.2021.126162.
10. L. Li, B. Fang, J. Zhu, Performance Analysis of the YOLOv4 Algorithm for Pavement Damage Image Detection with Different Embedding Positions of CBAM Modules, Applied Sciences (Switzerland) 12 (2022). https://doi.org/10.3390/app121910180.
11. P. del Río-Barral, M. Soilán, S.M. González-Collazo, P. Arias, Pavement Crack Detection and Clustering via Region-Growing Algorithm from 3D MLS Point Clouds, Remote Sens (Basel) 14 (2022). https://doi.org/10.3390/rs14225866.
12. H.B. Ibrahim, M. Salah, F. Zarzoura, M. El-Mewafi, Smart monitoring of road pavement deformations from UAV images by using machine learning, Innovative Infrastructure Solutions 9 (2024). https://doi.org/10.1007/s41062-023-01315-2.
13. N.D. Hoang, Q.L. Nguyen, Fast Local Laplacian-Based Steerable and Sobel Filters Integrated with Adaptive Boosting Classification Tree for Automatic Recognition of Asphalt Pavement Cracks, Advances in Civil Engineering 2018 (2018). https://doi.org/10.1155/2018/5989246.
14. H. Zhang, Z. Qian, Y. Tan, Y. Xie, M. Li, Investigation of pavement crack detection based on deep learning method using weakly supervised instance segmentation framework, Constr Build Mater 358 (2022). https://doi.org/10.1016/j.conbuildmat.2022.129117.
15. M. Salman, S. Mathavan, K. Kamal, M. Rahman, Pavement crack detection using the Gabor filter, in: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, 2013. https://doi.org/10.1109/ITSC.2013.6728529.
16. H. Ahmad, M. Salman, S. Hussain, K. Khurshid, Automation of Optimized Gabor Filter Parameter Selection for Road Cracks Detection, International Journal of Advanced Computer Science and Applications 7 (2016). https://doi.org/10.14569/ijacsa.2016.070339.
17. J. Wang, X. Li, Y. Xu, Z. Zhou, W. Wu, Z. Li, Optimizing CNN for pavement distress detection via edge-enhanced multi-scale feature fusion, PLoS One 20 (2025) e0319299. https://doi.org/10.1371/journal.pone.0319299.
18. P. Kamranfar, D. Lattanzi, A. Shehu, S. Stoffels, Pavement Distress Recognition via Wavelet-Based Clustering of Smartphone Accelerometer Data, Journal of Computing in Civil Engineering 36 (2022). https://doi.org/10.1061/(asce)cp.1943-5487.0001022.
19. M. Quintana, J. Torres, J.M. Menéndez, A simplified computer vision system for road surface inspection and maintenance, IEEE Transactions on Intelligent Transportation Systems 17 (2016). https://doi.org/10.1109/TITS.2015.2482222.
20. S. Mathavan, K. Kamal, M. Rahman, A Review of Three-Dimensional Imaging Technologies for Pavement Distress Detection and Measurements, IEEE Transactions on Intelligent Transportation Systems 16 (2015). https://doi.org/10.1109/TITS.2015.2428655.
21. Y.-A. Hsieh, Y.J. Tsai, Machine Learning for Crack Detection: Review and Model Performance Comparison, Journal of Computing in Civil Engineering 34 (2020). https://doi.org/10.1061/(asce)cp.1943-5487.0000918.
22. E. Kaartinen, K. Dunphy, A. Sadhu, LiDAR-Based Structural Health Monitoring: Applications in Civil Infrastructure Systems, Sensors 22 (2022). https://doi.org/10.3390/s22124610.
23. T. Yi, D. Ting, Z. Jingyu, Z. Zhixiang, LiDAR-Based Automatic Pavement Distress Detection and Management Using Deep Learning and BIM, J Constr Eng Manag 150 (2024) 04024069. https://doi.org/10.1061/JCEMD4.COENG-14358.
24. P. Asadi, H. Mehrabi, A. Asadi, M. Ahmadi, Deep convolutional neural networks for pavement crack detection using an inexpensive global shutter rgb-d sensor and arm-based single-board computer, Transp Res Rec 2675 (2021). https://doi.org/10.1177/03611981211004974.
25. Y.-T. Huang, M.R. Jahanshahi, F. Shen, T.G. Mondal, Deep Learning–Based Autonomous Road Condition Assessment Leveraging Inexpensive RGB and Depth Sensors and Heterogeneous Data Fusion: Pothole Detection and Quantification, Journal of Transportation Engineering, Part B: Pavements 149 (2023). https://doi.org/10.1061/jpeodx.pveng-1194.
26. A. Mahmoudzadeh, A. Golroo, M.R. Jahanshahi, S.F. Yeganeh, Estimating pavement roughness by fusing color and depth data obtained from an inexpensive RGB-D sensor, Sensors (Switzerland) 19 (2019). https://doi.org/10.3390/s19071655.
27. S. Wang, S. Zhao, I.L. Al-Qadi, Continuous real-time monitoring of flexible pavement layer density and thickness using ground penetrating radar, NDT and E International 100 (2018). https://doi.org/10.1016/j.ndteint.2018.08.005.

28. S. Wang, Z. Leng, Z. Zhang, X. Sui, Automatic asphalt layer interface detection and thickness determination from ground-penetrating radar data, Constr Build Mater 357 (2022) 129434. https://doi.org/10.1016/J.CONBUILDMAT.2022.129434.
29. W. He, W. Wai-Lok Lai, X. Sui, A. Giannopoulos, Delamination characterization in thin asphalt pavement structure using dispersive GPR data, Constr Build Mater 402 (2023) 132834. https://doi.org/10.1016/J.CONBUILDMAT.2023.132834.
30. P. Li, M. Bai, X. Li, C. Liu, Research on the Forward Simulation and Intelligent Detection of Defects in Highways Using Ground-Penetrating Radar, Applied Sciences 14 (2024). https://doi.org/10.3390/app142210183.
31. F. Outay, H.A. Mengash, M. Adnan, Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges, Transp Res Part A Policy Pract 141 (2020). https://doi.org/10.1016/j.tra.2020.09.018.
32. L. Loures, E. Azar, Condition Assessment of Unpaved Roads Using Low-Cost Computer Vision–Based Solutions, Journal of Transportation Engineering, Part B: Pavements 149 (2023). https://doi.org/10.1061/jpeodx.pveng-1006.
33. A. Taraneh, B. Raj, T.D. D, Drones for Road Condition Monitoring: Applications and Benefits, Journal of Transportation Engineering, Part B: Pavements 151 (2025) 04024055. https://doi.org/10.1061/JPEODX.PVENG-1559.
34. K. Mahdy, A. Zekry, M. Moussa, A. Mohamed, H. Mahdy, M. Elhabiby, Pavement distress instance segmentation using deep neural networks and low-cost sensors, Innovative Infrastructure Solutions 9 (2024). https://doi.org/10.1007/s41062-023-01308-1.
35. C. Chen, H. Seo, Y. Zhao, A novel pavement transverse cracks detection model using WT-CNN and STFT-CNN for smartphone data analysis, International Journal of Pavement Engineering 23 (2022). https://doi.org/10.1080/10298436.2021.1945056.
36. C. Shao, X. Feng, J. Li, Crack Detection and Measurement Using PTZ Camera–Based Image Processing Method on Expressways, Journal of Transportation Engineering, Part B: Pavements 148 (2022). https://doi.org/10.1061/jpeodx.0000390.
37. Z. Sun, L. Zhu, S. Qin, Y. Yu, R. Ju, Q. Li, Road Surface Defect Detection Algorithm Based on YOLOv8, Electronics (Basel) 13 (2024). https://doi.org/10.3390/electronics13122413.
38. L. Fan, S. Tang, M.K.A. b. M. Ariffin, M.I.S. Ismail, X. Wang, Impact of Image Preprocessing and Crack Type Distribution on YOLOv8-Based Road Crack Detection, Sensors 25 (2025). https://doi.org/10.3390/s25072180.
39. Y. Xie, D. Du, Z. Wang, Y. Liu, M. Bi, YOLO-SFT: Road Damage Detection Algorithm Based on Feature Diffusion, Journal of Transportation Engineering, Part B: Pavements 151 (2025) 4025004. https://doi.org/10.1061/JPEODX.PVENG-1726.
40. X. Xu, M. Zhao, P. Shi, R. Ren, X. He, X. Wei, H. Yang, Crack Detection and Comparison Study Based on Faster R-CNN and Mask R-CNN, Sensors 22 (2022). https://doi.org/10.3390/s22031215.
41. Q. Zhao, Z. Liu, F. Meng, Z. Ma, A. Tuerhong, G. Guo, HWCNet: A Semantic Segmentation Model for Highway Asphalt Pavement Cracks, Journal of Transportation Engineering, Part B: Pavements 151 (2025) 4025035. https://doi.org/10.1061/JPEODX.PVENG-1635.
42. D.P. Yadav, B. Sharma, S. Chauhan, F. Amin, R. Abbasi, Enhancing Road Crack Localization for Sustainable Road Safety Using HCTNet, Sustainability 16 (2024). https://doi.org/10.3390/su16114409.
43. J. Zhong, M. Zhang, Y. Ma, R. Xiao, G. Cheng, B. Huang, A Multitask Fusion Network for Region-Level and Pixel-Level Pavement Distress Detection, Journal of Transportation Engineering, Part B: Pavements 150 (2024) 4024002. https://doi.org/10.1061/JPEODX.PVENG-1433.
44. T. Wen, H. Lang, S. Ding, J.J. Lu, Y. Xing, PCDNet: Seed Operation–Based Deep Learning Model for Pavement Crack Detection on 3D Asphalt Surface, Journal of Transportation Engineering, Part B: Pavements 148 (2022) 4022023. https://doi.org/10.1061/JPEODX.0000367.
45. H. Abohamer, M. Elseifi, N. Dhakal, Z. Zhang, C.N. Fillastre, Development of a Deep Convolutional Neural Network for the Prediction of Pavement Roughness from 3D Images, Journal of Transportation Engineering, Part B: Pavements 147 (2021) 4021048. https://doi.org/10.1061/JPEODX.0000310.