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AI-BASED PAVEMENT CRACK DETECTION AND ROAD CONDITION ASSESSMENT USING COMPUTER VISION

***Krishiv Gupta**

Genesis Global School

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***Corresponding Author: Krishiv Gupta**

Genesis Global School.

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ABSTRACT

Road transportation networks are critical components of modern infrastructure, supporting economic growth, urban mobility, and public safety. However, continuous exposure to traffic loading, environmental conditions, and aging causes pavement deterioration in the form of longitudinal, transverse, alligator, and pothole-type cracks. Conventional pavement inspection methods rely primarily on manual surveys, which are labor-intensive, time-consuming, subjective, and often incapable of providing continuous large-scale monitoring. Recent developments in artificial intelligence (AI), deep learning, and computer vision have enabled automated pavement inspection systems capable of detecting and classifying pavement defects with high accuracy and efficiency.

This paper presents an AI-based framework for pavement crack detection and road condition assessment using computer vision techniques. The proposed framework integrates image acquisition, preprocessing, convolutional neural network (CNN)-based feature extraction, crack segmentation, defect classification, and Pavement Condition Index (PCI) estimation into a unified workflow. Representative deep learning models, including ResNet-50, EfficientNet-B0, YOLOv8, U-Net, and Mask R-CNN, are reviewed and compared in terms of detection accuracy, computational efficiency, inference speed, and suitability for real-time road monitoring applications. Publicly available benchmark datasets such as Crack500, CFD, GAPs384, and RDD2022 are examined to evaluate the effectiveness of modern computer vision algorithms under varying pavement conditions.

Comparative analysis demonstrates that AI-driven inspection systems substantially outperform conventional manual inspection by reducing processing time, minimizing human error, and enabling predictive maintenance through continuous monitoring. Among the evaluated approaches, segmentation-based deep learning architectures provide superior crack

localization, whereas object detection models offer faster inference suitable for mobile and unmanned aerial vehicle (UAV)-based inspections. The study also discusses practical implementation challenges, including illumination variability, weather conditions, shadow interference, dataset imbalance, and computational requirements.

The findings indicate that integrating AI-based pavement assessment into intelligent transportation systems can significantly improve maintenance planning, optimize infrastructure investment, enhance road safety, and support the development of sustainable smart cities. Future research should focus on multimodal sensing, transformer-based vision models, edge AI deployment, and digital twin technologies for real-time infrastructure management.

KEYWORDS: Artificial Intelligence, Computer Vision, Pavement Crack Detection, Deep Learning, Convolutional Neural Networks, Road Condition Assessment, Intelligent Transportation Systems, Smart Infrastructure.

I. INTRODUCTION

Road transportation infrastructure serves as the backbone of economic development by facilitating the movement of people, goods, and services. Governments around the world invest substantial resources in constructing and maintaining road networks to ensure safe, reliable, and efficient transportation. Despite these investments, pavement deterioration remains an inevitable consequence of repeated traffic loading, environmental exposure, material aging, temperature fluctuations, moisture infiltration, and inadequate maintenance practices. As pavement defects progress from minor surface cracks to severe structural failures, they increase maintenance costs, reduce driving comfort, and elevate the risk of road accidents.

According to global transportation studies, deterioration begins with microscopic surface damage that gradually develops into longitudinal cracks, transverse cracks, block cracks, alligator cracking, rutting, and potholes. Detecting these defects during their early stages is essential because timely maintenance can substantially reduce rehabilitation costs while extending pavement service life. Delayed identification often leads to accelerated structural degradation, requiring extensive reconstruction rather than preventive maintenance.

Traditional pavement inspection techniques primarily rely on trained engineers conducting visual surveys or vehicle-based inspections. Although these methods remain widely adopted, they suffer from several inherent limitations. Manual inspections are labor- intensive,

expensive, time-consuming, and susceptible to observer bias. Inspection quality frequently depends on individual experience, lighting conditions, traffic density, and weather, leading to inconsistencies in pavement condition assessment. Furthermore,
large highway networks make comprehensive manual inspection impractical on a frequent basis.

Advances in artificial intelligence and computer vision have transformed infrastructure monitoring by enabling automated analysis of pavement images collected using smartphones, vehicle-mounted cameras, unmanned aerial vehicles (UAVs), and specialized inspection vehicles. Computer vision algorithms automatically identify crack patterns, classify pavement distress, estimate severity levels, and generate quantitative condition indices. These technologies significantly reduce inspection time while improving consistency and scalability.

Deep learning, particularly Convolutional Neural Networks (CNNs), has become the dominant approach for image-based pavement inspection because CNNs can automatically learn hierarchical visual features directly from training images without requiring handcrafted feature engineering. Modern architectures such as ResNet, EfficientNet, U-Net, YOLO, and Mask R-CNN have demonstrated high performance in crack detection, semantic segmentation, and object localization. Their ability to generalize across diverse pavement textures and lighting conditions makes them suitable for real- world deployment.

The emergence of publicly available pavement image datasets has accelerated research in automated road inspection. These datasets include thousands of annotated images representing various crack types, pavement materials, environmental conditions, and geographic regions. The availability of standardized benchmarks enables objective comparison of deep learning models and supports reproducible research.

Beyond defect detection, integrating AI with Pavement Condition Index (PCI) evaluation enables infrastructure agencies to transition from reactive maintenance toward predictive asset management. By continuously monitoring pavement conditions, authorities can prioritize repairs, allocate maintenance budgets efficiently, and reduce lifecycle costs. Such capabilities are increasingly important within smart city initiatives, where transportation infrastructure forms an essential component of digital urban ecosystems.

Despite significant progress, several challenges continue to limit large-scale deployment
of AI-based pavement inspection systems. Image quality may be degraded by shadows, rain, varying illumination, vehicle speed, and occlusions. Class imbalance among different
crack categories can reduce model robustness, while computational requirements may constrain

real-time implementation on edge devices. Addressing these challenges requires improvements in dataset diversity, model optimization, multimodal sensing, and edge computing technologies.

This paper presents a comprehensive study of AI-based pavement crack detection and road condition assessment using computer vision. It reviews contemporary deep learning techniques, proposes an integrated inspection framework, compares state-of-the-art CNN architectures, evaluates representative benchmark datasets, and discusses future research directions for intelligent pavement management systems. The objective is to demonstrate how AI-driven inspection technologies can improve road safety, reduce maintenance costs, and contribute to sustainable infrastructure management in modern smart cities.

II. LITERATURE REVIEW

Artificial Intelligence (AI) and Computer Vision have transformed pavement inspection by enabling automated, accurate, and scalable road condition assessment. Over the past decade, researchers have developed numerous machine learning and deep learning techniques capable of identifying pavement defects from digital images captured using smartphones, vehicle-mounted cameras, unmanned aerial vehicles (UAVs), and dedicated road inspection systems. This section reviews the evolution of pavement crack detection techniques, major deep learning architectures, benchmark datasets, and current research trends.

A. Evolution of Pavement Inspection Techniques

Road pavement inspection has traditionally been conducted through manual visual surveys performed by trained engineers. During these inspections, experts evaluate pavement conditions by identifying visible defects such as longitudinal cracks, transverse cracks, block cracking, alligator cracking, rutting, and potholes. While manual inspection has long been regarded as the standard practice, it presents several limitations. It is labor-intensive, time-consuming, expensive, and often affected by subjective judgment, resulting in inconsistent evaluations.

To address these shortcomings, automated image-processing techniques were introduced in the early 2000s. These methods relied on handcrafted features such as edge detection, threshold segmentation, histogram analysis, and texture descriptors. Although effective under controlled conditions, their performance deteriorated significantly when pavement images contained shadows, varying illumination, water accumulation, oil stains, or complex road textures.

The emergence of deep learning has fundamentally changed pavement inspection. Instead of manually designing image features, Convolutional Neural Networks (CNNs) automatically learn hierarchical representations directly from raw image data. This capability has enabled significant improvements in crack detection accuracy across diverse environmental conditions.

B. Computer Vision in Pavement Crack Detection

Computer vision provides computers with the ability to interpret pavement images similarly to human inspectors. A typical computer vision-based inspection system consists of five sequential stages:

1. Image acquisition using cameras, UAVs, or mobile devices.
2. Image preprocessing to reduce noise and improve contrast.
3. Feature extraction using deep neural networks.
4. Crack detection and classification.
5. Road condition assessment and maintenance recommendation.

Modern inspection systems can process thousands of pavement images within a short period, making them suitable for highway-scale monitoring. Automated inspection also improves worker safety by reducing the need for personnel to operate in active traffic environments.

C. Deep Learning Models for Pavement Crack Detection 1) Convolutional Neural Networks (CNNs)

CNNs have become the foundation of automated pavement inspection. Their layered architecture extracts increasingly complex visual features, enabling accurate recognition of cracks with different orientations, widths, and textures.

Compared with traditional machine learning algorithms, CNNs require minimal manual feature engineering and demonstrate stronger generalization capabilities.

2) ResNet

Residual Networks (ResNet) introduced residual learning, allowing extremely deep neural networks to be trained effectively without suffering from vanishing gradients. ResNet-50 and ResNet-101 are widely adopted for pavement crack classification because they achieve high accuracy while maintaining computational efficiency.

Studies report that ResNet performs well under varying lighting conditions and complex pavement backgrounds, making it a reliable backbone for road inspection applications.

3) EfficientNet

EfficientNet scales network depth, width, and image resolution simultaneously through compound scaling. Compared with conventional CNNs, EfficientNet achieves comparable or better accuracy while requiring fewer parameters and reduced computational resources.

This characteristic makes EfficientNet particularly attractive for deployment on embedded devices and edge-computing platforms used in intelligent transportation systems.

4) YOLO (You Only Look Once)

YOLO is a real-time object detection framework capable of identifying pavement defects in a single forward pass. Recent versions, including YOLOv8, offer high detection speed while maintaining strong localization accuracy.

YOLO-based inspection systems are increasingly integrated into vehicle-mounted cameras for continuous road monitoring because they can process video streams in real time.

5) U-Net

Unlike classification networks, U-Net performs semantic segmentation by assigning a class label to every pixel within an image. This enables precise localization of crack boundaries and measurement of crack dimensions.

U-Net is particularly effective for identifying thin and irregular pavement cracks that may be difficult to detect using conventional object detection models.

6) Mask R-CNN

Mask R-CNN extends object detection by simultaneously generating segmentation masks for detected objects. This allows accurate estimation of crack geometry, area, and severity, making it suitable for detailed pavement condition analysis.

Although computationally more demanding than YOLO, Mask R-CNN provides superior segmentation performance for complex pavement distress patterns.

D. Publicly Available Pavement Image Datasets

The availability of benchmark datasets has accelerated research in automated pavement inspection by enabling standardized model evaluation.

Crack500 contains hundreds of high-resolution pavement images with pixel-level crack annotations and is widely used for segmentation research.

CFD (CrackForest Dataset) focuses on urban pavement images captured under realistic environmental conditions, including shadows and varying surface textures.

GAPs384 includes asphalt pavement images from multiple geographical locations and supports studies on crack classification and severity estimation.

RDD2022 (Road Damage Dataset 2022) is among the largest publicly available datasets, comprising tens of thousands of annotated road images collected from several countries.

It contains multiple distress categories, including longitudinal cracks, transverse cracks, alligator cracks, and potholes, making it suitable for evaluating robust deep learning models.

These datasets provide diverse pavement conditions and facilitate fair comparison among different AI algorithms.

E. Pavement Condition Assessment

Detecting cracks alone is insufficient for effective infrastructure management. Transportation agencies require quantitative indicators to prioritize maintenance activities.

One of the most widely adopted evaluation methods is the Pavement Condition Index (PCI), which rates pavement quality on a numerical scale ranging from 0 (failed pavement) to 100 (excellent pavement).

AI-based systems estimate PCI automatically by combining detected defect type, crack density, crack length, and severity level. Automated PCI estimation supports predictive maintenance, reduces inspection costs, and enables more efficient allocation of maintenance resources.

F. Current Research Trends

Recent research has shifted from standalone crack detection toward intelligent pavement management systems integrating AI, cloud computing, Internet of Things (IoT), Geographic Information Systems (GIS), and edge computing.

Researchers are increasingly investigating:

- Transformer-based vision models for improved feature extraction.
- Edge AI for real-time deployment on mobile devices and inspection vehicles.
- UAV-based pavement monitoring covering large highway networks.
- Digital twin technologies for continuous infrastructure monitoring.
- Multimodal sensing combining RGB images with LiDAR and thermal imaging.
- Federated learning to enable collaborative model training while preserving data privacy.

These developments aim to create autonomous road monitoring systems capable of continuously assessing pavement health and supporting smart city infrastructure.

G. Summary of the Literature

The reviewed literature demonstrates that AI-based pavement inspection has advanced significantly over the last decade. Deep learning models consistently outperform traditional image-processing techniques in crack detection accuracy, robustness, and scalability. Among current approaches, U-Net and Mask R-CNN provide highly accurate segmentation, while YOLO-based models enable fast real-time detection. EfficientNet offers a favorable balance between accuracy and computational efficiency, and ResNet remains a reliable architecture for feature extraction and classification.

Despite these advances, important challenges remain. Many existing models struggle under adverse weather conditions, varying illumination, and highly heterogeneous pavement textures. Additionally, the lack of universally standardized datasets and the computational requirements of advanced neural networks continue to limit large-scale deployment. These limitations motivate the research gap presented in the next section.

III. RESEARCH GAP, PROBLEM STATEMENT, OBJECTIVES, AND SCOPE OF THE STUDY A. Research Gap

The literature review demonstrates that significant advancements have been achieved in automated pavement crack detection using Artificial Intelligence (AI) and Computer Vision. Deep learning models such as ResNet, EfficientNet, YOLO, U-Net, and Mask R-CNN have shown remarkable improvements in detecting and classifying pavement defects. However, despite these developments, several technical and practical limitations remain unresolved, restricting the widespread deployment of AI-based pavement inspection systems.

One major limitation is the lack of robustness under real-world environmental conditions. Many existing models are trained using images collected under controlled environments with consistent lighting and clear pavement surfaces. In practical scenarios, road images often contain shadows, rainwater, oil stains, faded lane markings, fallen leaves, parked vehicles, and varying illumination, all of which reduce detection accuracy. Consequently, models that perform exceptionally well in laboratory environments frequently experience performance degradation when deployed in real traffic conditions.

Another significant challenge is the limited generalization capability of existing deep learning models. Most research utilizes a single benchmark dataset for model training and testing. Although these datasets provide valuable benchmarking opportunities, they may not adequately represent the diversity of pavement materials, climatic conditions, and road construction practices observed worldwide. As a result, models trained on one dataset often perform poorly when applied to roads from different geographical regions.

The majority of published studies also concentrate exclusively on crack detection rather than comprehensive pavement condition assessment. While identifying cracks is an important first step, road maintenance agencies require additional information such as crack severity, defect density, Pavement Condition Index (PCI), and maintenance priority. Few studies integrate these components into a unified decision-support framework.

Computational complexity represents another limitation. High-performance segmentation networks such as Mask R-CNN and large transformer-based architectures require considerable computational resources and memory, making them difficult to deploy on edge devices, smartphones, or embedded inspection systems. Lightweight models capable of maintaining high accuracy while operating in real time remain an active area of research.

Furthermore, there is currently no universally accepted evaluation framework for comparing AI-based pavement inspection systems. Different researchers employ varying datasets, preprocessing techniques, evaluation metrics, and experimental protocols, making direct comparison among published models difficult. Standardized benchmarking procedures are therefore essential for reliable performance evaluation.

Finally, relatively few studies integrate automated pavement inspection with predictive maintenance strategies. Most existing research terminates after crack detection and classification, whereas transportation agencies require maintenance recommendations that optimize repair schedules, reduce costs, and extend pavement service life.

These limitations indicate that further research is required to develop robust, efficient, and integrated AI-based pavement management systems capable of operating reliably under diverse environmental conditions while supporting intelligent maintenance planning.

B. Problem Statement

Road transportation infrastructure experiences continuous deterioration due to increasing traffic loads, environmental exposure, aging materials, and inadequate maintenance. Early pavement defects such as fine cracks often remain undetected until they develop into severe structural failures requiring costly rehabilitation.

Traditional pavement inspection methods depend primarily on manual visual surveys conducted by trained engineers. These inspections are expensive, time-consuming, subjective, and difficult to perform frequently across extensive road networks. In addition, manual assessments may produce inconsistent results due to differences in inspector experience, fatigue, weather conditions, and traffic constraints.

Although recent AI-based methods have improved automated crack detection, many existing systems continue to face challenges related to environmental variability, computational efficiency, model generalization, and integration with pavement condition assessment. Consequently, there is a need for an intelligent computer vision framework capable of accurately detecting pavement cracks, classifying road damage, estimating pavement condition, and supporting data-driven maintenance decisions in real time.

C. Research Objectives

The primary objective of this research is to investigate the application of Artificial Intelligence and Computer Vision techniques for automated pavement crack detection and road condition assessment.

The specific objectives are:

1. To examine the causes and characteristics of pavement deterioration.
2. To review existing AI and deep learning techniques used for pavement crack detection.
3. To compare the performance of major CNN architectures including ResNet-50, EfficientNet-B0, YOLOv8, U-Net, and Mask R-CNN.
4. To develop an integrated AI-based framework for automated pavement inspection. 5. To evaluate publicly available pavement image datasets for model development and benchmarking.
6. To analyze the advantages of AI-based inspection over traditional manual surveys. 7. To investigate the use of automated Pavement Condition Index (PCI) estimation for intelligent maintenance planning.
8. To identify current challenges and future research opportunities in AI-driven pavement management systems.

D. Scope of the Study

This study focuses on image-based pavement crack detection using modern computer vision and deep learning techniques. The research covers both asphalt and concrete pavements commonly found in highways, urban roads, and transportation infrastructure.

The scope includes:

- Pavement crack detection using digital images.
- Classification of longitudinal, transverse, alligator cracks, and potholes.
- Comparison of state-of-the-art CNN architectures.
- Image preprocessing and enhancement techniques.
- Public benchmark pavement datasets.
- Automated pavement condition assessment.

- Integration of AI with intelligent transportation systems.
- Applications in smart city infrastructure.

The study does not include physical pavement testing, laboratory material analysis, structural finite element modeling, or the development of proprietary datasets. Instead, it emphasizes the synthesis of existing research and the design of a comprehensive AI-based inspection framework suitable for future implementation.

E. Expected Contributions

This research is expected to make the following contributions:

- A comprehensive review of AI techniques for pavement crack detection.
- A comparative evaluation of leading deep learning models for road inspection.
- A unified framework integrating crack detection, classification, and Pavement Condition Index estimation.
- Practical recommendations for implementing AI-based pavement monitoring in smart transportation systems.
- Identification of key research challenges and future directions, including edge AI, digital twins, and transformer-based vision models.

The proposed framework aims to support transportation agencies in improving inspection efficiency, reducing maintenance costs, enhancing road safety, and enabling predictive infrastructure management.

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One major limitation is the lack of robustness under real-world environmental conditions. Many existing models are trained using images collected under controlled environments with consistent lighting and clear pavement surfaces. In practical scenarios, road images often contain shadows, rainwater, oil stains, faded lane markings, fallen leaves, parked vehicles, and varying illumination, all of which reduce detection accuracy. Consequently, models that perform exceptionally well in laboratory environments frequently experience performance degradation when deployed in real traffic conditions.

Another significant challenge is the limited generalization capability of existing deep learning models. Most research utilizes a single benchmark dataset for model training and testing. Although these datasets provide valuable benchmarking opportunities, they may not adequately represent the diversity of pavement materials, climatic conditions, and road construction practices observed worldwide. As a result, models trained on one dataset often perform poorly when applied to roads from different geographical regions.

The majority of published studies also concentrate exclusively on crack detection rather than comprehensive pavement condition assessment. While identifying cracks is an important first step, road maintenance agencies require additional information such as crack severity, defect density, Pavement Condition Index (PCI), and maintenance priority. Few studies integrate these components into a unified decision-support framework.

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Furthermore, there is currently no universally accepted evaluation framework for comparing AI-based pavement inspection systems. Different researchers employ varying datasets, preprocessing techniques, evaluation metrics, and experimental protocols, making direct comparison among published models difficult. Standardized benchmarking procedures are therefore essential for reliable performance evaluation.

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- Practical recommendations for implementing AI-based pavement monitoring in smart transportation systems.
- Identification of key research challenges and future directions, including edge AI, digital twins, and transformer-based vision models.

The proposed framework aims to support transportation agencies in improving inspection efficiency, reducing maintenance costs, enhancing road safety, and enabling predictive infrastructure management.

V. PROPOSED AI FRAMEWORK AND DEEP LEARNING MODEL ARCHITECTURE A. Proposed AI-Based Pavement Inspection Framework

Based on the limitations identified in existing pavement inspection systems, this study proposes an integrated Artificial Intelligence (AI) framework for automated pavement crack detection and road condition assessment. The framework combines computer vision, deep learning, and pavement condition analysis into a unified pipeline capable of supporting intelligent maintenance decision-making.

Unlike traditional inspection methods that rely on periodic manual surveys, the proposed framework continuously analyzes road images acquired from multiple platforms, including vehicle-mounted cameras, smartphones, unmanned aerial vehicles (UAVs), and mobile mapping systems. The framework automates the complete inspection process, from image acquisition to maintenance recommendation, thereby reducing inspection time, minimizing human error, and improving consistency.

The proposed workflow consists of the following stages:

1. Road Image Acquisition
2. Image Preprocessing
3. Feature Extraction
4. Deep Learning-Based Crack Detection
5. Crack Classification
6. Pavement Condition Index (PCI) Estimation
7. Maintenance Decision Support

This sequential process enables rapid and accurate identification of pavement defects while providing actionable information for infrastructure managers.

B. System Architecture

The proposed architecture consists of four major modules:

1. Data Collection Module

Road surface images are captured using:

- Smartphone cameras
- Vehicle-mounted inspection cameras
- UAVs (drones)

- Mobile Mapping Systems (MMS)

These images serve as the primary input for the AI system.

2. Image Processing Module

The collected images undergo preprocessing to improve quality before analysis. Operations include image resizing, denoising, normalization, contrast enhancement, and augmentation. These steps reduce variability caused by lighting, weather, and camera settings.

3. AI Detection Module

The preprocessed images are processed by convolutional neural networks that automatically extract visual features and detect pavement defects. Depending on the task, classification, object detection, or semantic segmentation models may be employed.

4. Decision Support Module

The detected defects are translated into engineering indicators such as crack severity and Pavement Condition Index (PCI). Based on these values, the system recommends suitable maintenance strategies ranging from routine monitoring to complete reconstruction.

C. Deep Learning Models Evaluated

Five state-of-the-art deep learning architectures were selected because of their widespread adoption in pavement inspection research.

1. ResNet-50

ResNet-50 is a residual convolutional neural network consisting of 50 layers. Residual connections mitigate the vanishing gradient problem, allowing the network to learn complex visual features effectively.

Advantages

- High classification accuracy
- Stable training
- Strong feature extraction capability
- Robust under varying illumination

Limitations

- Moderate computational complexity
- Primarily designed for image classification

2. EfficientNet-B0

EfficientNet employs compound scaling to optimize network depth, width, and input resolution simultaneously.

Advantages

- High accuracy with fewer parameters
- Lower computational cost
- Suitable for mobile and embedded devices

Limitations

- Slightly slower convergence during training
- Sensitive to preprocessing quality

3. YOLOv8

YOLOv8 is a real-time object detection algorithm capable of detecting multiple pavement defects within a single image.

Advantages

- Extremely fast inference
- Suitable for real-time inspection
- High localization accuracy
- Lightweight deployment

Limitations

- Less effective for extremely thin cracks
- Pixel-level segmentation is limited

4. U-Net

U-Net is a semantic segmentation network specifically designed for precise pixel-level object detection.

Advantages

- Excellent crack boundary detection
- Highly accurate segmentation
- Suitable for measuring crack width and area

Limitations

- Longer training time
- Higher memory consumption

5. Mask R-CNN

Mask R-CNN combines object detection with instance segmentation by generating pixel-level masks for each detected defect.

Advantages

- Precise localization
- Accurate crack geometry estimation
- Supports severity analysis

Limitations

- High computational requirements
- Slower inference than YOLO

D. Comparative Analysis of CNN Models

Model	Primary Task	Strength	Limitation	Typical Application
ResNet-50	Classification	Robust feature extraction	Moderate computation	Crack classification
EfficientNet-B0	Classification	Lightweight andaccurate	Sensitive preprocessing	Edge devices
YOLOv8	Object Detection	Real-time detection	Limited segmentation	Highway monitoring
U-Net	Semantic Segmentation	Pixel-level accuracy	Higher memory usage	Crack measurement
Mask R-CNN	Instance Segmentation	Precise defect localization	Computationally intensive	Detailed pavement analysis

The comparison demonstrates that no single model is universally optimal. The choice depends on the inspection objective. YOLOv8 is well suited for real-time applications, whereas U-Net and Mask R-CNN are preferred for detailed crack analysis. EfficientNet offers an attractive balance between accuracy and computational efficiency for resource-constrained systems.

E. Benchmark Datasets

To evaluate AI algorithms objectively, publicly available benchmark datasets are commonly employed.

Dataset	Images	Annotation Type	Primary Use
Crack500	500+	Pixel-level segmentation	Crack segmentation
CFD (CrackForest Dataset)	118	Crack masks	Urban road inspection
GAPs384	1,969	Image classification	Pavement distress classification
RDD2022	26,000+	Bounding boxes	Multi-class road damage detection

These datasets include images collected under diverse environmental conditions and support comparative evaluation of deep learning algorithms.

F. Model Training Procedure

The deep learning models are trained using supervised learning with annotated pavement images.

The training workflow includes:

1. Dataset preparation 2. Image preprocessing 3. Dataaugmentation
4. Training-validation-test split 5. Model training
6. Hyperparameter optimization 7. Performance evaluation

Data augmentation techniques such as horizontal flipping, rotation, scaling, brightness adjustment, and random cropping increase dataset diversity and improve model generalization.

G. Hyperparameter Configuration

Representative training parameters are summarized below.

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Epochs	100
Loss Function	Cross-Entropy / Dice Loss
Activation Function	ReLU
Validation Split	20%

These values are widely adopted in pavement crack detection research and provide a reasonable balance between convergence speed and model accuracy.

H. Performance Evaluation Metrics

The performance of AI models is evaluated using standard classification and segmentation metrics.

Accuracy

Measures the proportion of correctly classified samples among all predictions. Precision

Indicates the proportion of detected cracks that are true cracks. Recall

Measures the proportion of actual cracks successfully detected. F1-Score

Provides a balanced evaluation by combining precision and recall. Intersection over Union (IoU)

Evaluates segmentation quality by measuring the overlap between predicted and ground- truth crack regions.

Mean Average Precision (mAP)

Measures object detection performance across multiple confidence thresholds and is commonly used for evaluating YOLO-based models.

These metrics collectively provide a comprehensive assessment of model effectiveness.

I. Summary of the Proposed Framework

The proposed AI framework integrates image acquisition, preprocessing, deep learning, defect classification, Pavement Condition Index estimation, and maintenance recommendation into a unified intelligent pavement management system. By combining robust computer vision techniques with state-of-the-art deep learning architectures, the framework supports accurate, scalable, and efficient road condition assessment. It is designed to be adaptable to different inspection platforms and can serve as a foundation for future integration with edge AI, digital twins, IoT sensors, and smart city infrastructure management systems.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

A. Comparative Performance Analysis of Deep Learning Models

To evaluate the effectiveness of Artificial Intelligence (AI) for pavement crack detection, representative deep learning models reported in the literature were comparatively analyzed. Rather than relying on handcrafted image-processing techniques, these models automatically learn hierarchical features from pavement images, resulting in higher detection accuracy and improved robustness under varying road conditions.

The comparison focused on five widely adopted architectures: ResNet-50, EfficientNet-B0, YOLOv8, U-Net, and Mask R-CNN. These models represent the major categories of image classification, object detection, and semantic segmentation used in pavement inspection research.

Table VI. Performance Comparison of Representative AI Models Reported in Published Studies

Model	Primary Task	Typical Strength	Common Limitation	Suitable Application
ResNet-50	Classification	Robust feature extraction	Moderate computational cost	Crack classification
EfficientNet-B0	Classification	High efficiency with fewer parameters	Sensitiveto preprocessing	Mobileand edge devices
YOLOv8	Object Detection	Real-time detection speed	Limited pixel-level segmentation	Highway monitoring
U-Net	Semantic Segmentation	Accurate crack boundary extraction	Higher memory requirement	Crack measurement
Mask R-CNN	Instance Segmentation	Precise localization and segmentation	Longer inference time	Detailed pavement assessment

The comparison indicates that segmentation-based models generally provide superior crack localization, whereas object detection models offer faster processing suitable for continuous road monitoring. EfficientNet demonstrates an effective balance between computational efficiency and classification performance, making it attractive for deployment on resource-constrained devices.

B. Manual Inspection Versus AI-Based Inspection

Traditional pavement inspection depends on trained engineers visually identifying pavement defects during scheduled field surveys. Although this approach has been widely used for decades, it requires considerable labor, is time-consuming, and is susceptible to subjective interpretation.

AI-based inspection systems automate defect identification using computer vision algorithms, allowing rapid analysis of large image datasets while maintaining consistent evaluation criteria.

Table VII. Comparison Between Manual and AI-Based Pavement Inspection

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Epochs	100
Loss Function	Cross-Entropy / Dice Loss
Activation Function	ReLU
Validation Split	20%

The comparison demonstrates that AI-based systems significantly improve operational efficiency while reducing variability associated with manual assessment.

C. Pavement Condition Assessment

Crack detection alone does not provide sufficient information for maintenance planning. Therefore, detected defects should be translated into engineering indicators such as the Pavement Condition Index (PCI), enabling transportation agencies to prioritize maintenance activities.

Table VIII. Pavement Condition Classification

PCI Range	Road Condition	Recommended Maintenance
85–100	Excellent	Routine monitoring
70–84	Good	Preventive maintenance
55–69	Fair	Minor rehabilitation
40–54	Poor	Major rehabilitation
0–39	Failed	Reconstruction

Automated PCI estimation allows agencies to shift from reactive repairs toward predictive maintenance strategies, optimizing infrastructure investment and reducing long-term lifecycle c
osts.

D. DISCUSSION

The comparative analysis confirms that Artificial Intelligence has significantly improved pavement inspection capabilities. Deep learning algorithms consistently outperform conventional image-processing methods because they automatically learn discriminative visual features from pavement images.

Among the reviewed models, YOLOv8 offers the fastest inference, making it suitable for real-time vehicle-mounted inspection systems. U-Net and Mask R-CNN provide highly detailed crack segmentation and are better suited for applications requiring accurate measurement of crack geometry and severity. EfficientNet-B0 achieves a favorable compromise between computational efficiency and predictive performance, particularly for mobile or edge-computing environments.

Despite these advantages, several challenges remain. Environmental factors such as shadows, rain, snow, oil stains, and uneven illumination continue to affect model performance. Dataset diversity is another concern, as many publicly available datasets represent limited geographic regions and pavement types. Computational requirements for advanced deep learning models may also restrict deployment on low-power devices without optimization.

Future developments in transformer-based vision models, multimodal sensing, edge AI, and digital twin technologies are expected to improve robustness, scalability, and real- time decision-making capabilities.

Overall, the reviewed evidence demonstrates that AI-based pavement crack detection provides substantial benefits in terms of inspection speed, consistency, and maintenance planning. Continued advances in deep learning and intelligent transportation systems are likely to accelerate the adoption of automated pavement management solutions in smart cities.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This study reviewed the application of Artificial Intelligence (AI) and Computer Vision for automated pavement crack detection and road condition assessment. Traditional manual inspection methods are labor-intensive, time-consuming, and susceptible to subjective errors, whereas AI-based approaches provide faster, more consistent, and scalable solutions. A comparative analysis of deep learning models, including ResNet-50, EfficientNet-B0, YOLOv8, U-Net, and Mask R-CNN, demonstrated that each model offers unique advantages depending on the inspection objective. The proposed AI framework integrates image acquisition, preprocessing, crack detection, defect classification, and Pavement Condition

Index (PCI) estimation to support predictive maintenance and intelligent infrastructure management. Overall, AI-driven pavement inspection has significant potential to improve road safety, optimize maintenance planning, and contribute to the development of sustainable smart transportation systems.

B. Future Work

Future research should focus on improving the robustness of AI models under varying environmental conditions such as rain, shadows, and low illumination. The integration of transformer-based vision models, edge AI, Internet of Things (IoT) sensors, and digital twin technologies can further enhance real-time pavement monitoring. Additionally, developing larger and more diverse benchmark datasets and validating AI systems through large-scale field deployments will improve model generalization and support practical implementation in smart city infrastructure.

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