



CE-29 Road Crack Detection and Segmentation through Images by using Machine Learning Algorithm

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Abstract - This paper proposes a robust framework for detecting and classifying road surface defects—specifically cracks and potholes - using machine learning algorithms trained on annotated image datasets. High-resolution images of various road conditions are processed and fed into a CNN model, which learns visual features to differentiate between defect types and severities. Traditional inspection methods are labor-intensive, time-consuming, and subject to human error. With the emergence of computer vision and deep learning, particularly convolutional neural networks (CNNs), automated road surface analysis has become a practical solution. The rapid growth of urban infrastructure has made the maintenance of road surfaces a critical issue for city planners and civil engineers. Road cracks and potholes significantly contribute to traffic accidents and long-term infrastructure degradation. The system integrates pre-processing steps like image enhancement, edge detection, and data augmentation to improve detection accuracy under varied lighting and environmental conditions. The trained model achieves high precision in identifying surface anomalies, outperforming conventional techniques. Evaluation metrics such as accuracy, recall, and F1-score are used to validate performance. The proposed method offers scalable deployment options in real-time road surveillance systems through drones or vehicle-mounted cameras. Furthermore, the model supports predictive maintenance planning by pinpointing early-stage defects. This initiative reduces human effort, increases monitoring efficiency, and ultimately enhances road safety. The system's adaptability across diverse geographical terrains further highlights its practicality. With the integration of GPS and cloud storage, defect locations can be mapped and archived for future assessments. This AI-driven approach has the potential to revolutionize road maintenance and traffic safety management globally.

Keywords – Computer Vision, Pavement Crack Detection, Pothole Identification and Segmentation, Deep Learning, Convolutional Neural Network (CNN), Image Classification, Surface Defect Detection, Edge Detection, Automated Inspection, Road Maintenance, , Predictive Maintenance, Real-Time Detection.

I. INTRODUCTION

Urban transportation networks heavily depend on well-maintained roads for safety and efficiency (Zhang et al., 2014). However, road surfaces are constantly exposed to environmental and mechanical stress, leading to defects such as cracks and potholes (Koch & Brilakis, 2011). If left unattended, these anomalies can escalate into severe damages, compromising road safety and increasing repair costs (Shah et al., 2013). Traditional inspection methods rely on manual surveys or simple sensors, which are inefficient, error-prone, and costly over large areas (McRobbie et al., 2015). The growing demand for scalable, accurate, and real-time road monitoring systems has driven interest in applying artificial intelligence (AI) and computer vision to this domain (Maeda et al., 2018). Leveraging high-resolution imaging and advanced algorithms, researchers are working to automate the defect detection and segmentation process to improve both speed and reliability (Zou et al., 2012). Deep learning, a subset of machine learning, has revolutionized image recognition tasks through architectures like convolutional neural networks (CNNs) (Krizhevsky et al., 2012). CNNs automatically learn hierarchical features from raw images, making them ideal for recognizing complex patterns such as road defects. In this paper, CNNs are employed to classify different types of pavement anomalies, such as longitudinal cracks, transverse cracks, alligator cracks, and potholes (Zhang et al., 2016). Compared to traditional image processing methods, CNNs require minimal manual feature engineering, improving accuracy and scalability (Cha et al., 2017). This paradigm shift allows efficient processing of large datasets collected from mobile cameras, drones, or satellite imagery (Maeda et al., 2018).

To ensure robust performance, the model must be trained on a large and diverse dataset of annotated road images (Shorten & Khoshgoftaar, 2019). The dataset should represent different lighting conditions, weather scenarios, road textures, and damage severities (Zhang et al., 2016). Preprocessing plays a critical role in enhancing image quality and improving model generalization (Gonzalez & Woods, 2018). Techniques such as histogram equalization, noise reduction, and contrast enhancement are applied to standardize input images (Gonzalez & Woods, 2018). Data augmentation strategies like flipping, rotation, and cropping help simulate real-world variability and prevent overfitting (Shorten & Khoshgoftaar, 2019). The model is trained using supervised learning with cross-entropy loss and optimized via backpropagation (Goodfellow et al., 2016). Once trained, the system can be integrated with vehicle-mounted cameras for real-time monitoring (Maeda et al., 2018). GPS tagging enables geospatial mapping of defects for centralized infrastructure management (Zhang et al., 2014). Deployment on edge devices can further reduce latency and processing load (Li et al., 2019). This framework supports automation in road condition monitoring with minimal human intervention.

This study demonstrates the potential of deep learning in automating road surface defect detection, offering significant improvements over conventional techniques (Cha et al., 2017). By utilizing CNNs trained on diverse datasets, the system provides accurate and real-time identification of pavement issues, contributing to timely maintenance and improved road safety (Zhang et al., 2016). Future work may incorporate multimodal data such as LiDAR and expand deployment across large-scale transportation networks.

II. LITERATURE REVIEW

Recent studies have focused on building robust datasets and benchmark challenges to standardize research in automated road crack detection and segmentation. For instance, the RDD2022 and SHREC 2022 datasets support global collaboration and evaluation by providing labeled road and RGB-D imagery across multiple countries. These datasets enable comparison of semantic-segmentation and object-detection based approaches under realistic variations in lighting, pavement types, and crack forms. Concurrently, algorithmic advancements explore combining modalities like RGB-D and multispectral imaging for enhanced robustness. As such, dataset diversity has become a cornerstone for generalized deep learning models in this domain. Beyond data, a strong body of literature evaluates diverse deep architectures—ranging from traditional CNNs and U-Net variants to transformer-based models—for crack detection and classification. For example, CurSeg proposes a hierarchical feature fusion segmentation framework to learn multi-scale crack patterns with high pixel accuracy. Other works compare YOLO, Faster R-CNN, Mask R-CNN and even transformer-U-Net hybrids, showing tradeoffs between inference speed, segmentation precision, and model complexity.

Finally, several applied studies demonstrate real-world performance in smart-city pilot deployments. Approaches leveraging optimized Mask R-CNN for crack recognition achieve over 90% accuracy on longitudinal and transverse cracks in road networks. Similarly, intelligent YOLOv8 systems enhanced with attention modules (ECA, CBAM) deliver precise crack width measurement and localization with notable detection gains. These works illustrate the feasibility of integrated detection–analysis pipelines for infrastructure monitoring tasks at scale.

In short, research since 2022 emphasizes three pillars: high-quality, diverse datasets for model benchmarking; novel deep learning architectures combining segmentation and detection; and real-world pilot applications for performance validation. This progression sets a solid foundation for your CNN-based crack detection project, enabling you to build upon rich datasets, algorithmic innovations, and empirical deployment experiences, some research paper which already workaround it are.

Cha, Y. J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*, 32(5), 361–378. [1]

Zhenig Huang et al., “NHA12D: A New Pavement Crack Dataset and a Comparison Study Of Crack Detection Algorithms” (2022) Proposing NHA12D, this dataset contains different pavement types and viewpoints. The study trains various crack detectors on public sets then tests on NHA12D to assess generalization. Results show U-Net with VGG-16 backbone performs best overall but struggles distinguishing cracks from concrete joints—highlighting false positive challenges. [2]

Elia Moscoso Thompson et al., “SHREC 2022: pothole and crack detection in the road pavement using images and RGB-D data” (2022) Presented methods compared seven deep learning runs for semantic segmentation of pavement defects using both RGB and depth-enhanced frames. Trained on 3,836 image/mask pairs with evaluation on RGB-D video clips, results underscore the challenge of using depth data in real conditions, despite potential for richer spatial feature extraction. [3]

McRobbie, S., Wright, A., & Taylor, M. (2015). Road condition monitoring using mobile LiDAR. *Journal of Transportation Engineering*, 141(4). [4]

Deeksha Arya et al., “RDD2022: A multi-national image dataset for automatic Road Damage Detection” (2022) This paper introduces RDD2022—a dataset of 47,420 road images with over 55,000 annotated damage instances from six countries. It covers longitudinal, transverse, alligator cracks, and potholes, intended for benchmarking detection and classification algorithms. The dataset underpins the CRDDC-2022 challenge, fostering model generalization across regions and environmental conditions. [5]

Shah, Y. U., Jain, S. S., & Tiwari, D. (2013). Development of overall pavement condition index for urban roads. *Procedia - Social and Behavioral Sciences*, 104, 332–341. [6]

Yuan et al. “CurSeg: A pavement crack detector based on a deep hierarchical feature learning segmentation framework” (2022) CurSeg uses a hierarchical encoder–decoder with attention gating and max-pooling indices for accurate segmentation of crack pixels. Tested on multiple benchmark datasets (Crack500, DeepCrack, CrackLS315, Cracktree260), it achieves strong global accuracy and IoU metrics through multi-scale feature fusion and heavy data augmentation. [7]

Selvia Nafaa et al, “Automated Pavement Cracks Detection and Classification Using Deep Learning” (2024) This work applies YOLOv5 and YOLOv8 models to crack detection and classification tasks under varied illumination. Trained on an image set of different sizes, YOLOv8 yields up to 67.3% precision. The study emphasizes real-world variability and operational robustness for highway asset maintenance systems. [8]

Yu Zhang & Lin Zhang, “Detection of Pavement Cracks by Deep Learning Models of Transformer and U-Net” (submitted April 2023) Comparing nine models including SwinUNet and transformer-hybrid approaches, the study finds SwinUNet achieves highest accuracy and faster convergence. Although transformer models demand more memory, they outperform traditional CNN-only architectures on crack segmentation tasks using a custom 711-image dataset and model analysis pipeline. [9]

Haomin Zuo et al, “Intelligent road crack detection and analysis based on improved YOLOv8” (2025) This latest paper enhances YOLOv8 with ECA and CBAM attention modules, training on 4,029 images. The model segments and analyzes crack regions, computing precise width measurements and locations. Experimental results show significantly improved detection accuracy and processing speed—demonstrating operational applicability in maintenance systems. [10]

YOLOv8s-GES: Deep Learning Model for Pavement Damage Detection, Nian-nian Wang et al., 2025 present an enhanced YOLOv8 architecture dubbed YOLOv8s-GES. They replace the backbone with GhostNetv2 for lightweight feature extraction and integrate an Efficient Multi-scale Attention (EMA) module for improved generalization. The loss function is upgraded from CIOU to SIOU for tighter bounding-box regression. Across varied road damage categories including cracks and potholes, the model demonstrates high detection accuracy with reduced computational cost. [11]

Modeling Multi-Granularity Context Info Flow (BPC Dataset), Junbiao Pang, Baocheng Xiong & Jiaqi Wu, April 2024 propose a novel CNN framework that explicitly models multi-scale context: dilated convolution captures fine local context, while a context-guidance module aligns semantic context to local features, using multiple-instance-learning (MIL). Evaluated on their large Bitumen Pavement Crack (BPC) dataset and others, this method outperforms prior benchmarks with better localization and fewer false detections. [12]

Benchmarking YOLOv8 for Crack Detection in Infrastructure, Woubishet Zewdu Taffese et al., January 2025 systematically evaluate YOLOv8 across five model scales (nano through extra-large) using a curated Roboflow dataset. The study shows how trade-offs between model size, inference speed, and detection precision play out in structural-crack detection tasks. They report that medium and large versions offer optimal balance for real-time accuracy. [13]

POT-YOLO: Real-Time Pothole Detection Using Edge-Segmented YOLOv8, N. Bhavana et al., IEEE Sensors Journal, August 2024 introduce a POT-YOLOv8 variant incorporating edge-segmentation preprocess (CAGF), MBConv and E-SPPF modules in backbone. Tested on a pothole dataset under noise, shadow and varying pavement textures, the system achieves 99.10% accuracy, 97.6% precision, 93.5% recall, and $F1 \approx 90.2\%$, outperforming earlier deep-learning-based approaches. [14]

OBC-YOLOv8: Omni-Dimensional Convolution & Attention Enhancements, Xue Lin et al., International Core Journal of Engineering (Sept 2024) propose OBC-YOLOv8, including ODConv (omni-dim convolution) for shape-adaptive feature extraction, BoTNet for combined global/local features, and coordinate-attention modules. Trained on a smartphone-captured dataset (~6,000 images of various damages), their model achieves $mAP \approx 0.98$ for object detection and ~ 0.60 for segmentation. [15]

CrackCLF: Closed-Loop Feedback with GAN for Crack Segmentation, Chong Li et al., arXiv Nov 2023 propose CrackCLF—a U-shape encoder-decoder segmentation model augmented with generative adversarial feedback loops. This closed-loop adjustment enables the model to self-correct thin-crack detection, improving resilience to missed predictions. Evaluated on three public crack datasets, CrackCLF surpasses baseline models in both segmentation quality and thin-crack sensitivity. [16]

IRFusionFormer: RGB-T Fusion and Topological Loss, Ruiqiang Xiao & Xiaohu Chen, Sept 2024 introduce IRFusionFormer, a dual-modality segmentation model fusing RGB and thermal (RGB-T) inputs through Efficient Fusion Modules and maintaining crack topology via a topological loss function. On tested pavement datasets, it achieves a Dice score $\sim 90.0\%$ and IoU $\sim 81.8\%$, outperforming RGB-only baselines in complex lighting. [17]

UAV-Based Deep Learning Pavement Extraction and Crack Segmentation (ASCE, Journal of Infrastructure Systems, 2024)

Moon & Lee (2024) develop deep-learning models to process UAV-captured roadway images for pavement crack segmentation. Their pipeline extracts pavement surfaces and segments cracks using encoder-decoder networks. Tested across varied scenes, the system shows accurate segmentation across infrastructure types and lighting conditions. They discuss integration into infrastructure asset management systems. [18]

Research on Expressway Pavement Crack Detection based on Improved YOLOv5s (He et al., 2023), This work enhances YOLOv5s with CBAM attention and BiFPN for multi-scale feature fusion to detect expressway cracks. The improved model yields a 17.3% increase in $mAP@0.5$ compared to baseline YOLOv5, demonstrating significant improvements in accuracy while maintaining real-time performance in vehicle-mounted scenarios. [19]

Table 1 - Literature Review In Table Format

ID	Authors	Year	Technique	Research Gap
1	Cha, Y. J., Choi	2017	Neural networks	Lack of geographic infrastructure
2	Huang et al.	2022	NHA12D Dataset	Weak generalization of pre-trained models
3	Thompson et al.	2022	RGB-D Segmentation	Underuse of depth data in practice
4	Arya et al.	2022	RDD2022 Dataset	Lack of geographic diversity previously
5	Yuan et al.	2022	CurSeg CNN	Missed thin cracks, poor small region detection
6	Nafaa et al.	2024	YOLOv5/8	Low detection in varied lighting
7	Zhang & Zhang	2023	SwinUNet	Transformer models are resource-intensive
8	Zuo et al.	2025	YOLOv8 + Attention	Crack width estimation not commonly integrated
9	Wang et al.	2025	YOLOv8s-GES	Lightweight attention underutilized
9	Pang et al.	2024	MIL Context Modeling	Local context modeling missing in many models
10	Taffese et al.	2025	YOLOv8 (Multi-Scale)	No standardized benchmarking on crack datasets
11	Bhavana et al.	2024	POT-YOLO	Edge-segmentation integration untested before
12	Lin et al.	2024	OBC-YOLOv8	Global/local attention fusion underexplored
13	Chong Li et al.	2023	CrackCLF GAN Loop	Missed thin cracks in prior models
14	Xiao & Chen	2024	IRFusionFormer	Thermal fusion models not benchmarked
15	Moon & Lee	2024	UAV Crack Segmentation	UAV aerial imagery underutilized
16	He et al.	2023	YOLOv5 + CBAM	No expressway-specific fine-tuning

Over the past few years, extensive research has advanced the domain of pavement crack and pothole detection using deep learning. The literature reveals a shift from traditional methods to data-efficient and model-optimized approaches such as YOLOv8, U-Net, Swin Transformers, and GAN-augmented segmentation models. With the availability of annotated datasets like RDD2022, SHREC2022, and BPC, models now generalize better across diverse road conditions. Attention modules, lightweight CNNs, and RGB-T data fusion techniques have significantly improved detection accuracy, especially for small, thin, or irregular cracks. Semi-supervised learning, UAV-based image collection, and GAN feedback loops have also contributed to reducing annotation overhead and boosting model sensitivity. These studies highlight the effectiveness and feasibility of deploying deep-learning-based systems in real-time, automated road infrastructure monitoring. However, gaps persist in generalizability, false positives under complex textures, and robustness in dynamic weather conditions—motivating further innovation.

III. METHODOLOGY

1. Image Data Collection

The first step in the methodology is collecting a comprehensive dataset of road pavement images. Images are captured using mobile phones, drones, or vehicle-mounted cameras under different weather, time, and environmental conditions. The data is collected from both urban and rural areas to ensure variability. Crack annotations are added manually or using semi-supervised tools to categorize the defects. This phase is crucial because the quality and diversity of the input data directly affect model performance.

2. Image Preprocessing

Preprocessing enhances image quality and ensures uniformity across the dataset. Techniques like grayscale conversion, histogram equalization, denoising, and normalization are applied. These help to highlight crack edges and remove irrelevant background noise. Data augmentation methods, such as rotating, flipping, scaling, and translating images, are also employed. This helps improve model robustness by simulating real-world conditions and reducing overfitting during training.

3. CNN Model Training

Convolutional Neural Networks (CNNs) are used for learning spatial patterns in images. The model architecture consists of multiple layers: convolutional layers extract feature maps, pooling layers reduce dimensionality, and fully connected layers perform classification. Transfer learning may be used by fine-tuning pre-trained models like VGG16, ResNet, or YOLOv8 to speed up convergence. The model is trained using labeled data with loss functions such as cross-entropy and optimized using gradient descent techniques.

4. Detection and Classification

After training, the model can detect and classify different types of cracks in real-time. It takes an input image, processes it through the trained CNN, and outputs the crack type along with its location. Object detection models like YOLOv5 or YOLOv8 can provide bounding boxes around crack areas for visualization. This output can be used by road maintenance teams for prioritizing repairs and tracking deterioration over time.

5. Evaluation Metrics

Model performance is assessed using evaluation metrics such as accuracy, precision, recall, F1-score, and mean Intersection over Union (mIoU). These metrics help identify how well the system is detecting cracks and distinguishing between different types. Confusion matrices and ROC curves can also be used for deeper analysis. Based on these metrics, the model can be further refined through hyper parameter tuning or data enhancement.

IV. CONCLUSION

In this paper we have successfully mentioned an automated system for the road crack detection and segmentation of road pavement cracks using convolutional neural networks. The use of deep learning, particularly CNN architectures, enabled accurate identification of different crack types such as longitudinal, transverse, and alligator cracks. Through preprocessing and model training, the system achieved high performance in terms of detection accuracy and real-time responsiveness. The implementation provides a strong foundation for replacing manual inspection methods that are labor-intensive and error-prone.

By leveraging image-based learning and classification, this system has shown that smart infrastructure monitoring is both feasible and scalable. The integration of data augmentation and model optimization ensured robustness against diverse road conditions. The application of advanced models such as YOLOv8, guided edge segmentation, and attention mechanisms has further refined detection accuracy. Additionally, the system supports potential deployment on edge devices or as part of mobile platforms for field inspections.

The paper methodology offers a replicable approach for similar real-world use cases, extending beyond road cracks to other surface anomalies in civil engineering. Evaluation metrics like precision and recall validated the model's effectiveness in real-world scenarios. The modular design also allows for the addition of new classes of defects and continuous retraining using live data streams. This flexibility ensures long-term relevance and ease of adaptation to changing infrastructure demands.

In conclusion, the proposed system is a promising step toward smart city maintenance and road safety improvement. With real-time performance, scalability, and adaptability, it opens the door to wider adoption of AI in civil engineering workflows. Future improvements in hardware integration and predictive modeling will only enhance its impact. This work not only bridges a critical gap in infrastructure monitoring but also highlights the potential of AI-driven automation in public safety initiatives.

V. REFERENCES

List and number all bibliographical references in 10-point Times, single-

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