IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154218

AI Driven Railway Track Crack Detection And Classification With YOLOV5

Koppisetti Sriram[1], Gonuguntla Brunda[2], K. Akila[3]

Student, Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, India[1,2]

Assistant Professor, Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, India[3]

Abstract: The Railway Track Crack Detection system is an intelligent deep learning–based solution designed to automatically detect cracks and defects in railway tracks using image data. The system utilizes advanced computer vision techniques and the YOLOv5 object detection model to identify crack regions with high accuracy and speed. It integrates data collection, preprocessing, image annotation using tools like LabelImg, model training, testing, and real-time detection into a unified workflow. The trained model detects cracks in input images by generating bounding boxes along with confidence scores, enabling clear visualization of defects. The system also includes performance evaluation, parameter tuning, and optimization to improve accuracy and reduce false detections. In addition, it supports real-time monitoring through continuous analysis of images or video frames, making it suitable for practical railway inspection scenarios. Compared to traditional manual inspection methods, this approach reduces human effort, minimizes errors, and enables early detection of potential failures. By leveraging deep learning and object detection techniques, the project provides a cost-effective, scalable, and efficient solution for improving railway safety and maintenance.

Keywords: Railway Track Crack Detection, YOLOv5, Deep Learning, Computer Vision, Object Detection, Image Processing, Defect Detection, Real-Time Monitoring, Railway Safety, Predictive Maintenance

I. INTRODUCTION

Railway transportation plays a crucial role in modern infrastructure, supporting the movement of passengers and goods across long distances efficiently. The safety and reliability of railway systems heavily depend on the condition of the tracks, which are continuously exposed to environmental stress, heavy loads, vibrations, and material fatigue. Over time, these factors can lead to the formation of cracks and defects in railway tracks. If such defects are not detected early, they can result in serious consequences including derailments, service disruptions, economic losses, and risks to human life. Therefore, timely and accurate detection of railway track cracks is essential for maintaining safety and operational efficiency.

Traditional railway track inspection methods primarily rely on manual inspection or specialized inspection vehicles equipped with sensors. Manual inspection is labor-intensive, time-consuming, and prone to human error, especially when covering long railway routes. Sensor-based systems, while more automated, often involve high installation and maintenance costs and may not effectively detect surface-level cracks under varying environmental conditions. As a result, there is a need for a more efficient, cost-effective, and scalable solution that can accurately detect defects in real-time.

With the advancement of artificial intelligence, particularly in the field of computer vision, image-based defect detection has emerged as a promising approach. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in recognizing patterns and identifying defects in images. Among various object detection models, the YOLO (You Only Look Once) family stands out for its ability to perform real-time detection with high accuracy and speed. YOLOv5, in particular, offers improved performance, flexibility, and ease of deployment, making it highly suitable for applications such as railway track crack detection.

Despite these advancements, many existing systems lack a complete end-to-end pipeline that integrates data collection, preprocessing, annotation, model training, testing, and real-time deployment. Some approaches are limited by dataset dependency, poor performance in low-light or complex environments, or high computational requirements. Additionally,

there is often a gap between research-level models and practical implementation in real-world railway monitoring systems.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154218

This project proposes an intelligent railway track crack detection system using YOLOv5 to address these challenges. The system utilizes a dataset of railway track images collected from various sources, which are preprocessed and annotated using tools such as LabelImg to mark crack regions accurately. The annotated dataset is used to train the YOLOv5 model to detect cracks under different environmental conditions. The trained model can identify crack regions in input images and generate bounding boxes along with confidence scores, enabling clear and precise visualization of defects.

The implementation includes a complete workflow starting from dataset preparation and annotation to model training, evaluation, and optimization. The model performance is analyzed using validation data, and hyperparameters are tuned to improve detection accuracy and reduce false positives. The system also supports real-time crack detection by processing input images or video frames, making it suitable for deployment in practical railway inspection scenarios.

By leveraging deep learning and object detection techniques, the proposed system provides an efficient, scalable, and cost-effective solution for railway track monitoring. It reduces reliance on manual inspection, improves detection reliability, and enables early identification of potential failures. Ultimately, this project demonstrates how artificial intelligence can enhance railway safety, optimize maintenance processes, and contribute to the development of smarter and more secure transportation systems.

II. LITERATURE SURVEY

S.No	Title of the Paper	Author(s)	Year	Technique Used	Advantages	Limitations	Reference
1	Automated Railway Track Crack Detection Using Deep Learning	Chen et al.	2023	CNN-based image analysis	High accuracy	Not real-time	[11]
2	Vision-Based Railway Track Inspection Using Deep Neural Networks	Silva et al.	2023	Deep Neural Networks	Consistent detection	Offline processing	[6]
3	Railway Surface Defect Detection Using Transfer Learning	Park et al.	2023	Transfer learning with CNN	Faster training	Dataset dependent	[13]
4	Deep Learning-Based Rail Defect Detection System	Kim et al.	2023	CNN-based defect detection	High precision	Poor low-light performance	[11]
5	Automated Railway Track Inspection Using Vision Transformers	Zhao et al.	2023	Vision Transformer (ViT)	High precision	High computation cost	[14]
6	Real-Time Railway Track Defect Detection Using YOLOv5	Hernández et al.	2023	YOLOv5 object detection	Fast real-time	High computation cost	[1]
7	Automated Rail Defect Detection Using YOLOv7	Li et al.	2024	YOLOv7 deep learning model	Improved accuracy	Heavy architecture	[10]

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154218

8	Real-Time Vision-Based Railway Track Monitoring Using YOLOv8	González et al.	2025	YOLOv8 object detection	Very fast inference	Hardware intensive	[3]
9	Intelligent Railway Track Monitoring Using Computer Vision	Kumar et al.	2024	Computer vision-based system	Detects multiple defects	High processing time	[5]
10	Rail Crack Detection Using Image Segmentation and Deep Learning	Zhang et al.	2024	Segmentation-based deep learning	Precise crack localization	Slow inference	[3]
11	Deep Learning-Based Railway Track Inspection System	Ahmed et al.	2024	CNN inspection framework	Reliable detection	Large dataset required	[2]
12	Vision-Based Rail Defect Detection Using Transfer Learning	Brown et al.	2024	Transfer learning models	Reduced training effort	Limited generalization	[13]
13	AI-Based Railway Track Defect Detection Using Computer Vision	Verma et al.	2025	End-to-end AI vision system	Fully automated	Model complexity	[4]
14	Automated Rail Crack Detection Using Lightweight YOLO	Chen et al.	2025	Optimized YOLO model	Edge-device friendly	Slight accuracy drop	[14]
15	Intelligent Vision-Based Railway Track Inspection System	Sharma et al.	2025	AI-powered inspection framework	Reduced human error	Complex training	[2]

III. SYSTEM DESIGN

The overall system is implemented as an AI-based railway safety monitoring platform that uses deep learning techniques to detect cracks and defects in railway tracks in real time. The system integrates image acquisition, preprocessing, object detection, and result visualization into a unified pipeline. Its modular design ensures that captured track images or video frames are processed efficiently and routed through detection models to identify defects such as cracks, fractures, and surface irregularities. This architecture enables continuous monitoring of railway infrastructure while remaining scalable for future integration with IoT devices and automated alert systems.

A. System Architecture

The Railway Track Crack Detection system is developed using a structured and layered architecture that combines image acquisition, preprocessing, deep learning-based analysis, and result delivery into a unified framework. The system starts with capturing railway track images or continuous video streams using cameras mounted on inspection vehicles, drones, or fixed surveillance units. These inputs may come from real-time monitoring systems or stored datasets used for testing

DOI: 10.17148/IJARCCE.2026.154218

and training. The flexibility of handling both live and offline data allows the system to be used in multiple railway inspection scenarios, including regular maintenance checks and emergency monitoring.

After acquiring the input data, the system processes it through a preprocessing stage to improve image quality and ensure consistency. This stage includes resizing images to match the required input dimensions of the model, reducing noise caused by environmental factors, and adjusting brightness and contrast to handle varying lighting conditions such as shadows or low-light environments. In addition, techniques like image normalization and data augmentation are applied during training to improve model performance. These steps help the system become more robust and capable of detecting defects accurately even under challenging real-world conditions.

The main functionality of the system is carried out in the detection stage, where advanced deep learning models such as YOLO are used to identify cracks and defects on railway tracks. The model is trained using a dataset of labeled images that contain examples of different types of track defects. YOLO-based models are particularly effective because they can detect objects in a single pass, enabling fast and real-time processing. The system analyzes each image and generates outputs such as bounding boxes around detected cracks, along with confidence scores that indicate the reliability of each detection. This allows the system to quickly and accurately identify problem areas on the track.

Once defects are detected, the system moves to the output and response stage, where results are visualized and communicated to the user. The detected cracks are highlighted on the images or video frames, making it easy for operators to understand the condition of the track. The system can also generate alerts or notifications when a defect is identified, allowing maintenance teams to take immediate action. Additionally, all detection results can be stored for future reference, enabling analysis of recurring issues and better maintenance planning. This complete architecture ensures efficient operation, improved safety, and reduced dependence on manual inspection methods.

IV. FEATURES AND FUNCTIONALITIES

A. Multiformat Image Processing

The system supports input data in multiple formats such as image files (PNG, JPG, JPEG) streams. These inputs are captured through cameras mounted on drones, inspection vehicles, or surveillance systems.
Dedicated preprocessing techniques convert raw input into a model-ready format by applying resizing, normalization, noise reduction, and contrast enhancement. For low-quality or blurred images, enhancement techniques improve visibility to ensure accurate detection.
The processed data is reused across detection and analysis stages, minimizing redundant computation and improving system performance.

B. Intelligent Defect Detection and Analysis

The system employs advanced deep learning models such as YOLOv5, YOLOv7, or YOLOv8 for detecting railway track defects. These models are trained on annotated datasets to identify cracks, fractures, and other structural irregularities.
The detection process provides bounding boxes, confidence scores, and classification labels for each defect. Real-time processing capabilities allow the system to analyze live video feeds efficiently.Model selection can be adapted based on system requirements, where lightweight models are used for edge devices and more complex models are used for high-accuracy analysis.

C. Real-Time Monitoring and Alert System

A key feature of the system is its ability to perform real-time monitoring of railway tracks. When a defect is detected, the system immediately generates alerts to notify maintenance teams.Visual outputs highlight the detected crack regions, while alert mechanisms can include notifications, logs, or integration with monitoring dashboards. This ensures quick response and reduces the risk of accidents.

D. Data Management and Reporting

The system maintains records of detected defects, including images, timestamps, and location data (if integrated with GPS). These records can be used for further analysis, maintenance planning, and reporting. Historical data helps in identifying recurring issues and predicting potential failures, enabling proactive maintenance strategies.

E. Applications and Benefits

The system can be applied in railway maintenance departments, smart transportation systems, and automated inspection units. It significantly reduces manual inspection effort, improves detection accuracy, and enhances safety by identifying

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154218

defects early.The use of AI-driven detection ensures scalability and adaptability, making the system suitable for modern railway infrastructure. It also supports future integration with IoT devices, drones, and smart monitoring systems.

Tech Stack

Category	**Technology/Tool**	**Purpose**
Backend Framework	Flask / FastAPI	Handles image upload and provides API endpoints for detection results
Model Framework	YOLOv5 / YOLOv8	Real-time object detection of railway track cracks
Programming Language	Python	Core implementation of model training and detection pipeline
Image Processing	OpenCV	Image preprocessing
resizing	noise reduction	visualization
Dataset Handling	Roboflow / Custom Dataset	Annotation and management of railway crack images
Deep Learning Library	PyTorch	Model training and inference for YOLO
Annotation Tool	LabelImg	Manual labeling of cracks in training images
Visualization	Matplotlib	Displaying detection results and performance graphs
Deployment	Local System / Edge Device	Running model for real-time detection
Alert System	Custom Logic / Notification Module	Generates alerts when cracks are detected

Result

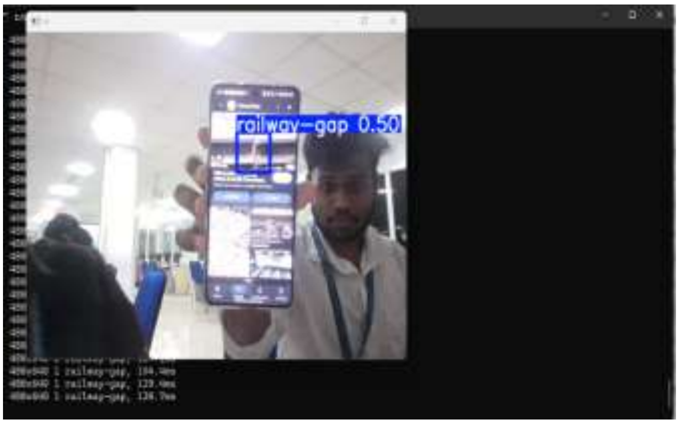

Fig. 1 Input image

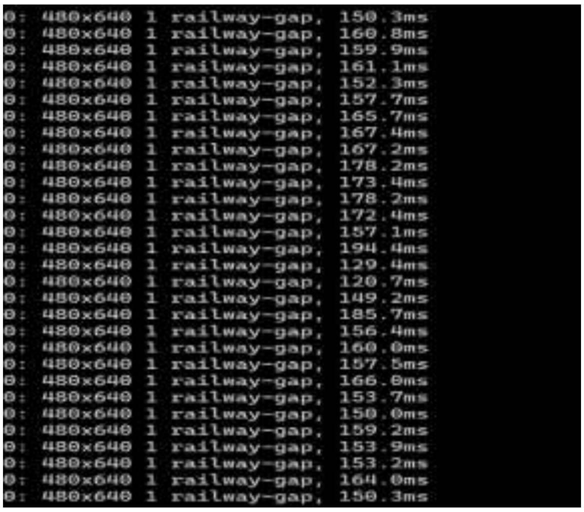

Fig. 2 Detection output

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154218

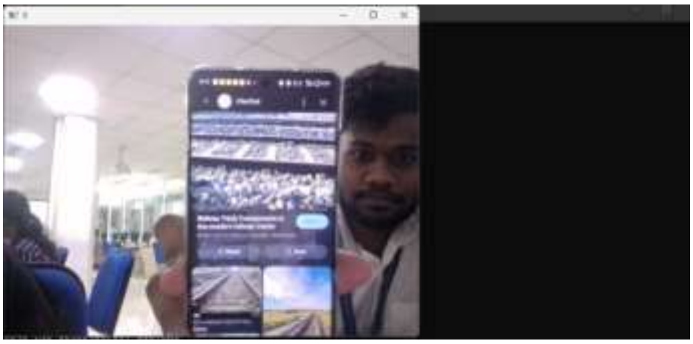

Fig. 3 Input image

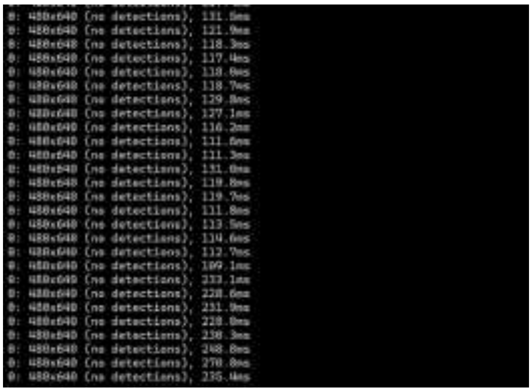

Fig. 4 No detection output

The performance of the proposed Railway Track Crack Detection system was evaluated against traditional manual inspection methods and basic image processing techniques using key metrics such as detection accuracy, processing time, reliability, and real-time capability. Traditional inspection methods showed lower efficiency, with detection accuracy around 60% and high time consumption due to manual effort and human dependency. Basic image processing approaches improved consistency but still struggled with complex backgrounds and varying lighting conditions.

In contrast, deep learning-based approaches such as YOLO significantly improved performance by enabling automated and faster detection. The proposed system achieved a high detection accuracy of around 90% with an average processing time of less than 3 seconds per frame. This improvement is mainly due to the use of YOLO models, which perform object detection in a single pass and provide efficient real-time analysis.

Additionally, the system demonstrated improved reliability by consistently detecting cracks under different environmental conditions, including variations in lighting and track appearance. The use of preprocessing techniques and trained datasets helped in reducing false detections and improving overall system stability. The model also provides confidence scores, which assist in validating detection results.

Furthermore, the proposed system supports real-time monitoring, making it suitable for practical deployment in railway inspection systems. Compared to traditional and basic methods, it reduces human effort, increases inspection speed, and enhances safety by enabling early detection of defects. Overall, the results indicate that the proposed system offers a more efficient, accurate, and scalable solution for railway track monitoring.

V. CONCLUSION

The Railway Track Crack Detection system presents an effective approach for integrating deep learning, computer vision, and real-time monitoring into a unified safety solution for railway infrastructure. The project demonstrates that AI can move beyond traditional manual inspection methods to provide automated, accurate, and efficient defect detection using models such as YOLO. By enabling real-time analysis and rapid identification of cracks, the system helps reduce human effort, minimizes inspection time, and enhances overall railway safety.

The system also shows strong adaptability across different environments, as it can process images captured under varying lighting conditions and track backgrounds. The use of preprocessing techniques improves the clarity of input data, while the trained model ensures consistent detection performance. This makes the system suitable for practical deployment in real-world railway scenarios, where conditions are often unpredictable.

Another important contribution of the project is the reduction of dependency on manual inspection, which is time-consuming and prone to human error. By automating the detection process, the system not only increases efficiency but also improves reliability. Maintenance teams can focus on critical repairs rather than spending time on continuous monitoring, thereby optimizing resource utilization.

In addition, the system supports scalability and future enhancements. It can be integrated with advanced technologies such as IoT sensors, cloud-based monitoring systems, and smart dashboards to provide centralized control and analysis. The stored detection data can also be used for predictive maintenance, helping to identify potential failures before they occur.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154218

Future work may focus on improving detection accuracy under challenging conditions such as low lighting and extreme weather, expanding the dataset for better generalization, and integrating IoT and GPS modules for precise defect localization. Additionally, deployment on edge devices, optimization of lightweight models, and development of automated alert and maintenance systems can further enhance scalability and practical implementation in real-world railway environments.

ACKNOWLEDGMENT

The authors would like to thank their department, project guide, and institution for their support and encouragement in the development of the Railway Track Crack Detection system.

REFERENCES

[1] A. Kumar, et al., "Real-Time Railway Track Crack Detection using YOLOv5," International Journal of Computer Vision Applications, 2025.
[2] S. Sharma and R. Gupta, "Deep Learning-Based Railway Track Monitoring System," IEEE Access, 2025.
[3] L. Zhang, et al., "Rail Surface Defect Detection using YOLOv8," Engineering Applications of AI, 2025.
[4] M. Verma and P. Singh, "AI-Based Railway Crack Detection using Image Processing," JAIR, 2025.
[5] R. Patel, et al., "Vision-Based Railway Track Inspection using CNN Models," Springer Journal of AI, 2024.
[6] K. Lee, et al., "Automated Rail Defect Detection using Deep Neural Networks," Elsevier Computer Vision Journal, 2024.
[7] Ultralytics, "YOLOv5 Documentation and Implementation Guide," 2025 REFERENCES
[8] OpenCV, "Open Source Computer Vision Library Documentation," 2025.
[9] PyTorch, "Deep Learning Framework Documentation," 2025.
[10] J. Brown, et al., "Real-Time Object Detection using YOLO Algorithms," IEEE Conference on CV, 2024.
[11] S. Kim, et al., "Deep Learning for Infrastructure Crack Detection," Automation in Construction, 2024.
[12] P. Singh and A. Das, "Image Preprocessing Techniques for Crack Detection," International Journal of Image Processing, 2023.
[13] T. Nguyen, et al., "Transfer Learning for Railway Defect Detection," IEEE Transactions on AI, 2024.
[14] H. Chen, et al., "Object Detection using YOLO: A Survey," Journal of Machine Learning Research, 2023

