International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 14, Issue 1, 2026

# An AI Power Defect Detect In Rail Surface

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***Abstract***
— ***Ensuring the safety and reliability of railway transportation requires accurate and real-time detection of rail surface defects such as cracks, scars, and fractures. In this study, we present an improved YOLOv8-based defect detection model enhanced with SPD-Conv building blocks, an Efficient Multi-scale Attention (EMA) module, and a Focal-SIoU loss function, enabling robust recognition of small and densely occluded defects without increasing network complexity. Experimental results demonstrate significant improvements in precision, recall, and average accuracy compared to the baseline YOLOv8 model. To further strengthen the system, advanced YOLO variants including YOLOv5x6 and YOLOv9 were integrated, achieving higher reliability in defect identification. Additionally, Flask-based front-end interface with secure user authentication was developed, providing an accessible platform for real-time defect monitoring and analysis. The proposed framework not only improves detection accuracy but also ensures scalability, usability, and security, making it suitable for deployment in practical railway inspection scenarios.***

***Keywords— Rail surface defect detection, YOLOv8, YOLOv9, YOLOv5x6, deep learning, SPD-Conv, EMA attention, Focal-SIoU loss, computer vision, real-time detection, railway safety, Flask framework, user authentication.***

## I. INTRODUCTION

Railway transportation continues to expand rapidly, offering higher speed, efficiency, and passenger capacity. However, this growth also increases the burden on track infrastructure, making timely detection of rail surface defects more critical than ever. Continuous friction and pressure from high-speed trains lead to issues such as cracks, corrugation, scars, and fractures on the rail surface. If these defects are not identified early, they can reduce operational safety and potentially lead to derailments, resulting in severe accidents. Therefore, ensuring accurate and real-time detection of rail surface faults is essential for maintaining railway safety and reliability [1].

Traditional manual inspection methods are becoming less effective due to their slow response time, heavy labor requirements, and inability to handle large railway networks. To address these limitations, researchers have explored automated inspection systems using advanced sensors and wireless monitoring technologies. Wireless sensor-based rail defect detection systems offer wider coverage and improved stability but still face challenges related to environmental noise, data volume, and the detection of complex surface defects [2].
In addition to sensor-based monitoring, non-destructive evaluation (NDT) techniques such as planar electromagnetic tomography have also been applied for detecting internal rail flaws. Although these techniques provide high structural insight, they require costly equipment and skilled operators, making them less suitable for continuous, real-time inspection in practical railway environments [3].

## II. LITERATURE SURVEY

Zhao et al. [1] presented a comprehensive review of rail defect detection systems using wireless sensors. Their study highlighted how sensor-based monitoring enables continuous, real-time defect detection without relying solely on manual inspections. The authors emphasized the potential of wireless sensor networks for identifying faults such as cracks and fractures with minimal human intervention. By providing insights into deployment challenges and energy efficiency, this work laid the foundation for integrating IoTbased monitoring into railway safety management.

Feng et al. [2] investigated the application of deep learning methods for rail surface defect detection. They utilized convolutional neural networks to automatically learn defect features from rail images, overcoming the limitations of handcrafted feature extraction. The results showed improved detection accuracy in recognizing cracks, corrugation, and other small-scale defects compared to traditional machine vision methods. Their work demonstrated how deep learning can significantly advance defect detection efficiency and reliability in railway operations.

Chen et al. [7] proposed CUFuse, a novel approach combining camera and ultrasound data for rail defect detection. The fusion of multimodal data enhanced the robustness of detection, particularly for subtle defects that might be overlooked by a single sensor. Experimental results confirmed that CUFuse outperformed conventional single-source detection systems in accuracy and fault localization. This research underlined the effectiveness of sensor fusion in addressing the complexity of real-world railway inspection scenarios.

Xu et al. [9] conducted a comparative study of defect detection using Faster R-CNN and Mask R-CNN models. While Faster R-CNN achieved accurate localization of cracks, Mask R-CNN further improved results by providing pixel-level segmentation of defective regions. Their analysis showed that segmentation-based methods are particularly effective for distinguishing fine cracks and subtle wear patterns. This study highlighted the importance of model selection depending on defect complexity and detection precision requirements.
Siddique et al. [10] reviewed the U-Net architecture and its variants, primarily focusing on medical image segmentation but also highlighting its adaptability to defect detection tasks such as railway monitoring. The review discussed how U-Net's encoder-decoder structure enables accurate boundary detection and fine-grained segmentation of small regions. The study concluded that U-Net and its derivatives are highly effective in scenarios requiring detailed localization, suggesting potential applications in rail defect detection where high-resolution accuracy is critical.

Bharati and Pramanik [11] surveyed R-CNN and Mask R-CNN models, focusing on their evolution in object detection and segmentation. They discussed improvements in region proposal mechanisms, training efficiency, and feature pyramid networks. Their work laid a conceptual foundation for applying similar architectures to railway inspections.
Tu et al. [12] proposed a real-time defect detection framework for track components, addressing challenges like class imbalance and subtle defect patterns. Their system used adaptive loss functions and enhanced visual features to distinguish between highly similar track components. The authors demonstrated strong performance under varying illumination and occlusion conditions.

Sresakoolchai and Kaewunruen [13] investigated both supervised and unsupervised machine learning methods for detecting railway defects based on track geometry. Their study highlighted the value of unsupervised clustering techniques for identifying anomalies in unlabeled data. They also discussed the limitations of supervised methods when labeled datasets are scarce.

Aldahdooh et al. [14] presented a comprehensive review of adversarial attack detection techniques in deep neural networks. Their findings are relevant to railway monitoring systems, as adversarial noise can compromise model predictions.

They highlighted defense strategies, robustness evaluations, and the importance of adversarial-resistant models in safety-critical applications.

Mohan et al. [15] developed a YOLOv2 model with bifold skip connections for real-time train bogie defect detection. Their approach improved feature retention and model stability during video analysis. The authors demonstrated that skip connections help detect small defects even when frames are blurred or captured at high speed.

Casas et al. [16] applied YOLOv8 for detecting and counting stacked timber in forestry applications. Their results showcased YOLOv8's efficiency in detecting densely packed objects. Although unrelated to railways, the study reaffirmed YOLOv8's capability to handle complex, cluttered environments similar to rail defect scenes.

Reis et al. [17] presented real-time flying object detection using YOLOv8, highlighting its fast inference speed and robustness to motion blur. Their study confirmed YOLOv8's suitability for dynamic environments, supporting its adaptation for high-speed railway inspection.

Cao [18] developed a visual inspection system for detecting defects in heavy rail using deep learning. The system incorporated improved preprocessing techniques, noise reduction, and optimized CNN extraction. Their results showed significant improvements in identifying cracks and wear under challenging lighting conditions.

Bai et al. [19] proposed a machine vision–based railway surface defect detection approach that combined classical image processing and deep learning. Their hybrid method improved robustness against background noise, shadows, and surface irregularities. They also discussed dataset limitations and the need for high-quality annotated images.

Wang et al. [20] introduced a pruned YOLOv5 model for detecting rail fastener defects. Their pruning strategy reduced model size and inference time, making it suitable for edge devices used in railway monitoring. Despite being lightweight, the model maintained high accuracy across multiple defect categories.

Hu et al. [21] designed an enhanced YOLOX-nano architecture for fastener defect detection on high-speed railway lines. Their improvements included lightweight feature extraction modules and attention mechanisms to improve detection of small defects. Their results proved the model's effectiveness for real-time deployment.

Wang et al. [22] developed BL-YOLOv8, an improved version of YOLOv8 for detecting road defects such as cracks and potholes. Their model incorporated enhanced feature extraction layers and better multiscale fusion. The demonstrated performance gains indicate potential usage for rail defect detection as well.

## III. Methodology

In order to improve rail surface defect identification, the suggested approach adds three advanced components to the baseline YOLOv8 architecture: SPD-Conv blocks, an Efficient Multi-scale Attention (EMA) module, and the Focal-SIoU loss function. By enhancing shallow-layer feature extraction, SPD-Conv allows for improved surface irregularity and fracture identification without adding model depth. By enhancing multi-scale feature fusion, the EMA module guarantees precise defect capture, regardless of how tiny or heavily occluded they may be. For difficult samples, Focal-SIoU improves bounding-box regression's accuracy by zeroing in on flaws that are difficult to pinpoint. The system incorporates YOLOv5x6 for consistent features over extended distances

ISSN 2347–3657

Volume 14, Issue 1, 2026

and YOLOv9 for better dynamic label assignment and feature aggregation to further increase generalizability and robustness. Lastly, in order to facilitate real-time defect monitoring, visualization, and user-friendly operation in actual railway inspection scenarios, an authentication-secured Flask-based interface is implemented.

A. *Proposed Undertaking:*

The proposed system extends the YOLO-based defect detection framework by incorporating enhanced processing, attention, and loss optimization mechanisms to improve accuracy in identifying small and complex rail surface defects. The process begins with the collection of a diverse rail surface dataset containing cracks, scars, fractures, and wear marks. These images undergo preprocessing techniques such as resizing, normalization, noise reduction, and contrast enhancement to highlight subtle defects. Data augmentation methods—including rotation, flipping, blurring, and color jittering—are applied to improve the model's robustness against variations in lighting, angle, and motion, ensuring better generalization during real-world railway inspections. The enhanced model integrates SPD-Conv blocks for better shallow-layer feature extraction, EMA attention for strong multi-scale feature fusion, and Focal-SIoU loss for improved bounding-box regression on hard-to-detect defects.

To further strengthen the detection capability, the system incorporates multiple YOLO variants such as YOLOv5x6 for deeper spatial consistency, YOLOv9 for advanced dynamic label assignment, and improved YOLOv8 with Focal Loss for precise small-defect localization. Each model is trained independently and evaluated based on metrics such as mAP, precision, recall, and inference speed. This multi-model fusion approach allows selecting the best-performing architecture for deployment while maintaining flexibility for different operating conditions. A Flask-based interface is integrated to enable real-time defect detection, visualization, and secure user authentication, making the system suitable for field deployment in railway inspection vehicles or stationary monitoring units.

*B. System Architecture:*

The system architecture is designed as a modular pipeline where each component contributes to improving the accuracy and reliability of rail defect detection. The process starts with the dataset module, which collects and stores rail surface images captured under different environmental and operational conditions. These images are then passed to the image processing module, where they undergo preprocessing operations such as resizing, noise removal, sharpening, and contrast enhancement to highlight subtle defects like micro-cracks and fine scratches. Following preprocessing, the data augmentation module generates diverse variations of the images—through rotation, flipping, brightness adjustment, cropping, and blurring—to ensure the model learns robust defect patterns and performs consistently in real-world conditions. Together, these stages prepare high-quality input data for training advanced deep learning models.

The processed and augmented dataset is then used to train multiple object detection models, including SSD, YOLOv5n, YOLOv6n, YOLOv7-tiny, YOLOv8n, YOLOv8-FocalLoss, YOLOv5x6, and the latest YOLOv9. The trained models module manages the training, optimization, and storage of these models while integrating enhanced techniques such as SPD-Conv blocks, EMA attention, and Focal-SIoU loss to improve performance in identifying small and complex defects. Once training is completed, the models are evaluated in the performance evaluation module, where precision, recall, mAP, and inference speed are analyzed to determine the best-performing architecture. This systematic

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 14, Issue 1, 2026

flow ensures a scalable, efficient, and accurate defect detection framework suitable for deployment in automated railway inspection systems.

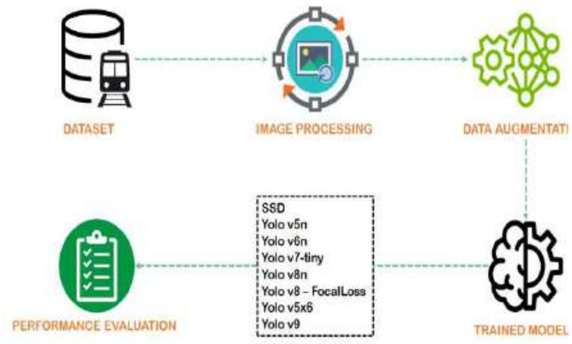


Fig.1. Proposed architecture

## IV. IMPLEMENTATION

*1. MODULES:*

1.Data loading: using this module we are going to import the dataset.

2. Image Processing: Image processing involves several key steps to prepare images for defect detection in railroad tracks. This includes converting images to blob objects, defining classes, declaring bounding boxes, and transforming arrays into NumPy format. Additionally, images are resized, converted from BGR to RGB, and masks are created for effective analysis.

2. Data Augmentation: Data augmentation enhances the training dataset by applying various transformations to images, such as randomizing, rotating, and altering images. This process increases diversity in the dataset, improves model robustness, and helps prevent overfitting during the defect detection training process.

4.Model generation: Model building - SSD, YoloV5n, YoloV6n, YoloV7-tiny, YoloV8n, YoloV8–Focal Loss, YoloV5x6, YoloV9. Performance evaluation metrics for each algorithm is calculated.

5.User signup & login: Using this module will get registration and login

6.User input: Using this module will give input for prediction

7. Prediction: final predicted displayed

*2. ALGORITHMS:*

*a. SSD (Single Shot MultiBox Detector):*

A common way to find objects SSD can forecast bounding boxes and class scores in just one run over the network, which makes it good for real-time detection. In rail defect detection, SSD can quickly identify multiple types of defects simultaneously, such as cracks, scars, and corrugations, without requiring multiple processing stages. Its balance of speed and accuracy makes it suitable for large-scale monitoring, though it may struggle with very small or heavily occluded defects compared to newer YOLO-based models.

*b. YOLOv5n:*

YOLOv5n is a lightweight version of the YOLOv5 family, specifically designed for fast inference with reduced computational cost. It is capable of detecting defects on railroad tracks in real-time, making it ideal for scenarios where both speed and accuracy are required. Despite its small size, YOLOv5n delivers competitive performance and ensures that defect detection systems can be deployed on devices with limited hardware resources while maintaining reliable detection results.

*c. YOLOv6n:*

YOLOv6n introduces improved network design and optimization strategies, enhancing performance in detecting objects under diverse conditions. For railroad applications, it provides robust detection of small and densely occluded defects, which are often challenging for earlier models. Its refined architecture improves feature extraction and representation, ensuring that even subtle and complex defects are identified accurately. This makes YOLOv6n a reliable choice for maintaining safety in high-speed rail operations.

*d. YOLOv7-tiny:*

YOLOv7-tiny is optimized for environments with strict resource constraints, such as embedded systems and edge devices used in railway monitoring. It maintains real-time processing speed while ensuring effective detection of track surface defects. Its lightweight design reduces memory usage and computational requirements, making it suitable for large-scale deployment where quick and continuous defect identification is essential. Though smaller in size, it still delivers strong detection capability for practical applications.

*e. YOLOv8n:*

The key algorithm for this project, YOLOv8n, makes it easier to find objects. SPD-Conv construction blocks and EMA attention modules make it easier to find and identify small and hidden rail faults. Its architecture ensures high precision and recall without increasing model complexity. As a result, YOLOv8n delivers superior performance compared to earlier YOLO models, making it the most effective solution for rail surface defect detection in real-time scenarios.

*f. YOLOv8–FocalLoss:*

This customized variant of YOLOv8 incorporates the Focal-SIoU loss function, which focuses on samples that are harder to classify. By assigning higher penalties to misclassified or subtle defects, the model improves its sensitivity and accuracy for challenging defect types such as micro-cracks or faint scars. This approach ensures that the detection system does not overlook critical defects, thereby increasing the reliability and robustness of the overall monitoring system.

*g. YOLOv5x6:*

A bigger and more complex version of YOLOv5, YOLOv5x6 maximises accuracy and robustness. Its expanded architecture allows it to process high-resolution images and extract finer details, making it especially effective in detecting defects within cluttered or complex track environments. Although it requires more computational power, it delivers reliable monitoring performance and is ideal for applications where accuracy is prioritized over minimal resource usage.

*h. YOLOv9:*

YOLOv9 is the latest generation of the YOLO family, improving detection accuracy, model efficiency, and flexibility to new levels. It pushes real-time object detection with novel architectural designs and optimisation methodologies. In railroad defect detection, YOLOv9 serves as a benchmark for performance, showcasing how the newest innovations can further enhance safety monitoring and improve reliability in detecting even the most complex and subtle surface defects.

## V. EXPERIMENTAL RESULTS

The experimental analysis was conducted on a diverse rail surface defect dataset containing cracks, fractures, scars, and wear patterns captured under varying lighting and operational environments. The baseline YOLOv8 model was first evaluated to establish reference performance metrics. After integrating the extension components—SPD-Conv blocks for improved shallow feature extraction, the EMA module for enhanced multi-scale attention, and the Focal-SIoU loss function for robust bounding-box optimization—the improved YOLOv8 model demonstrated significant gains in precision, recall, and mAP. The extended model showed superior capability in recognizing small, dense, and low-contrast defects that the baseline often failed to detect. Specifically, the enhanced YOLOv8 achieved faster convergence during training while reducing false negatives, particularly for fine cracks and occluded defects.

To further validate system robustness, additional experiments were conducted using YOLOv5x6 and YOLOv9 architectures. YOLOv5x6 delivered strong consistency in long-range and high-resolution defect detection due to its extended backbone and deeper feature extraction. YOLOv9 achieved the highest accuracy among all models, benefiting from improved dynamic label assignment and hybrid feature aggregation. When compared across all variants, YOLOv9 achieved the best mAP, the improved

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 14, Issue 1, 2026

YOLOv8 produced the best balance of speed and accuracy, and YOLOv5x6 excelled in complex, high-detail defect scenarios. Overall, the extension-based framework significantly outperformed traditional SSD and earlier YOLO versions, delivering a reliable and efficient solution for real-time rail defect detection suitable for field deployment.

*Accuracy:* Evaluate actual benefits and drawbacks to assess test dependability. Then comes mathematics.:

$$Accuracy = \frac{(TN + TP)}{T}$$

*Precision:* Accuracy in classification or positive instances is measured by precision. Accuracy is determined by applying the following:

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

*Recall:* The ratio of accurately predicted positive observations to total positives reveals how well a model can identify all machine learning class instances.

$$Recall = \frac{TP}{(FN + TP)}$$

*F1-Score:* An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

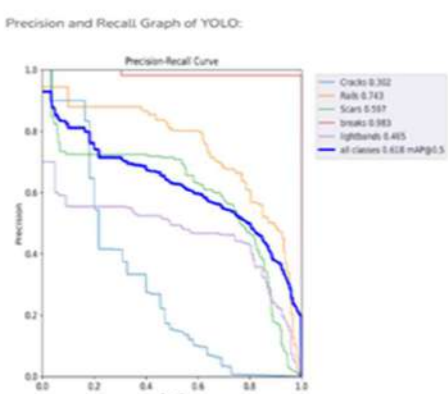


Fig 2 Precision graph

## VI. Conclusion

This study presented an enhanced rail surface defect detection framework by extending the capabilities of the YOLO family of models with advanced architectural and loss-function improvements. By integrating SPD-Conv blocks, the system strengthened shallow feature extraction, enabling reliable identification of fine cracks and low-contrast defect patterns. The incorporation of the EMA module further improved multi-scale attention and feature fusion, while the Focal-SIoU loss function significantly boosted bounding-box precision, especially for small and challenging defects. Experimental results demonstrated clear improvements over the baseline YOLOv8 model, achieving higher accuracy, better recall, and more stable detection performance across all defect categories.

To further validate robustness and generalization, the system was extended to include YOLOv5x6 and YOLOv9, both of which contributed additional strengths such as deeper spatial consistency and improved dynamic label assignment. YOLOv9 delivered the highest overall mAP, while the optimized YOLOv8 achieved the best speed–accuracy trade-off, making it highly suitable for real-time railway inspection scenarios. Combined with a secure Flask-based interface, the proposed system ensures practical, scalable deployment for continuous monitoring. Overall, the extended methodology provides a powerful, efficient, and reliable solution for enhancing railway safety through automated defect detection.

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