Design of a Rail Damage Detection System Based on AI Vision Technology

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Abstract

To address the issues of low efficiency, high missed detection rates, and significant interference from environmental lighting in manual inspection of high-speed railway rail surface damage, this paper designs a rail damage detection system based on artificial intelligence (AI) vision technology. In terms of hardware system construction, the system selects a Huarui Technology (iRAYPLE) 6-megapixel high-resolution industrial camera paired with a Microvision low-distortion high-definition industrial fixed-focus lens to ensure clear imaging of minute defect features. In response to the reflective characteristics of the rail surface and complex on-site lighting conditions, a high-density LED ring light source system is specially designed, which employs uniform cold white light irradiation to effectively suppress shadows and highlight defect edges. Building upon this, advanced deep learning algorithms are integrated to process the captured images, enabling the automated identification of rail surface damages such as cracks, spalling, and abrasions. The research demonstrates that through the synergistic optimization of software and hardware, this system effectively overcomes the limitations of traditional detection methods, significantly improving the accuracy and efficiency of rail damage detection, thereby providing reliable intelligent technical support for railway maintenance.

Keywords

Artificial intelligence vision technology, Deep learning, Defect detection, Rail damage, Industrial camera

Introduction

With the rapid development of global rail transit infrastructure, railway transportation has become a vital pillar of modern socioeconomic development. By the end of 2024, the continuous expansion of high-speed railway networks had greatly improved both freight and passenger transport efficiency, while simultaneously imposing unprecedented challenges on operational safety and maintenance. As a key component directly bearing train loads in the railway track structure, rails are exposed to complex natural environments for extended periods and are subjected to high-frequency, heavy-load service conditions, making them vulnerable to wave wear and various forms of damage. If such defects cannot be detected and repaired in time, they may aggravate vibration and noise in the wheel-rail system, shorten the service life of the track, and in severe cases even induce rail fracture accidents, resulting in enormous economic losses and casualties [1]. Therefore, achieving efficient and accurate detection of rail surface damage is of great practical significance for ensuring train operation safety.

Traditional rail damage detection mainly relies on manual inspection, which is labor-intensive and inefficient, and highly dependent on inspectors' subjective experience. This results in a relatively high missed detection rate and makes it increasingly difficult to meet the maintenance requirements of modern high-speed railways, which are characterized by high traffic density and short maintenance windows [2]. Although nondestructive testing methods such as ultrasonic testing and eddy current testing perform well in detecting internal defects, visual inspection technology possesses irreplaceable advantages. It delivers superior intuitiveness and high resolution, especially for subtle surface texture defects and early-stage fatigue damage [3,4]. In recent years, with the rapid development of artificial intelligence, especially deep learning, automated inspection systems based on machine vision have gradually become a major research focus. By acquiring high-resolution images through industrial cameras and automatically identifying defects using algorithms such as convolutional neural networks (CNNs), this technology is expected to fundamentally transform the traditional inspection mode of "visual observation and manual recording", thereby promoting railway maintenance inspection toward intelligent and unmanned operation [5,6].

Overall system framework

As shown in Figure 1, after system startup is initiated, rail images are acquired through a high-definition camera or a rail inspection vehicle. The collected images are then subjected to preprocessing operations such as denoising, enhancement, and normalization to improve image quality. Subsequently, the AI vision model performs inference on the processed images to identify damage features such as cracks, spalling, and crushing. Once such features are detected, the system proceeds to damage localization and classification. If no significant damage is detected, the rail segment is directly labeled as normal. The system then performs confidence evaluation and threshold judgment on the detection results. When the confidence level meets the required threshold, a detection report containing the damage location, type, and severity level is generated automatically. If the confidence is insufficient, a manual review procedure is triggered to ensure the accuracy and reliability of the detection results.

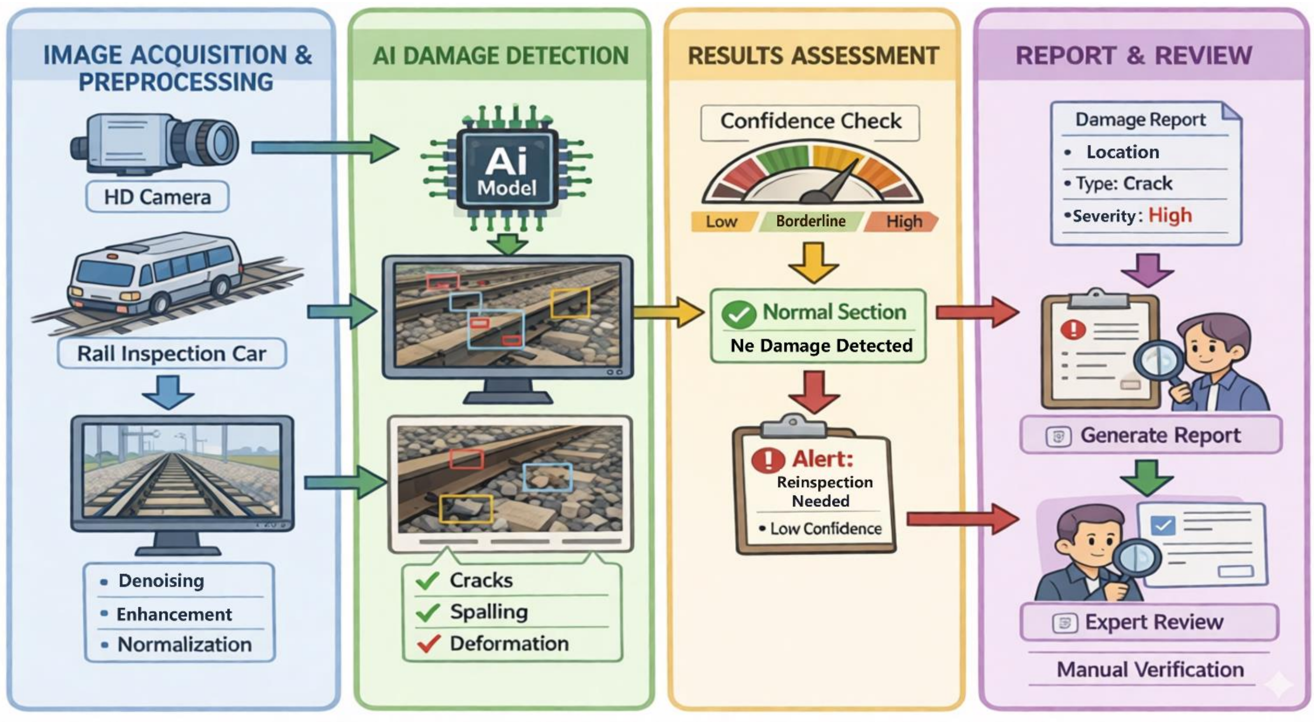

Figure 1. Overall system architecture.

Hardware system design

Industrial camera

(1) Camera parameters

As shown in Figure 2, the proposed system employs the iRAYPLE A3600CG18 color industrial area-scan camera. Its core specifications are as follows: resolution of 3072 × 2048 (6 megapixels); sensor type Sony IMX178 (1/1.8" CMOS); pixel size 2.4 μm × 2.4 μm; shutter mode rolling shutter; maximum frame rate 18 fps; data interface GigE Ethernet, supporting PoE power supply, multiple ISP image enhancement algorithms, and external trigger mode.

(2) Selection rationale

First, the camera provides a 6-megapixel high resolution, which offers a wider field of view and richer detail features than conventional 5-megapixel cameras, thereby meeting the requirements of minute defect detection and high-precision localization. Second, the IMX178 sensor features high sensitivity and low noise, allowing high-quality color images to be captured even under moderate illumination conditions. Finally, the GigE interface combined with PoE technology ensures high-speed and stable data transmission while simplifying power cabling and reducing system wiring complexity, making it highly suitable for industrial field integration.

Figure 2. Industrial camera.

Industrial lens

(1) Lens parameters

As shown in Figure 3, the system adopts a Microvision high-definition industrial fixed-focus lens, specified as 16 mm 1:2.0 1/1.8”. Its key parameters are as follows: focal length 16 mm; mount type C-Mount; maximum compatible image format 1/1.8” (perfectly matching the camera sensor size); maximum aperture F2.0; distortion controlled within 0.1%; support for manual aperture and focus adjustment.

Figure 3. Industrial lens.

(2) Selection rationale

First, the lens image format is 1/1.8”, which is fully consistent with the selected camera sensor size, ensuring complete optical imaging on the sensor without edge vignetting. Second, the 16 mm focal length provides an appropriate field of view under the preset working distance, allowing the target object to occupy a suitable proportion of the image. In addition, the F2.0 aperture ensures sufficient light intake while providing an appropriate depth of field, which helps maintain image clarity even when slight positional deviations of the workpiece occur. The excellent low-distortion characteristics of the Microvision lens also establish a solid foundation for subsequent high-precision image measurement.

Light source

(1) Light source parameters

As shown in Figure 4, a high-density LED ring light source is employed in this system. Its major specifications are as follows: cold white color; input voltage 24 V DC; outer diameter 90 mm; inner diameter 60 mm; housing made of high-quality aluminum alloy;

and equipped with a dedicated digital controller supporting 256-level brightness adjustment and external triggering.

Figure 4. Light source.

(2) Selection rationale

In machine vision systems, the quality of illumination directly determines the contrast of the original image. A white LED ring light is selected because it provides uniform illumination, effectively suppresses surface shadows and uneven reflections, and enhances edge features. Since the camera adopts a rolling shutter, stable and high-brightness LED illumination can compensate for illumination inconsistency during exposure. Through 360-degree circumferential illumination, the contour of the target becomes more distinct, significantly reducing the difficulty of subsequent image segmentation and feature extraction algorithms [7].

Hardware parameter

Table 1 summarizes the hardware components and their specifications. The setup includes a 6-megapixel industrial camera, a 16 mm fixed-focus lens (F2.0), and a 24 V DC cold-white LED ring light source.

Table 1. Hardware parameter.

No.	Component	Parameters
1	iRAYPLE A3600CG18 color industrial area-scan camera	3072 × 2048 (6 megapixels), 1/1.8” CMOS, rolling shutter
2	Microvision high-definition industrial fixed-focus lens	Focal length: 16 mm, maximum aperture: F2.0
3	LED ring light source	Cold white, input voltage: 24 V DC

Software system design

Software architecture

The software design and development are divided into four major layers.

(1) Core monitoring module

As the main interface of the system, this module simulates the real-time operation status of high-speed inspection tasks and dynamically displays rail images and inspection progress, ensuring that the monitoring process is intuitive and visualized.

(2) Intelligent analysis log

Located on the right side of the interface, this module presents AI inference results in the form of a list, including damage type, position coordinates, and confidence level, while also supporting historical data traceability and review.

(3) Data overview dashboard

This module performs real-time statistical analysis and visual display of key maintenance indicators, such as inspected mileage, total number of detected defects, and AI recognition accuracy, thereby providing data support for performance evaluation.

(4) Hardware status monitoring

As shown in Figure 5, this module monitors the operating status of the camera, light source, and communication links in real time, and automatically issues alerts in case of abnormalities, fully reflecting the reliability of coordinated software–hardware design.

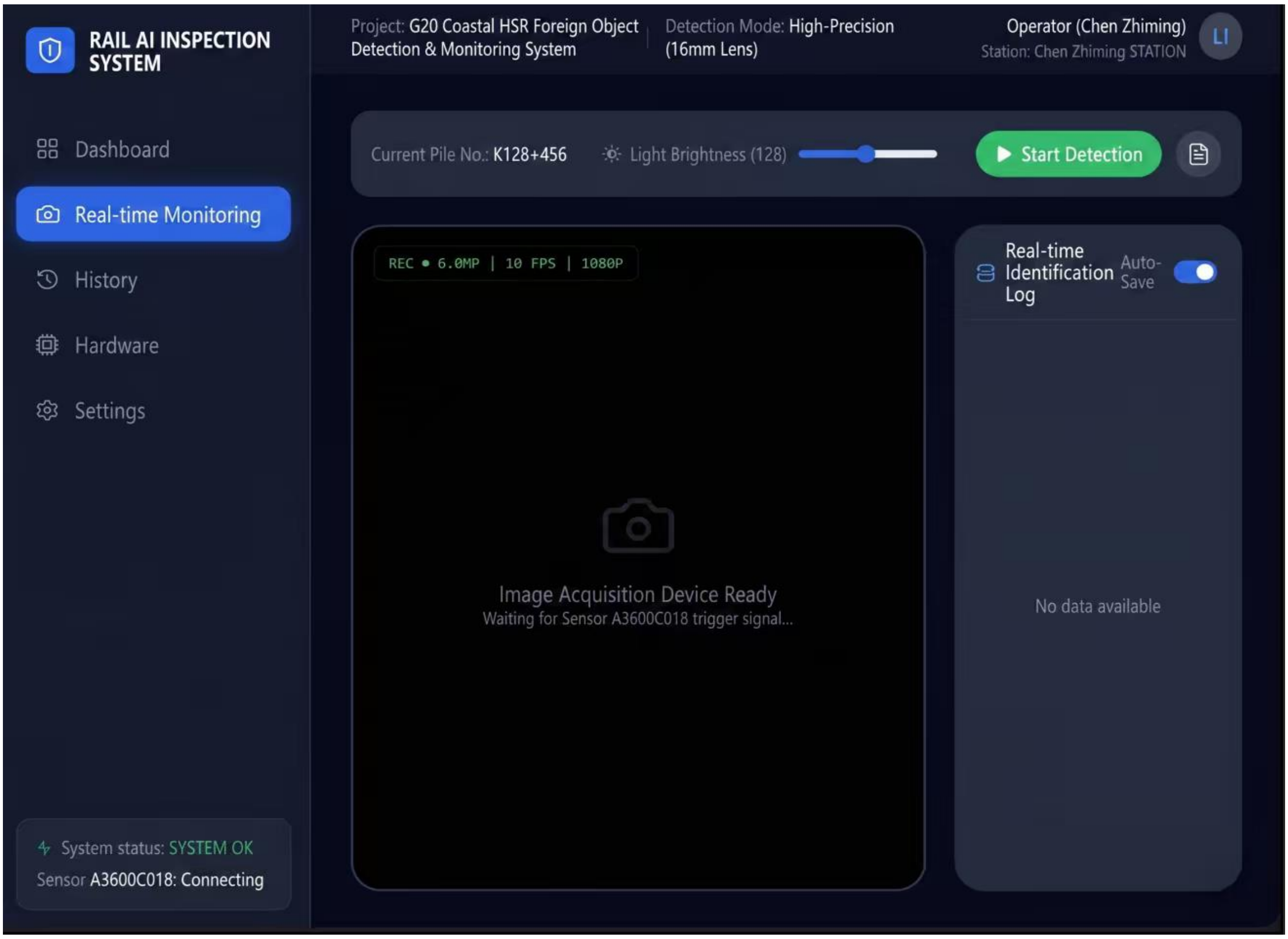

Figure 5. Software operation interface.

Algorithm flow

The system first acquires high-contrast raw images of the rail surface through the coordinated operation of the high-definition industrial camera and ring light source, followed by denoising and enhancement processing. Deep learning algorithms are then used to automatically extract features and realize the automatic identification and classification of defects such as cracks, spalling, and abrasions [8,9]. The recognition results are subsequently combined with odometer information for accurate localization, and the AI confidence score is used to determine whether a manual review procedure should be triggered. Finally, the system automatically generates a digital inspection report containing the defect location, type, and severity level, thus providing support for intelligent railway maintenance [10].

Conclusion

In summary, this study designs and implements a rail damage detection system based on AI vision technology. Through the deep integration of high-precision imaging hardware and advanced deep learning algorithms, the system effectively solves various difficulties of rail damage detection in complex railway operating environments. At the hardware level, the system adopts a high-resolution industrial camera from iRAYPLE and a low-distortion lens from Microvision. It is also equipped with a specially designed high-density LED ring light source. These devices jointly eliminate the interference of rail surface reflection and shadows during image acquisition and thus ensure that defect features can be clearly presented. At the software level, relying on an end-to-end object detection model, the system achieves automated identification and accurate localization of various, including cracks, spalling, and abrasions, effectively compensating for the low efficiency and strong subjectivity of traditional manual inspection.

The results indicate that, while improving detection accuracy, the proposed system also greatly enhances the reliability of inspection results through the closed-loop mechanism of confidence evaluation-manual review. As China's high-speed railway network continues to advance toward high-density and intelligent maintenance, such integrated and efficient vision-based detection solutions can not only significantly reduce maintenance costs and labor intensity, but also provide solid technical support for ensuring train operation safety and extending track service life. In the future, with the further integration of lightweight algorithms and edge computing technologies, the proposed system is expected to be widely deployed in various rail inspection equipment, thereby promoting railway maintenance toward a new era of unmanned and precision-oriented operation.

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Conflicts of Interests

The authors declare no conflict of interest.

References

[1] Wang, Y., Miao, B., Zhang, Y., Huang, Z., Xu, S. (2025) Review on rail damage detection technologies for high-speed trains. *Applied Sciences*, 15(14), 7725.

[2] Luo, H., Cai, L., Li, C. (2023) Rail surface defect detection based on an improved YOLOv5s. *Applied Sciences*, 13(12), 7330.

[3] Aguirre, E., García-Silvente, M. (2023) Detecting and tracking using 2D laser range finders and deep learning. *Neural Computing and Applications*, 35(1), 415-428.

[4] Huang, Z., Fu, H. L., Fan, X. D., Meng, J. H., Chen, W., Zheng, X. J., Zhang, J. B. (2021) Rapid surface damage detection equipment for subway tunnels based on machine vision system. *Journal of Infrastructure Systems*, 27(1), 04020047.

[5] Choi, J. Y., Han, J. M. (2024) Deep learning (Fast R-CNN)-based evaluation of rail surface defects. *Applied Sciences*, 14(5), 1874.

[6] Saiz, F. A., Barandiaran, I., Arbelaiz, A., Graña, M. (2022) Photometric stereo-based defect detection system for steel components manufacturing using a deep segmentation network. *Sensors*, 22(3), 882.

[7] Kumar, A., Harsha, S. P. (2025) A systematic literature review of defect detection in railways using machine vision-based inspection methods. *International Journal of Transportation Science and Technology*, 18, 207-226.

[8] Wang, H., Li, M., Wan, Z. (2022) Rail surface defect detection based on improved Mask R-CNN. *Computers and Electrical Engineering*, 102, 108269.

[9] Bai, T., Fu, H., Xu, G., Xin, X., Duan, J., Zong, H. (2025) Crack-YOLOv8: multi-class crack detection method for track slabs based on improved YOLOv8. *Measurement Science and Technology*, 36(5), 055012.

[10] Mi, Z., Chen, R., Zhao, S. (2023) Research on steel rail surface defects detection based on improved YOLOv4 network. *Frontiers in Neurorobotics*, 17, 1119896.