International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Railway Track Crack Detection Techniques: A Survey

Mr. G. Umamaheshwaran[1], Arulprasath T[2], Ashok Kumar M[3], Deepak K[4]
Department of Electronics and Communication Engineering
Er. Perumal Manimekalai College of Engineering
Hosur, Tamil Nadu, India

Abstract - Railway tracks carry passengers and goods every day. Over time, heavy train loads and changes in weather can cause cracks and other damage in the rails. If this damage is not found early, it may become serious and affect railway safety. Manual inspection is important, but checking long railway lines takes time and depends on the inspector's experience. For this reason, researchers are studying cameras, sensors, sound signals and computer-based methods to find rail defects. Some systems also use connected devices to send the detected fault and its location to railway staff. This paper reviews the main methods used for railway track defect detection, including image processing, deep learning, YOLO models, drones, sound and vibration analysis, ultrasonic guided waves and Internet of Things (IoT) systems. It discusses the findings, benefits and limits reported in the studies reviewed. It also explains common problems such as limited training data, changing weather, small cracks and false alarms. Finally, it identifies areas where further research and field testing are needed.

Keywords - Railway track inspection, crack detection, image processing, deep learning, Internet of Things (IoT), acoustic monitoring, vibration analysis, ultrasonic guided waves.

1. INTRODUCTION

Railways are widely used to transport people and goods. Their safe operation depends on the condition of the tracks. Rails carry heavy loads whenever trains pass over them. They are also exposed to rain, heat and changes in temperature. These conditions can cause damage on the rail surface or inside the rail. A small crack may grow over time. If it is not found and repaired, it can lead to rail failure and may increase the risk of accident.

In many places, railway workers inspect tracks by walking along the line and looking for visible damage. They may also use handheld tools. This approach is useful, but it takes time and depends on the skill and attention of the inspector [1], [2]. It is difficult to check very long railway lines often. Night-time, rain and fog can make the work harder. Special inspection vehicles and trolleys can cover more distance, but they may be expensive and may not be available everywhere.

Developments in cameras, computers and machine learning have created new ways to inspect railway tracks. Earlier image-processing systems used methods such as edge detection and shape analysis to find possible defects [7]. These methods can work in clear images, but dirt, rust and shadows may affect the result. Deep-learning methods can learn patterns from labelled images and have therefore become an important area of research [8]. Sensors and wireless devices are also being used to collect information and send alerts to railway staff [17], [20]. This paper reviews these methods, explains their main strengths and limits, and discusses the problems that still need to be solved.

2. LITERATURE REVIEW

2.1. Manual and Traditional Inspection Methods

Manual inspection is one of the oldest ways to check railway tracks. A trained worker examines the rail for visible cracks, wear and other damage. Handheld tools may be used when a closer check is needed. Ultrasonic testing is another established method. It sends sound waves through the rail to help find damage inside the metal. It can identify defects that may not be visible on the surface, but the test can take time and usually needs good contact between the equipment and the rail. Rough or coated surfaces may affect the result [2]. Mahajan and Banerjee discussed the use of ultrasonic and other monitoring methods, while Kou reviewed research on rail surface defects [1], [6].

2.2. Image Processing Based Methods

Image-processing methods use a camera to take pictures of railway tracks. A computer then studies the images to find areas that may contain defects. Common steps include improving the image, finding edges, separating important areas and measuring image features. A classifier, such as a support vector machine, may then decide whether an area is normal or damaged [7]. Banić et al. used images from a drone to support railway infrastructure inspection [15]. These methods can be simple and need less computing

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

power than some deep-learning systems. However, their results can change when the lighting or rail condition changes. Rust, shadows, grass, stones and oil marks may be mistaken for cracks.

2.3. Deep Learning Based Image Methods

Deep-learning methods allow a computer to learn patterns from many example images. Convolutional neural networks (CNNs) are often used for this purpose. Chitra et al. studied an improved CNN for identifying faults in railway track images [8]. Anita also reviewed the use of deep learning for detecting defects in railway tracks [7].

A study published in PeerJ Computer Science compared five neural-network methods for classifying railway faults. It also used generated images to increase the amount of training data. The faults considered included cracks, rail breaks, warping and misalignment. The study reported 0.99 accuracy for a random forest method on its test data [9]. This result applies to the dataset used in that study. It does not by itself prove that the same performance will be achieved on every railway line. Testing with images from different locations and conditions is also needed.

2.4. YOLO Based Detection Models

You Only Look Once (YOLO) is a group of object-detection models designed to identify objects in images quickly. Researchers have adapted these models to find defects on railway tracks. Chen et al. proposed RMSDNet, which is based on YOLOv8n and is designed to use fewer computing resources. It reported 78.0% mean average precision on the dataset used in the study [10]. PerMSCA-YOLO uses attention and features at different image scales to improve the detection of small defects and difficult backgrounds [11].

Zhang et al. developed an improved YOLOv8n model with multi-scale feature fusion for railway defect detection [2]. Wang and Zhao reported an improved YOLO11n model trained with 4,020 rail images and four defect classes. Their study reported 93.7% precision and 95.6% mean average precision [13]. DP-YOLO, based on YOLOv5s, was designed to detect rail fastener defects while reducing computing needs [12]. Lei et al. compared different YOLO versions for detecting cracks and water leakage in railway tunnels [14].

These studies show that YOLO models are an active area of railway inspection research. However, results from image datasets do not always show how a model will perform during long-term use on a real railway line. Camera-based models mainly identify visible surface defects. They may not be able to measure the depth of a crack.

2.5. Drone Based Inspection

Drones, also called unmanned aerial vehicles (UAVs), can take pictures of railway tracks and nearby structures. They may help inspect places that are difficult or unsafe for workers to reach. Vishal et al. compared YOLO and U-Net methods using high-resolution railway images captured by a drone. In their study, YOLO processed images faster, while U-Net produced more detailed crack shapes [16]. Earlier work by Banić et al. also examined the use of drone images for railway inspection [15].

Drones also have limits. Their batteries allow only a limited flight time. Strong winds, rain and poor lighting can affect image collection. For these reasons, drones may be useful for planned inspections, but they are not a complete replacement for continuous track monitoring.

2.6. Sound and Vibration Based Methods

Sound and vibration can provide information about the condition of railway tracks. Shafique et al. recorded sound near railway tracks and used machine-learning and deep-learning methods to identify normal and faulty conditions. Their study reported results close to 97% for some methods, including random forest and decision tree models [3]. The authors also discussed the need for further work on locating faults and sending results remotely.

Vibration data can also be collected while a train is moving. Winarno et al. reviewed machine-learning methods that use vibration signals to assess track condition [4]. This approach may allow information to be collected during normal train operation. However, vibration from wheels and vehicles, along with noise from the surroundings, can make it difficult to identify the signal caused by a small crack.

2.7. Ultrasonic Guided Wave Methods

Ultrasonic guided waves travel along a rail and can help identify damage inside the rail. This is useful when a defect cannot be seen clearly on the surface. Lv et al. studied guided waves with deep-learning methods to estimate the depth of cracks in turnout switch rails [5]. Mahajan and Banerjee also reviewed active and passive rail monitoring methods, including the use of machine learning [6].

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Guided-wave methods may provide information about hidden damage, but they need special equipment and careful testing. The shape of railway components can also affect the signals, making them harder to interpret.

2.8. Connected Monitoring Systems

Low-cost controllers, sensors and wireless communication devices have encouraged the development of IoT-based railway monitoring systems. Khan described a small robot vehicle that used two ultrasonic sensors to check railway tracks and send fault information wirelessly [18]. Pavani et al. presented a moving system that used infrared sensors and a camera. When it detected a possible fault, it stopped and sent the location and image to a cloud service and a messaging application [19]. Powar et al. described a motorised trolley with infrared and ultrasonic sensors, location support and mobile communication. The paper reported an accuracy of about 90–95% [20]. Kumar et al. used load cells in a system related to track damage and animal safety near railway lines [21]. Another review discussed methods such as cameras, acoustic sensors, ground-penetrating radar and edge computing [22].

These systems can be built using relatively low-cost parts. However, simple sensors may detect large gaps more easily than very thin cracks. Some systems have only been tested on small models or short track sections. More testing on real railway tracks is needed.

2.9. Combining Artificial Intelligence with Connected Devices

A newer approach combines artificial intelligence (AI) with the Internet of Things (IoT). In this type of system, AI examines images or sensor readings to identify a possible defect. The IoT part sends the result to railway staff. Sudha et al. described a system in which a convolutional neural network classified track images as cracked or normal, while a connected setup shared the result [17]. Lightweight models may be useful because they can run on smaller devices with limited computing power [2], [10], [12], [13]. Winarno et al. also identified real-time use as an important area for further research [4].

Although these systems are promising, many studies describe designs or early tests. Their performance during long periods of operation on working railway lines still needs to be studied.

2.10. Fault Location and Alert Systems

Finding a possible crack is not enough. Railway staff also need to know where it is so that they can inspect and repair the correct section. Some systems use location devices and mobile communication to send this information [18]–[20]. Others use cloud services or messaging applications to share an image and an alert [19]. Quick and clear information may help staff respond sooner.

However, false alerts can lead to unnecessary inspections. If a system sends too many incorrect alerts, staff may begin to trust it less. A useful monitoring system must therefore detect defects reliably and send clear location information.

2.11. Datasets and Data Shortage

The quality of a machine-learning system depends on the examples used to train and test it. Collecting real images of railway cracks can be difficult. Serious defects are not common, and access to railway tracks is controlled for safety reasons. Some researchers use computer-generated images to increase the amount of training data [9]. Other studies use datasets with a limited number of images or defect types, such as the 4,020-image dataset reported by Wang and Zhao [13].

Public datasets help researchers compare different methods. However, images from one railway location may not represent another location. Rail colour, camera position, lighting, weather and surrounding objects can all be different. A model should therefore be tested using data from more than one place.

3. COMPARISON OF EXISTING METHODS

The methods reviewed in this paper have different strengths and limits. Manual inspection can identify visible problems, but it takes time and depends on trained workers. Ultrasonic testing can help find damage inside a rail, but it needs suitable equipment and proper contact with the rail. Basic image processing is relatively simple, but changes in lighting and surface condition can affect its results. Deep-learning methods can learn defect patterns from images, but they need enough good-quality training data.

YOLO models are designed for fast detection and some versions are small enough to run on edge devices. Their performance still depends on the data used for training and testing. Drones can inspect areas that are difficult to reach, but their use is affected by battery life and weather. Sound and vibration methods can collect information during train movement, although noise may affect the signals. Ultrasonic guided waves can help find hidden damage, but they require special equipment. IoT systems can send alerts to staff, but simple sensors may fail to detect very small cracks. No single method can meet every inspection need. The right choice depends on the type of defect, cost, location, available equipment and required response time.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

4. MAJOR CHALLENGES

4.1. Changing Light and Weather

Railway tracks are exposed to sunlight, shadows, rain, fog and changes in temperature. These conditions can change how a rail appears in an image. A model that works well in bright daylight may give weaker results in the evening or during rain.

4.2. Rust, Dirt and Similar Marks

Rust, oil, mud, stones and normal wear marks may look similar to cracks in an image. This can cause a system to report a crack when there is none. Dirt and other material may also cover a real crack and make it harder to detect.

4.3. Small and Fine Cracks

A new crack may be very thin and may cover only a few pixels in an image. If the image is reduced in size or has low quality, important details may disappear. This can make early cracks difficult to identify [2], [13].

4.4. Limited Training Data

Real images of railway cracks are not easy to collect. Serious defects are uncommon, and railway areas cannot be accessed freely. If the training images do not show enough examples, a learning-based system may not work well in new situations [9].

4.5. Dataset Variation

A model trained using images from one railway location may not give the same results at another location. Rail types, cameras, lighting, weather and nearby objects may be different. These changes can affect detection performance.

4.6. Low Power and Low Cost Hardware

Small computers and embedded devices have limits on memory, processing speed and battery power. A large detection model may give good results on a powerful computer but may be too slow or too demanding for a low-cost device [2], [12].

4.7. Network Coverage and Power Supply

Some railway lines pass through places where mobile-network coverage is weak or unavailable. A monitoring system should be able to save important data and send alerts when the connection becomes available again [20].

4.8. False Alarms

A false alarm happens when a system reports a defect that is not present. Too many false alarms can waste the time of railway staff and reduce their trust in the system. Testing should therefore measure more than overall accuracy. It should also consider how many real defects are found and how many incorrect alerts are sent.

4.9. Field Testing

Many systems are tested using prepared images, laboratory setups or short track sections. These tests are useful for early development, but they do not show how the system will work over a long period. Testing on real railway lines in different seasons and operating conditions is also needed.

5. RECENT DEVELOPMENTS

Studies published in 2025 and 2026 show several areas of development in railway defect detection. One area is the design of smaller YOLO models that need less computing power while still detecting defects [2], [10], [12], [13]. Some researchers are also using attention methods and image features at different scales to improve the detection of small defects [2], [11].

Drone and robot-based inspection is another area of interest because it may reduce the need for workers to walk along tracks [16], [19], [20]. Generated images are being studied as a way to increase the amount of training data [9]. Researchers are also combining AI with IoT devices so that detection results can be sent to railway staff [17], [20]. Deep learning with ultrasonic guided waves is being studied to estimate crack depth, not only to identify surface damage [5].

6. FUTURE RESEARCH DIRECTIONS

Further research needs larger and more varied datasets. These datasets should include different rail types, crack sizes, seasons, lighting conditions and weather. Researchers should also test whether a model trained in one location can work well in another location.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Smaller models are needed for devices with limited memory and power. Using more than one type of sensor may also improve inspection. For example, cameras can show surface damage, while sound, vibration and guided-wave methods may provide information about other types of damage [3]–[5].

Alert systems should send clear information and continue to save data when the network is unavailable. Researchers should also work to reduce false alarms. Finally, systems should be tested for long periods on real railway lines. Laboratory results alone are not enough to show that a system is ready for safety-related use. Future systems may also study how cracks grow over time and help maintenance teams plan repairs before the damage becomes serious.

7. DISCUSSION

The studies reviewed in this paper show how railway inspection has moved from mainly manual checks towards the use of cameras, sensors and computer-based methods. Early image systems used features selected by researchers, while deep-learning systems learn patterns from training images [7], [8]. YOLO models are being studied because they can detect defects quickly and can be made smaller for use on limited hardware [2], [10], [11], [13]. IoT-based systems show how fault information can be sent to railway staff [18]–[20].

However, there is still a gap between detecting a defect and using the result in a complete railway monitoring system. Some studies focus on image-model performance but provide limited information about long-term field use. Other systems can send alerts but use simple sensors that may not detect fine cracks. A high accuracy value from one dataset does not guarantee good performance in every location. Systems must also be affordable, reliable and easy to maintain. Overall, future work should bring together accurate detection, fault location and dependable communication, followed by careful testing on real railway tracks.

8. Conclusion

This paper reviewed several methods used to detect defects in railway tracks. These include manual inspection, image processing, deep learning, YOLO models, drone inspection, sound and vibration analysis, ultrasonic guided waves and IoT-based monitoring. Manual inspection remains useful, but it takes time. Image-processing and deep-learning methods can help automate the search for visible defects. Sound, vibration and guided-wave methods may provide additional information about track condition, including damage that is not easy to see.

Recent studies have explored smaller YOLO models, drone-based inspection and systems that send alerts through connected devices [2], [10]–[13], [16]–[20]. However, no single method can detect every type of defect under all conditions. The success of a railway monitoring system depends on reliable detection, correct fault location, clear communication and suitable cost. More varied datasets, better detection of fine cracks, efficient devices and long-term field trials are still needed.

Reliable crack detection can support railway maintenance and help reduce risks to passengers, railway workers and infrastructure. Further research should focus not only on model results but also on whether the complete system works safely and consistently in real railway conditions.

REFERENCES

[1] L. Kou, “A review of research on detection and evaluation of rail surface defects,” Acta Polytechnica Hungarica, vol. 19, no. 3, 2022.
[2] Z. Zhang, L. Zhang, X. Lu, T. Ma, F. Huang, and S. Zhong, “An improved YOLOv8n with multi-scale feature fusion for real-time and high-precision railway track defect detection,” Frontiers in Artificial Intelligence, vol. 8, Art. no. 1711309, 2026. doi: 10.3389/frai.2025.1711309.
[3] R. Shafique, H.-R. Siddiqui, F. Rustam, S. Ullah, M. A. Siddique, E. Lee, I. Ashraf, and S. Dudley, “A novel approach to railway track faults detection using acoustic analysis,” Sensors, vol. 21, no. 18, Art. no. 6221, 2021. doi: 10.3390/s21186221.
[4] A. Winarno et al., “Roles of vibration-based machine learning algorithms in railway vehicle monitoring for track condition assessment: A review,” Journal of Vibration Engineering & Technologies, vol. 13, no. 4, 2025.
[5] C. Lv, P. Wang, and H. Sun, “Deep-learning-based ultrasonic guided wave detection of turnout switch rail cracks,” Sensors and Materials, 2025.
[6] H. Mahajan and S. Banerjee, “Active and passive monitoring of rail through the application of machine learning algorithm,” in Proceedings of Structural Health Monitoring 2021, DEStech Publications, 2021. doi: 10.12783/shm2021/36330.
[7] Anita, “Railroad track defect detection using deep learning,” International Journal of Engineering and Management Research, vol. 15, no. 2, pp. 89–96, 2025. doi: 10.5281/zenodo.15356939.
[8] R. Chitra et al., “Railway track fault detection using optimised convolutional neural network,” International Journal of Reliability and Safety, vol. 18, no. 2, 2024.
[9] A. Raza, R. Sehar, A. Moiz, A. S. Alluhaidan, S. A. El-Rahman, and D. S. AbdElminaam, “Novel conditional tabular generative adversarial network based image augmentation for railway track fault detection,” PeerJ Computer Science, vol. 11, Art. no. e2898, 2025. doi: 10.7717/peerj-cs.2898.
[10] Y. Chen et al., “RMSDNet: A lightweight object detection network for rail surface defect,” IEEE Transactions on Instrumentation and Measurement, vol. 74, 2025. doi: 10.1109/TIM.2025.3644563.
[11] “PerMSCA-YOLO: A perceptual multi-scale convolutional attention enhanced YOLOv8 model for rail defect detection,” Applied Sciences, vol. 15, no. 7, Art. no. 3588, 2025. doi: 10.3390/app15073588.
[12] L. Chen, Q. Sun, Z. Han, and F. Zhai, “DP-YOLO: A lightweight real-time detection algorithm for rail fastener defects,” Sensors, vol. 25, no. 7, Art. no. 2139, 2025. doi: 10.3390/s25072139.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

[13] H. Wang and J. Zhao, “Research on defect detection on steel rails based on improved YOLO11n algorithm,” Applied Sciences, vol. 16, no. 2, Art. no. 842, 2026. doi: 10.3390/app16020842.
[14] Y. Lei, K. Zhu, B. Jiang, Y. Wang, F. Jia, Z. Wang, F. Qi, and Q. Qu, “Task-specific YOLO optimization for railway tunnel cracks and water leakage: Benchmarking and lightweight enhancement,” Computers, Materials & Continua, vol. 87, no. 3, Art. no. 41, 2026. doi: 10.32604/cmc.2026.077314.
[15] M. Banić, A. Miltenović, M. Pavlović, and I. Ćirić, “Intelligent machine vision based railway infrastructure inspection and monitoring using UAV,” Facta Universitatis, Series: Mechanical Engineering, vol. 17, no. 3, pp. 357–364, 2019. doi: 10.22190/FUME190507041B.
[16] S. Vishal, H. Shanthan, and J. Vijay Arputharaj, “Railway track crack detection: A comparative study on YOLOv7 and U-Net in automated inspection,” in Proceedings of ICCIST, IEEE, 2025. [Publication details to be verified.]
[17] M. Sudha et al., “AI-driven railway crack detection system using convolutional neural network and IoT,” in Proceedings of ICAECA, IEEE, pp. 1–8, 2025. [Publication details to be verified.]
[18] M. Khan, “IoT-based railway tracking system,” EasyChair Preprint, no. 8375, 2022.
[19] G. Pavani et al., “Implementation of IoT-based defect detection in railway tracks,” EasyChair Preprint, no. 9781. [Year and full author/publication details to be verified.]
[20] P. Powar et al., “Smart IoT-based railway track fault detection system,” International Research Journal of Engineering and Technology (IRJET), vol. 13, no. 6, 2026. [Full publication details to be verified.]
[21] S. Praveen Kumar et al., “Enhancing animal safety measures by avoiding train collisions using Internet of Things (IoT) with advanced sensors association,” in Proceedings of ICRDICCT ’25, SciTePress, pp. 680–687, 2025. doi: 10.5220/0013871300004919.
[22] “Railway track broken detection for train accident prevention,” International Research Journal of Engineering and Technology (IRJET), vol. 12, no. 4, 2025. [Author and publication details to be verified.]

(This work is licensed under a Creative Commons Attribution 4.0 International License.)