

# Railway Track Fault Detection Using Deep Learning

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**Abstract**—In Just 10 years, the Railway network expanded across the country. Railways are the principal mode of transportation that requires regular inspection of the tracks for damages and faults. The traditional way of railway track inspection using railway carts is time-consuming and subject to human mistake. Any track damage may cause to railway accidents, which will lead to human and financial loss. Hence, there is a requirement for self-railway track fault detection to ensure safe and reliable train operation. In this paper present a solution to overcome the manual inspection system and its drawback by automating the train track fault detection based on Deep Learning. The tracks were of several types Normal tracks, Wheel burnt, and Superelevation and their natural prevalence. This paper developed an CNN algorithm for visual fault recognition and proposed a method based on signal processing theories to study the sample data. Based on the improved CNNs algorithm, a mean accuracy score of 94% based on the data available (through the analysis of experimental results). Note, that while this accuracy was significantly superior to that of existing approaches, the performance remains to be validated in real-world settings

**Index Terms**—Deep Learning, Convolutional Neural Network

## I. INTRODUCTION

Railway Networks are the lifeblood of a nation, particularly in developing countries, as they fulfill public transportation needs and serve as the backbone of trade and commerce. Over time, the railways sector has evolved, creating golden opportunities for both the public as well as economic sector. Railways are the most energy-efficient mode of land-based long-distance travelers and Merchandise. Despite carrying 8% of global passengers and freight, railways consume approximately 3% of total transportation energy and contribute just 0.3% of global CO<sub>2</sub> emissions. Rail transport uses 12 times less energy and emits 711 times fewer greenhouse gases per traveler-

kilometer compared to private vehicles running on roads and airlines, making it the most efficient form of motorized passenger travel. For Cargos, aside from shipping, rail is the also one of the most energy-efficient and low-carbon mode of transport. However, maintaining high-performance railway operations is essential to ensure uninterrupted train services and passenger safety [1].

The general community crowd, daily commuters, and tourists frequently rely on trains for travel, but their safety is at risk if railway tracks are inappropriate for regular operations. Similarly, the secure transport of freight, a vital component in the supply chain, necessitates fault-free and resilient railway tracks. Regular inspections are crucial to minimizing derailment incidents caused by mechanical or physical wear and tear. Between 2023 and 2024, global rail freight traffic saw an increase, with Europe and Turkey collectively handling approximately 4.1 trillion ton-kilometers in 2023, trailing slightly behind Oceania/Middle East regions, which managed over 3.5 trillion ton-kilometer of rail freight in the same period. China and India continue to dominate rail passenger traffic, serving an estimated 1,550 billion and 1,157 billion passenger kilometers, respectively, each year. Other nations with notable rail passenger traffic include Russia (133.6 billion), Japan (446.7 billion), Germany (100 billion), France (112.6 billion), and the United Kingdom (80.5 billion). In India, where rail travel is a preferred mode of transport, approximately 673 crore passengers used the railway system in 2023-24, marking a 5.2% increase from the previous financial year, according to the Economic Survey presented in Parliament [2].

Indian Railways (IR) achieved revenues of ₹2.40 lakh crores by March 15, 2024, a significant increase of ₹17,000 crores from the previous fiscal year's ₹2.23 lakh crores. Despite its extensive usage, the Indian railway system falls short of global benchmarks in infrastructure, efficiency, safety, and service quality.

Common issues include cracks, creeping tracks, loose fittings, damaged sleepers, ballast displacement, discontinuities, missing nuts and bolts, and wheel burns. Insufficient routine maintenance, delayed detection of problems, and a lack of preventive inspections have raised serious concerns about the safety of rail operations in India.

In recent years, the frequency and severity of train accidents have resulted in considerable loss of life and property. During the 2023-24 fiscal year alone, Indian Railways reported 40 accidents, leading to the tragic loss of 313 lives. A total of 748 lives have been lost in 638 train accidents in the last 10 years. Rising above these appalling statistics is an important call for improvements in infrastructure, technology and safety to prevent similar tragedies in the future. Example of Track anomalies that could potentially compromise the safety and operation of railway infrastructure can be categorized as; (Refer Figure1) [3].

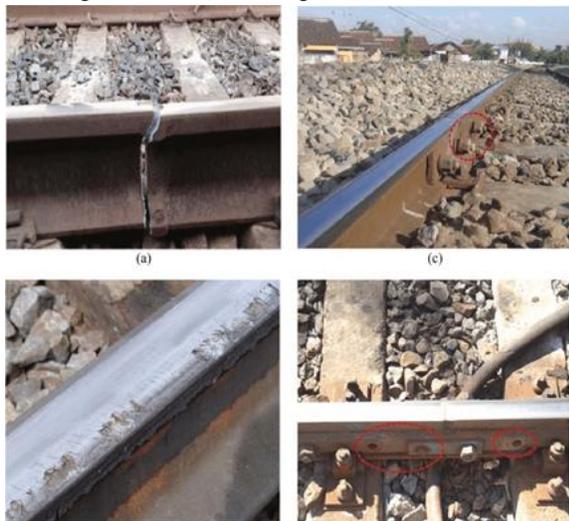


Figure 1: Example of Track anomalies that could potentially compromise the safety and operation of railway infrastructure can be categorized as cracks accompanied by deformation, rust-induced deformation on the rail surface, unsecured bolts, and absence of bolts.

The focus of this research is to find a reliable system which analyzes the tracks to decide if a track has been cracked or not. Artificial Intelligence, Machine Learning and Deep Learning are all relatively recent breakthroughs that have invariably resulted in solutions that are at the very least incremental improvements on what came before, and railway track detection is no different. As railway derailment can

have devastating impacts on human lives and the economy, the accomplishments have motivated researchers to implement machine-learning-based approaches to improve railway track detection. Most defects detection and track condition monitoring is carried out using image processing methods, either alone or integrated with other sensors and data sources. Using current machine learning, it can be used to analyze the data and finding out any possible issues that are causing the safety and importance of Railway systems.[6].

## II. RELEATED WORK

Automated systems using sensors, machine learning, and image processing have become essential for real-time railway track monitoring, improving inspection accuracy, efficiency, and safety while reducing human oversight risks. This shift enhances operational efficiency and safety standards by enabling proactive maintenance and continuous monitoring.

We conducted a detailed survey to compare deep learning classifiers for fault detection. Our study consisted of 11 relevant research papers published between 2017 and 2023. The contributions and gaps are presented in Table 1.

Authors and Year	Contributions of Papers	Gap Identification
Hui Luo, Lianming Cai * and Chenbiao Li (2023) [7].	The paper enhances rail defect detection through improved YOLOv5s, dataset augmentation, a new CDConv module, global attention mechanism, and Soft-SIoUNMS loss, achieving 96.9% mean	The study highlights insufficient training samples and low contrast between defects and backgrounds as significant challenges in rail surface defect detection.

	average precision.	
Furqan Rustam, Abid Ishaq, Muhammad Shadab Alam Hashmi (2023) [5].	The paper enhances railway track fault detection using selective MFCC features, achieving high accuracy through optimized feature selection and machine learning models.	Existing methods rely heavily on image processing, leading to high computational costs and poor accuracy in fault detection.
Adki Nishanth, Venkata rami reddy G (2023) [13].	This research utilizes deep learning, specifically Region-based Convolution-Neural-Networks, to detect rail track surface faults, enhancing maintenance efficiency	The study lacks diverse data, complex CNN optimization, and consideration of external factors affecting rail defect detection accuracy.

	and safety in railway infrastructure.	
R. S. rampriya , A. jenefa, Sahaya Beni Prathiba, Sabarinathan, Jerart Julus (2023) [14].	The paper contributes a deep fusion model combining SSD ResNet50 for component detection and Deep Residual U-Net for semantic segmentation, enhancing railway track inspection accuracy and efficiency.	The gap identified is the limited integration of advanced deep learning techniques in real-time railway track inspection, necessitating improved models for faster detection and segmentation of faults in diverse conditions
Adil Ali Saleem, Muhammad Amjad Raza, Kainat Zafar, Kashif Munir, Sandra Dudley (2022) [15].	The paper contributes by utilizing MFCC features for fault sound analysis, achieving 98.4% accuracy with MLP models, and proposing an IoT system for enhanced railway fault detection	The gap identified is the limited exploration of advanced deep learning techniques beyond MLP, and the need for real-time processing capabilities in railway fault detection systems for improved

	and data collection.	operational efficiency.
Muhammad Shada b Alam Hashmi, Muhammad Ibrahim, Imran Sarwar Baj wa, Hafeez-Ur-Rehman Siddiqui, Furqan Rustam, Ernesto Lee and Imran Ashraf (2022) [16].	The paper proposed a approach for generating spectrograms from acoustic datasets to detect railway track faults, comparing audio sample time slots and spectrogram types for performance analysis.	The study lacks exploration of alternative deep learning architectures and their comparative effectiveness, as well as the impact of varying environmental conditions on model performance in real-world railway track inspections
Xiukun Wei, Dehua Wei ,Da Suo, Limin Jia, Yujie Li (2020) [17]	The paper contributes by proposing a multi-target defect identification system for railway tracks using advanced image processing and an improved YOLOv3 model, enhancing detection accuracy and efficiency of model.	The research gap lies in the simultaneous detection of track and fastener defects, as existing methods typically address them separately, lacking a comprehensive automated solution for railway track line inspection
Chen-Chiung Hsieh, Ya-Wen Lin, Li-Hung Tsai, Wei-	The paper presents an innovative	The research gap lies in the limited use of

Hsin Huang, Shang-Lin Hsieh, and Wei-Hung Hung. (2020)[18]	sensing method using sport cameras for track fastener inspection, employs Yolo v3 for classification, and introduces a virtual detection circle for locating defects efficiently.	affordable imaging technology for defect detection in railway fasteners, particularly under varying environmental conditions and the need for real-time processing.
Mehmet Karakose , Orhan Yaman†, Kagan Murat, Erhan Akin(2018) [19]	The paper proposes a method based on computer vision for simultaneous detection of railway components and condition monitoring, utilizing multiple cameras for enhanced accuracy and efficiency in railway safety assessments.	The paper lacks a comprehensive detailing of its proposed method with already existing techniques, particularly in terms of efficiency, and real-time applicability across various railway conditions and components.

Aliza Raza Rizvi , Pervez Rauf Khan , Dr.Shafeeq Ahma d (2017) [20]	The paper presents a Innovative method based on computer vision for automatic crack detection in railway tracks, enhancing inspection efficiency, reducing human error, and improving safety through timely fault identification.	The research gap lies in the limited application of advanced automated inspection technologies in diverse railway environments , particularly in addressing varying track conditions and enhancing real-time fault detection capabilities.
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Table 1: Literature Review

### III. METHODOLOGY

#### A. Dataset

Table 2 [11] represents the dataset containing approximately 343 train and 19 test image which were then classified into 2 classes which are defective and non-defective.

Class	Number of Images
Defective	189
Non-Defective	192

Table 2:List of Dataset

Data is typically categorized in two groups: training data and testing data. The training dataset carries labeled outputs which is used by model to learn patterns and make predictions for future, unseen data whereas the testing dataset, is used to estimate how well the model performs. This process can be implemented in Python using the TensorFlow library, particularly with the Keras framework.

Deep learning relies on collecting a huge amount of historical image data. This data is used to train as well as test the model to ensure its predictions are accurate and reliable. The Data flow for fault detection is presented in figure 2.

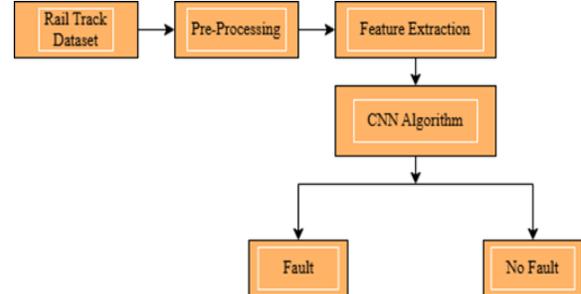


Figure 2: Workflow for fault Detection

#### B. Workflow

To work with the image dataset, we use the Keras preprocessing image data generator function to import and prepare the data. This involves setting parameters like image size, rescaling, range, zoom

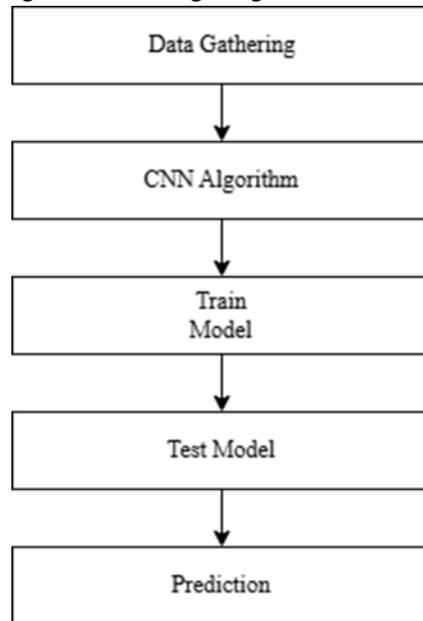


Figure 3: Steps of Data Flow

range, and enabling horizontal flips for data augmentation. The data generator is used to load the folder containing the image dataset, where we configure the testing, training and validation splits, along with defining the target size, class mode etc. This prepared data is then used to train our custom CNN network by adding the necessary layers. The

balanced Dataset distribution is represented in Table 3.

Train		Test		Validation	
Defective-150 Images	Non-Defective-150 Images	Defective-8 Images	Non-Defective-11 Images	Defective-131 Images	Non-Defective-131 Images

Table 3: Balanced Dataset Distribution

For training the model, we use a classifier as well as the fit generator functions. We specify the training steps per epoch, the total number of epochs, validation data, and validation steps. Using this setup, we can effectively train the model on the given dataset.

The simulation process in Figure 3 illustrate in providing an overview of the approach used to implement the optimization techniques and achieve optimal results. The subsequent subsections will elaborate on the methodology, detailing the key steps involved in the simulation process.

*a) Data Collection:* At the outset of this study, significant human and material resources were allocated to gather various track fault data, manually annotated by experts. The dataset comprises 362 images of diverse track faults captured under real-world conditions from railway tracks.

*b) Data Pre-processing:* It begins by organizing the data points. Next, the data is split according to the distribution specified in Table 3. The final step is the creation of an image generator object to facilitate the process.

*c) Feature Extraction:* This step focuses on identifying and retaining the most relevant variables that are crucial for model development. By eliminating irrelevant or potentially harmful features, the system ensures that the learning process is not hindered by unnecessary data

*d) Classification:* Classification involves using machine learning algorithms to categorize data into distinct classes based on the learned patterns. The

model is trained to associate different inputs with specific labels from the problem domain.

*e) Evaluation:* Performance is measured using various metrics like accuracy, error rate, kappa score, precision, recall, F1 score, mean absolute error, and log loss. These metrics help in assessing the quality of the predictions and guide the selection of the most appropriate feature selection method for the task at hand.

*C. Working Process of Different Layers in CNN Model*

A CNN is a deep learning technique designed to process and analyze input images by assigning learnable weights and biases to various aspects of the image. This enables the model to differentiate and identify objects in images effectively. Unlike traditional classification methods, CNNs require significantly less pre-processing, as they can automatically learn features and patterns from data during training, eliminating the need for manual feature engineering.

The architecture of a CNN is inspired by the structure of the human visual cortex, where neurons respond to specific regions of the visual field. Each neuron focuses on a small, localized area (the receptive field) and contributes to recognizing patterns in the image. The network structure typically involves layers such as convolutional layers, pooling layers, and fully connected layers. For example, a CNN might have an architecture consisting of an input layer, a series of hidden layers with varying numbers of neurons (e.g., 256 neurons in the first hidden layer, 8 in a subsequent layer), and an output layer for classification tasks.

*Input Layer:*

The input layer of a CNN processes image data, which is inherently a three-dimensional matrix (e.g., height, width, and colour channels). Before feeding the image into the network, it often needs to be flattened into a single-dimensional vector. For instance, an image of size 28x28x3 pixels, totalling 784 pixels, would be reshaped into a vector of dimensions 784x1. This reshaped vector then becomes the input to the network

*Convolutional Layer (Convo Layer):*

The convolutional layer, often called the feature extraction layer, identifies and captures important

characteristics of the input image. It applies a filter to a specific section of the image (known as the receptive field) and calculates the dot product between the filter and that section. This operation generates a single value that forms part of the output. The filter then shifts across the image in steps called strides, repeating the process for each receptive field until the entire image is processed. The resulting output is passed to the next layer for further processing.

*Pooling Layer:*

The pooling layer reduces the size of the image data, making computations more efficient and helping to prevent overfitting. It is typically placed between two convolutional layers. Without pooling, directly connecting a fully connected (FC) layer to the output of a convolutional layer would require significant computational power due to the large amount of data. One common pooling method is max pooling, which selects the largest value from a specified region of the input.

For example, applying max pooling with a stride of 2 to a  $4 \times 44 \times 44$  matrix reduces it to a  $2 \times 22 \times 22$  matrix. This process retains the most important information while reducing the overall data size.

*Fully Connected Layer (FC):*

The fully connected layer consists of interconnected neurons, each with associated weights and biases. It connects all neurons in one layer to every neuron in the next. The FC layer is responsible for interpreting the features extracted by earlier layers and making predictions or classifying the input into categories.

*Output Layer:*

The label is stored in the output layer as one-hot encrypted information. This layer converts the raw scores into distributions, enabling the model to predict.

IV. RESULT

Figures 4 and 5 illustrate the executive evaluation of the Convolutional Neural Network (CNN) model applied to the dataset, showcasing the results in terms of accuracy and loss. The visualizer

presents the average accuracy and loss values, which are derived from the algorithm's results during the validation phase. This approach enables an assessment of how well the CNN model performs on the given data, with higher accuracy and lower loss indicating better model performance.

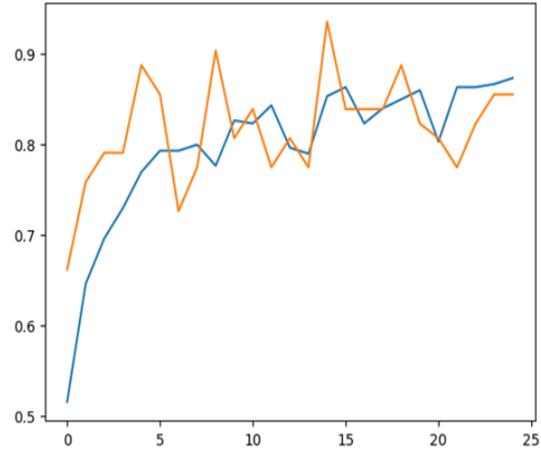


Figure 4: Validation Accuracy by Epochs

The graph presented in the showcases the performance of a Deep learning model in terms of its accuracy over several epochs, with the x-axis representing the number of epochs (ranging from 0 to 25), and the y-axis depicting accuracy values between 0.5 and 1.0.

The blue line, which represents the training accuracy, demonstrates an overall upward trend. Starting from a relatively low accuracy, it gradually improves over time, with occasional fluctuations. By the end of the training (around epoch 25), the training accuracy reaches approximately 0.9, indicating that the model is having productive learning from the training data.

On the other hand, the orange line corresponds to the validation accuracy and, while it also increases with some fluctuations, it is not as stable as the training accuracy. This fluctuation is typical, as the validation set consists of data that the model has not encountered during training. The validation accuracy reaches close to 0.9 at the final epoch, showing that the model operates well on hidden data. However, the occasional drops suggest that the model may face challenges in generalizing to all aspects of the validation set, which is common when testing on data that was not part of the training process.

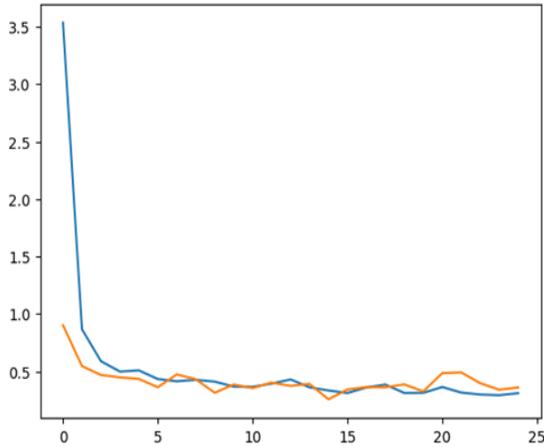


Figure 5: Validation Loss by Epochs

The graph in figure 5 displays the behaviour of two metrics—likely

the loss or error rates—over the course of 25 epochs during a machine learning training process, with one metric in blue and the other in orange. Initially, the blue curve shows a sharp drop followed by a stabilization at a low value, while the orange curve exhibits a larger initial fluctuation before converging slowly to a lower value.

The steep drop for the blue curve indicates that the model experienced a significant improvement in performance early on, which could be attributed to learning from the data during the initial training phases. After this drop, the model appears to stabilize, meaning it has likely reached a point where it is learning effectively and avoiding overfitting. The orange curve, on the other hand, seems to start with more variance and takes longer to converge, which could suggest a less effective learning process or greater difficulty in finding optimal patterns in the data initially.

## V. CONCLUSION

In conclusion, the intelligent system developed for railway track fault detection using Convolutional Neural Networks (CNN) has demonstrated significant improvements in classifying defective and non-defective tracks. The approach utilizes advanced deep learning techniques, and the implementation of the RMSprop optimizer has notably enhanced the system's ability to extract features and classify faults more effectively. The system's architecture, which adapts to

different track fault conditions, has been fine-tuned to achieve high accuracy, ensuring that it can detect even subtle defects that might otherwise be missed. Furthermore, integrating this fault detection model into an automated inspection tool with decision support functionalities offers several benefits. It provides real-time tracking of railway conditions, enables the synthesis of large amounts of inspection data generating detailed reports for maintenance personnel. This integration will not only streamline the maintenance process but also help in improve the overall safety and reliability of railway actions and operations. By leveraging predictive maintenance through the analysis of accumulated data, the system helps to forecast potential faults before they result in failures, thus reducing operational costs and preventing accidents.

The effectiveness of this intelligent fault detection system shows its potential as a crucial tool for modern railway infrastructure management. With continued development and integration of more data-driven approaches, it can evolve into a powerful solution ensuring the long-term safety and accuracy in terms of rail networks.

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