Fault Diagnosis in Railway Track using Efficient Net based CNN

Ravikant Mordia[1*] & Arvind Kumar Verma[2]

[1]Department of Mechanical Engineering, MBM University, Jodhpur, India 342011*

[2]Department of Production & Industrial Engineering, MBM University, Jodhpur, India 342011

E-mail: ravi.mordia@gmail.com

Abstract

Railway transportation is the most cost-effective and convenient means of passenger travel in India. The cress cross tracks are almost present in every part of India. Keeping in mind the security of people also the free running railway without any problem, we have to focus in the safety part of this system [1]. In India, the railway network accounts for over 80% of all transportation. Approximately 60% of accidents occur at crossings of railway tracks because of a railway track fracture, resulting in the loss of valuable life and economic damage. As a result, new technology is required for both fault detection and object detection in railway tracks. This technology must be resilient, efficient, and steady [2]. This paper presents a vision based method to find some common defects in railways. Some images have been collected of railway track and image processing method is used to preprocess these images and to detect the features related to defective parts. An EfficientNet based CNN model is developed to detect the defects which uses global average pooling, adam as optimizer, softmax as activation function and categorical_crossentropy as loss function. This research result consists of a classification report as defective and non-defective parts or image with accuracy of 91 percentages over 30 epochs.

Keywords: *Rail Track Images, Defects, Defect Detection Method, CNN and Defect Classification.*

1. Introduction

Rail track inspection is an important task in railway maintenance. The speed and loads of trains have been increasing greatly in recent years, and these factors inevitably raise the risk of producing rail defects. For the safe operation of railway systems, the quality of rails must be closely and frequently monitored. The wear and flaws on the rails may be recognized before they become hazardous, and this degradation can be controlled and repaired early if the rails are periodically inspected and maintained. In the past, a skilled worker would inspect the rail for deterioration by hand. This is a lengthy and per-haps risky examination. It is also influenced by the individual's view-point [3]. The rail is inspected by special inspection machines in touch with the rails in an-other traditional technique. When these units come into touch with the rails, they generate wear.

Visual inspection [4]–[6] or more modern techniques such as ultrasonic testing [7], [8], magnetic particle inspection [9], [10], liquid penetration testing [11], and eddy current testing [12], which are non-destructive testing (NDT), can be used to examine railway track faults.

Composite rail profile measurements on the railways was presented in [13]. The region in the picture recorded by a laser scanning camera that contains the rail profile was determined using a pre-processing method, and the rail profile was constrained using neural network techniques. An embedded system technique was presented for real-time rail profile analysis at railways. The rail profile information for all UK railways was examined [14]. The rail and the laser source were both monitored with two CCD cameras, and locations with damaged rail profiles were identified. For a Beijing-Tianjin inter-city high-speed railway, a rail profile ir-regularity's wavelet trans-form was conducted [15]. A wavelet transform and power spectrum density analysis may be used to determine the causes and locations of rail problems derived from various periodic components. The wavelet analysis results were used to assess the quality of rail construction on railways and to ad-vise rail maintenance. A systematic technique to analyzing rail wear and strain was developed [16]. In addition, a new fault diagnostic approach for determining structural surface flaws on railways was proposed [17]. The observations showed that the suggested approach may be utilized to successfully locate the damage. A deep convolutional neural network [18] was developed to evaluate rail image data and identify deterioration on the rail surface. The outcomes are superior to those achieved by conventional distributed systems. An algorithmic texture classification approach was applied to the railway track images to determine the current state of the rail surface [19]. In their experiments, they achieved an accuracy of 82 percent. To identify significant rail surface degradation, a morphology-based technique with a variational and dual-element was suggested [20]. In comparison to traditional approaches, they have lowered the detection rate.

Wear and cracks on the railway track are analyzed in this article. Image processing and analysis procedures are performed on the pictures recorded by the camera. The images are converted to a grey level image format in order to complete the transactions.

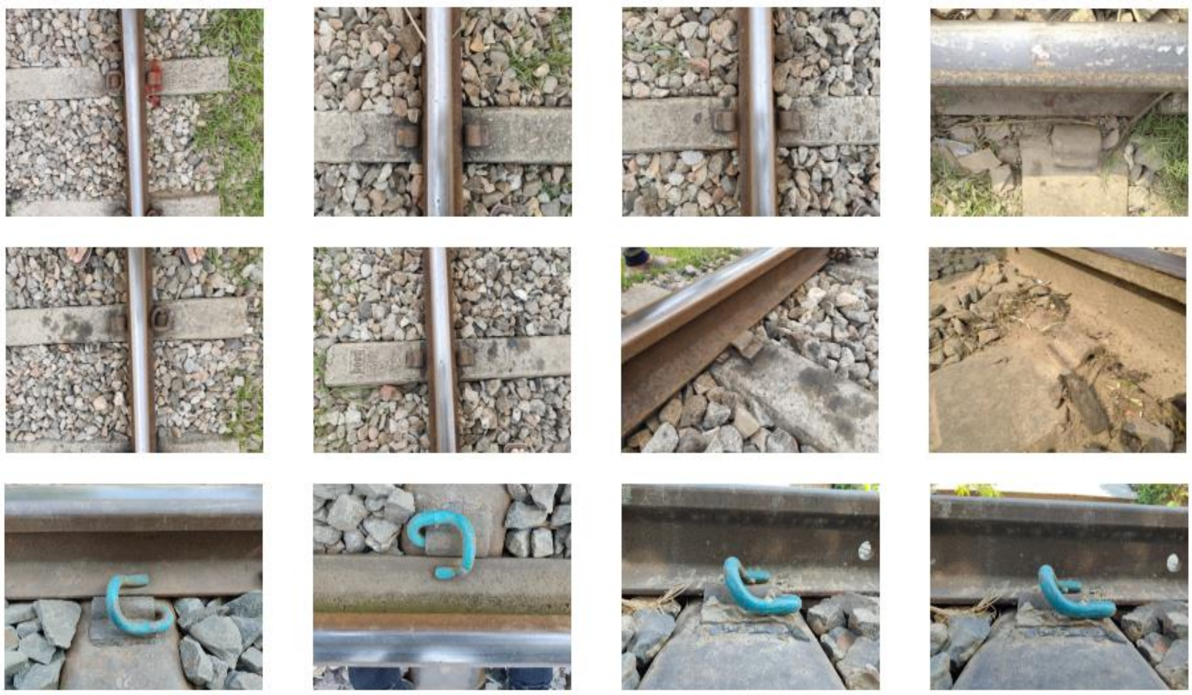

Figure 1. Railway track images with defective and non-defectives

The images of railway track are taken from the internet which were captured while the train is moving and some of these images are shown in Figure 1. First 8 images are from defective datasets and last 4 images are from non-defective datasets.

As a result, the image may get distorted. After that, noise reduction filters are used to remove these disruptions, resulting in a brighter image. Gaussian and median filters were used as filters. To avoid the impacts of light fluctuations that might occur on the railway track, the grey image is adjusted to the shadows. Because of the influence of light and things on the railway track, shadows can develop, resulting in a variety of hues. The identification of these shadows via colour segmentation may be difficult. The shadow elimination procedure is used to avoid such issues. Different gradations for each colour layer are created on RGB photographs, which are then blended into a single grayscale image that is free of shadows image scanner angles based on the direction of light entrance. The picture is then transformed to black and white by choosing a threshold after this step. The acquired image sections are then classified using the nearest neighbour method. The rail head is deter-mined using the Hough transform once the rail's nearest neighbour classification has been determined. The sections of the image generated using the nearest neighbour technique that depict the rail are chosen, and the rest of the image is destroyed. Both of these processes produce fresh pictures that are then blended. The rail wear is detected using a minimal error set. Finally, the detected image is presented as defective and non-defective and a classification report is presented showing the defective and non-defective railway track parts.

2. Defect Detection Methodology

As our project replaces manual inspection of the track section, by automatic inspection to detect any cracks in the track section. This will help to detect cracks immediately and reduce the possibilities of any mishaps. The system would be automatic and will require less manual intervention, utmost efficiency of the system can be ensured. Low-lighting and contrast-based image enhancement techniques make sure that the system is extremely accurate. The project is therefore feasible and is not susceptible to the judgement of the technicians. In practical scenario's the images of the tracks could be captured either manually or by drone cameras. The drone cameras also have a high-resolution capacity which could hover over the tracks to capture the images of the tracks. Images of various tracks have been collected from the internet. The image has been processed, hence converted into a RGB image. The image is also compressed according to the required size for image processing. Parameter are being monitored and different algorithms are being tested on the image to detect the crack. The flowchart of the proposed methodology is shown in Figure 2.

Those minor cracks are unnoticed by the track-man of the railway department who walks 16km/day along the railway track for the inspection of the track. This method of inspection is quite unreliable. Railway track image is taken and processed in Python software. Initially taken image is converted into a contrast stretched image. Then the RGB colour image is converted into grayscale image. A fine-tuned image is obtained by applying median filter. BOT hat output image is obtained by applying another filter. The resultant image is converted into a binary image. The background noise is reduced by applying filters. The obtained thinned image is called as skeleton image. The skeleton image is processed for defects detection. After detecting defects, classification is also done for defective and non-defective parts using nearest neighbor approach.

- Image is processed in Python software.
- Chosen image is converted into a contrast stretched image.
- The RGB color image s converted into grayscale image.
- Median filter is applied on the image to get a fine-tuned image.

- Another filter is applied to get a bot hat output image.
- Obtained image is converted into a binary image.

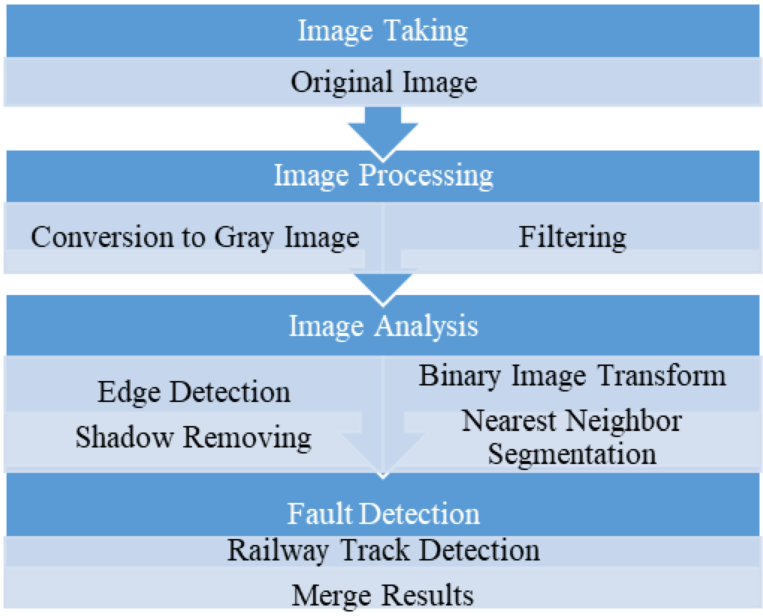

Figure 2. Flow diagram of proposed methodology

- The background noise is reduced by applying filters.
- The thinned clear image is ready for processing of defects.
- Abbreviations and Acronyms.
- Classification of defective and non-defectives using nearest neighbor algorithm.

3. Result and Discussion

Various photographs of tracks are taken and the original image with crack is processed in Python. If crack is found the image is contrast stretched and RGB to gray image is obtained. A median filtered image is obtained by applying median filter. A BOT HAT output image of the crack of the track is obtained and on binary image noise reduction techniques are applied via noise filter. Thinned image or skeleton image of crack is detected. This proposed crack detection algorithm can detect the cracks on the tracks. For this, a CNN model is developed to detect the defects which uses global average pooling, adam as optimizer, softmax as activation function and categorical_crossentropy as loss function. This re-search result consists of a classification report as defective and non-defective parts or image with accuracy of 91 percentages over 30 epochs. A classification report of the defective and non-defective images of railway track is shown in Figure 3. Figure 4 shows loss for training and validation history of the images. Accuracy of training and validation of the images over 30 epochs is shown in Figure 5.

	precision	recall	f1-score	support
Defective	0.89	0.73	0.80	11
Non Defective	0.77	0.91	0.83	11
accuracy			0.82	22
macro avg	0.83	0.82	0.82	22
weighted avg	0.83	0.82	0.82	22

Figure 3. Classification report of the defective and non-defective images of railway track

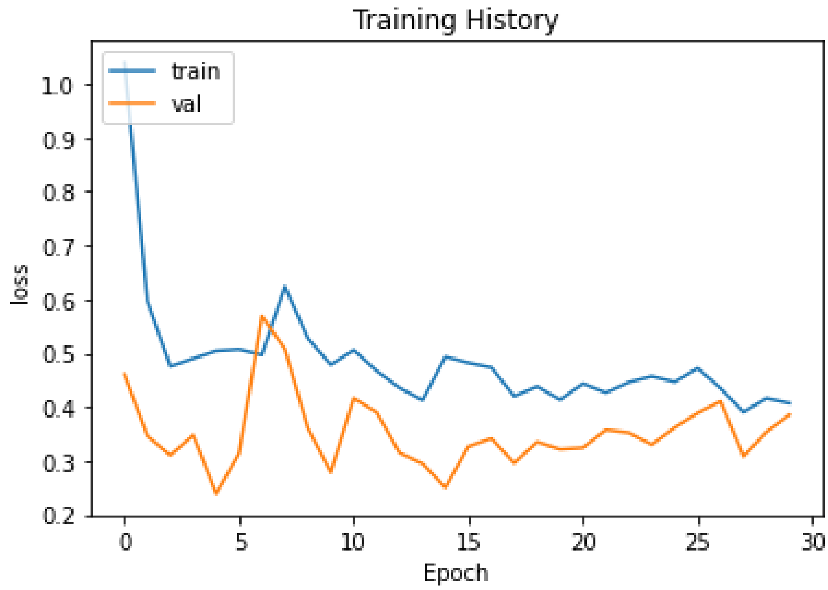

Figure 4. Loss for training and validation history of the railway track images

Figure 5. Accuracy for training and validation history of the railway track images.

4. Conclusion

We have performed a detailed literature survey. Collected the images of the non-defective and faulty tracks and modified the images for identification of the defects. We identified the cracks, applied different filters to get a clear image. We build an EfficientNet CNN model to find the defects in railway track. This research result consists of a classification report as defective and non-defective parts or image with accuracy of 91 percentages over 30 epochs. In further research, it can be applied to detect surface defects and internal defects in railway track. The model can be further modified to increase its efficiency and to classify the different types of surface defects.

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