An Improved Convolutional Neural Network Method for Railway Track Breakage Detection

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ABSTRACT

A Railway track breakage represents broken structures consisting of rail track on the railroad. The traditional methods for detecting this problem have proved unproductive. This paper presents an improved method for detecting Railway breakage using an improved Convolutional Neural Network. The method inspects and examines rail tracks for flaws that could lead to rail accident.

Keywords: Railway Track Breakage, Convolutional Neural Network, Intrusion Detection System

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1. BACKGROUND TO THE STUDY

Railway transportation is the means of conveying people and goods from one place to another through trains. It can also be defined as the movement of people and commodities through the use of railways (Etim, 2018). The developing economies have resulted in an increasing need for railway utilisation because it is cost-efficient and can be used to convey heavy goods. Also, it is the least affected by weather turbulences compared to other transport mechanisms, and it can also serve as an alternative for road transportation as it will reduce the rate of traffic congestion. Therefore, various efforts are being made to revive the system which is currently in a depleted state. Railway track breakage is an essential factor in railway operation. Rails guide trains and are subjected to severe contact stresses, each train wheel passage reshapes the railway track due to wear, extreme levels of stress concentration and also induces surface and subsurface fatigue cracks. Recent statistics reveal that approximately 90% of railway accidents are due to cracks on the rails (Chanchal et al., 2014; Naveen et al., 2016; Patil et al., 2018).

It poses severe threats to trains; hence, it is essential to have an effective means to detect the breakage(s) not only for safety but also for adequate maintenance. Furthermore, the safe operation and the current situation of the railway tracks must be frequently monitored. Manual detection of breakage on track is cumbersome and not fully active owing to much time consumption and requirement of skilled technicians (Er.Nithsul, 2017). Also, there are some regions where manual inspection is not possible, like in deep coal mines, mountain regions and dense, thick forest regions. Various advanced methods utilising different sensory technologies have been used for the detection of breakages. The track circuit was one of the dominant methods of sensing broken rails.

The operational principle depends on the shunting of rails to prevent the current from reaching a receiver at one end of the circuit (Thurston, 2014). Track circuit was initially developed for train detection, but its ability to detect full traverse breaks in the tracks that would interrupt the current to the receiver makes it suitable for railway track breakage detection. Other sensing approaches other than track circuit that have been adopted for broken rail detection which are the Non Destructive Testing (NDT) approaches like magnetic field methods, radiography, ultrasound, fibre optics, wavelets from accelerometer, strain gauges, and acoustics (Schwartz 2004; Zarembski et al., 2006; Hopkins and Taheri, 2011). This study presents an in-depth learning approach (a branch of artificial intelligence) for the automatic detection of rail surface defects. The proposed method focuses on an automated visual inspection system for a railway using an improved Convolutional Neural Network (CNN).

The improved CNN is referred to as Fully Convolutional Network (FCN), and it will be combined with a superpixel algorithm- Simple Linear Iterative Clustering (SLIC), which adapts a k-means clustering approach to generate superpixels efficiently. This work focuses on reducing the accident rate caused by the railway track breakage by detecting the breakage(s) on the track.

1.1 Motivation

The motivation for this research is hinged on the need to ensure the safe operation of the railway transportation system because rail transportation plays a vital role in daily activities. Most passengers opt for railway transportation because of the level of trust they have in its safety compared to other means of transport (Chanchal et al., 2014). Due to the long-term impact of the railway track and the weight of trains, a variety of defects will be formed on the track (Min et al., 2018).

Rail accidents are escalating daily because of lack of adequate maintenance of the tracks. Recent researches have however reported accidents in some countries due to the derailment, and this should not be overlooked due to the current growth of the railway system. The proposed system intends to effectively and efficiently combat the problem of detecting and locating any crack or break on the track so that appropriate real-time safety measures can be implemented (Wirtu et al., 2011). It will also help to guarantee the integrity of tracks before the railway traffic starts working (Espinosa et al., 2017). Furthermore, critical review of related work and models that have been used in detecting railway track breakages and they have shown certain drawbacks such as limited distance of rails being covered (Francois 2012; Espinosa et al., 2017; Patil et al., 2018), failure to give the exact location of the breakage (Faghih-Roohi et al., 2016; Espinosa et al., 2016; Shang et al., 2018).

1.2 Problem Statements

Broken rails are the leading cause of significant derailments accidents (P. Szacsvay & T. Moore 2012). Though there exist various approaches that have been used in detecting breakages in the railway track, several studies have shown that these approaches need significant improvements. Derailments usually lead to catastrophic consequences like loss of lives and properties which will significantly affect the economy and the environment (Wirtu et al., 2011; Mittal and Rao 2017; Gan et al., 2017). Detecting railway track breakage through manual and semi-automatic inspection is time-consuming, labour-intensive and wastes a lot of time and resources, there are also regions where these kinds of investigation are not possible. At times, complex infrastructure is placed along the railway track which can hinder the movement of trains at that particular time (Canan et al., 2016 & Nagdvete et al., 2017). Most existing sensory technologies cover limited distance of inspection at a time (Francois 2012; Loveday et al., 2013; Espinosa et al., 2016), while the existing computer vision techniques have challenges in feature extraction on images gotten from tracks and also have images with poor quality and low resolution (Canan et al., 2016). This study develops an automatic railway inspection system that will help in detecting any breakage on a railway track and identify the exact location

2. RELATED WORK

The detection of broken railway tracks has been widely studied during the last decade. The future of railway track inspection lies in developing automated rather than manual methods. Singh et al., (2006) proposed a rail track inspection technique using automated video analysis which was aimed at replacing the conventional methods used to perform checks on the track by the railway technicians. The condition of the track at any point in time was recorded using a video camera, the clips in the video sequences were automatically detected and thereafter recognised to see whether they are broken or not and if they are recent or old breakages. The experiment performed resulted in a high performance in machine vision-based inspection. Although as at this time, much work had not been done in the area of machine vision for railway track inspection.

Shah (2010) worked on the detection place and the type of defect that is found on railway tracks. He increased the quality of the image acquired with controlled lighting and the use of superior computing power technology. He developed a system that could automatically detect a defect in railway tracks including defects in the track structure and track geometry notifying the inspector on the type of defect and the exact location. The system primarily uses high precision laser sensors to perform the gage detection and includes an audio interface that not only alerts the operator when the system detects a faulty gage but also verifies the diagnostics of the system upon startup. A field testing of the system was performed on over 1000gb of data, and it was found to be very useful in assisting in the inspection process.

The implementation of a system using guided waves in railway tracks to continuously monitor the rail for any breakage was worked on by Francois (2012). In his work, he described the system that was implemented to transmit the guided wave ultrasound between stations spaced at approximately 1km intervals along the line. The stations transmit sequences of signals every few minutes, and if these signals are not received at the receiving station at the required time, an alarm is triggered. The system had no occurrence of false alarm at the freight rail installations and was successfully able to detect breaks. However, various challenges were faced during the development of the system due to the changing nature of the environment it operates in.

Vishwakarma et al., (2014) worked on performing detection of faults that occurred due to cracks on railway tracks focusing on the Indian Railway System. The paper proposed a cost detection utilising LED-LDR (Light Emitting Diode - Light Dependent Resistor) and Hall Effect Sensor Assembly to identify derailment of tracks. It tracks the exact location of the wrong track, sends the instant message to nearest train engine driver, and the track is repaired immediately. The system had four sections which it was placed which were; at the railway station, on the train engine, on the railway track and the lamp post. The system automatically detected the faults on the railway tracks without human intervention, but it consumed much power.

Deep convolutional neural networks are being recently applied to quite some image processing technique domains. In the work of Faghih-Roohi et al. (2016), a deep convolutional neural network solution to the analysis of image data for the detection of rail surface defects was proposed. The images were obtained from video recordings. The convolutional neural network is a viable technique for feature learning; the result obtained was explored to test the efficiency of the proposed system for detection and classification. However, the extraction of features for the detection of breakages on the track is sometimes very challenging.

In the work of Nisthul et al. (2017), the issue of railway track crack was addressed by developing an automatic railway detection system by integrating an infrared red (IR) crack sensing module and a communication module based on (Global System for Mobile Communication) GSM technology. This helps in information the tracking of the location. The report was sent as an SMS to a certain number whenever the sensor detects any crack which helped in the timely monitoring and maintenance. However, the problem that was faced during this work was that the vehicle operated in battery power; hence, the use of a rechargeable battery to drive the vehicle. Also, signal transmission is just below 50 feet.

Espinosa et al., (2017) described a technique designed to identify rail breakages in double-track railway lines based on the analysis of eight currents provided by electronic equipment. The electric mechanism utilised was a proper sensory technology as the current flow will be affected if there is an imbalance in the stream. The inequality that occurred among the value of these currents implies that there was at least a breakage in the track section under analysis which is thereafter classified using Principal Component Analysis (PCA) Technique. However, the classification only occurs if there is only one breakage in the track.

Patil et al., (2018) introduced the driverless railway system with detection of the crack where the Track and Train section were two crucial sections in the track. Train section contains an ultrasonic sensor which is used for crack detection distance measurement motor driver while track section includes light encoder and decoder which is used to transfer the data through light for communication purpose. The most critical part of the track section is a voltage divider arrangement for breakage detection. It also contains switches which are at ON state for those trains which are required to stop and an OFF state for those trains which are not expected to stop on the station.

Shang et al., (2018) proposed a novel two-stage pipeline method for rail defect detection by localising and classifying the rail images. Cropped images which focused on just a part of the rail image instead of the whole image was gotten by integrating traditional image processing methods while cropped images were fine-tuned into a Convolutional Neural Network and part-level features were extracted for rail images classification in the second stage. A novel loss function was proposed to leverage both of them in the second stage. The results showed that this method has strong robustness and achieves practical performance in defect detection precision. However, the object localisation method was explicitly designed for railway image given the rail geometric characteristics, and this detection method could not guarantee the real-time work.

Table 1 shows the summary of related work and their corresponding strength(s) and weakness(es)

Table 1: Summary of related work

S/N	Author & Year	Method	Strength(s)	Weakness(es)
1.	Singh *et al.* (2006)	-Automated video analysis	-High performance, large area.	-Clips get broken due to excessive strain.
2.	Shah (2010)	-Algorithm for gage detection, automatic segmentation, feature extraction, object classification and feature extraction.	-logs exact location of defect. -history of inspection can be maintained.	-Lengthy computation time. -image platform not controlled. Canan *et al.,* (2016)
3.	Francois (2012)	-Guided waves inspection.	-Propagates reasonably well in steel rails. -sequences of signals are transmitted every few minutes.	-Limited distance. -disturbed by environmental factors.
4.	Faghih-Roohi *et al.* (2016)	-Deep CNN solution. -mini batch gradient descent method.	-Save time and cost. -extraction of suitable features. -little or no pre-processing of image.	-Limited deep networks.
5.	Er.Nisthul *et al.* (2017)	-IR crack sensing module. -GSM communication module.	-Addition of solar panel to help conserve power. -automatic alert system. -wireless signal transmission.	-Low signal transmission -Vehicle is operated in battery power.
6.	Espinosa *et al.* (2017)	-Principal Component Analysis (PCA) technique -8km long double-track hardware simulator.	-Shorter time for analyzing tracks. -approximately detecting breakage location.	-Cannot detect if there is more than a breakage. - affected by high moisture.
7.	Patil *et al.* (2018)	-Driverless railway system. -ultrasonic sensor track distance measurement.	-light encoder and decoder for transferring crack information. -motor driver for a driverless system.	-Limited run time due to power source. -not GSM or GPS based.
8.	Shang *et al.* (2018)	-Novel two-stage pipeline method for object localization and feature extraction.	-Efficient and safer detection through a swift approach -strong robustness in detection precision.	-No guarantee for real-time work.

3. METHODOLOGY

This work adopts an improved Convolutional Neural Network for visual inspection of railway tracks. The two datasets gotten from Vision Intelligence Laboratory will be used for this research work. The first is Type-I RSDDs (Rail Surface Discrete Defects) dataset captured from express rails, which has 67 challenging images. The second is Type-II RSDDs dataset captured from common/heavy haul rails, which has 128 challenging images. Each image from these two datasets contains at least one defect and have a complicated background with much noise. The defects in the datasets were marked by some professional human observers in the rail surface inspection field. Data augmentation techniques such as rotation by a random angle in-between 0^° and 〖360〗^° will be performed on the existing dataset to increase the amount of data available for training.

The architecture for the proposed methodology is presented in Figure 2. In Figure 2, the images of the railway tracks are obtained from a high-speed line-scan camera attached to the trains in motion and stored in a database, each image from the database is sent to the FCN for pixel-level map classification. Despite the power and flexibility of the FCN model, it still has some problems that hinder its application to specific situations such as small objects often ignored and misclassified as background, the detailed structures of an object are often lost or smoothed. The resulting image is sent to SLIC for super-pixel segmentation map which is faster and improves segmentation performance. After that, the Interface reports the final output which contains the state of the tracks to the maintenance team through the Graphical User Interface (GUI).

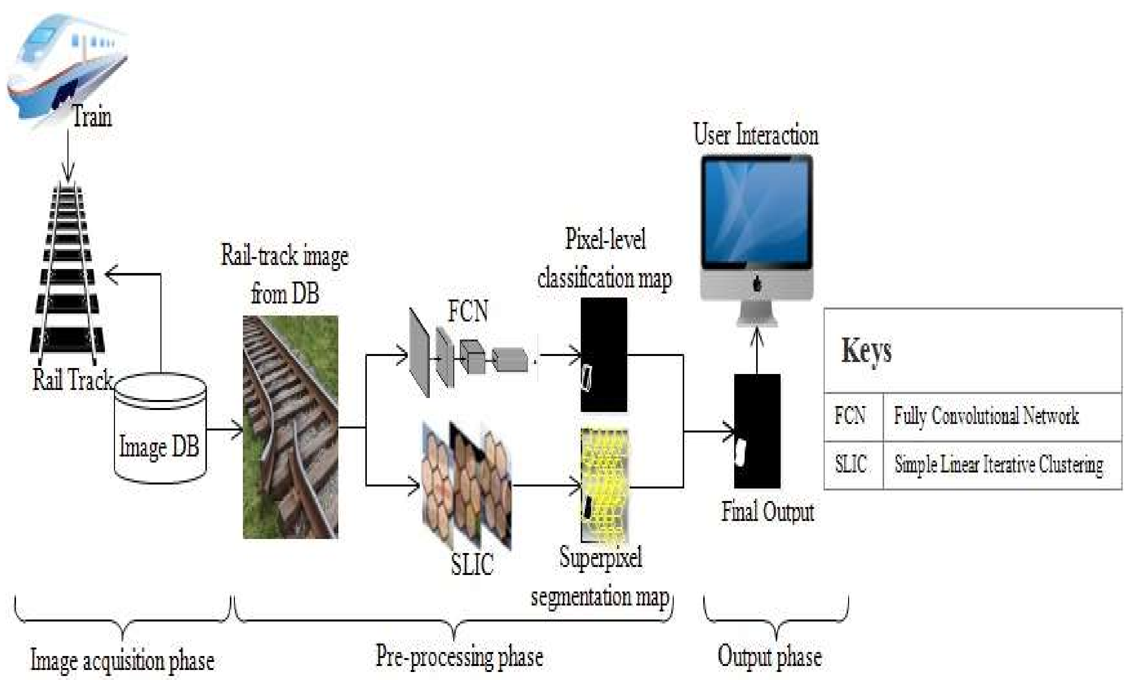

Figure 4: A Railway Track Breakage Detection Architecture using Improved Convolutional Neural Network

3.1 The Detected Procedure

(i) The Image Acquisition Phase
Image quality has a direct impact on the accuracy of inspection; hence, the images are gotten from a GPS- based high-speed line-scan camera which is capable of acquiring a maximum line rate of 56,000 lines per seconds with the resolution of each line being 2048 pixels. The images are fed into the image database which serves as an input to the system, and the GPS keeps the record of the rail area from the detected image by tagging each image, thus saving time for subsequent processing.

The camera will be augmented by adding LED light sources which will be installed under a train carriage to mainly achieve the elimination of external stray light or imbalanced lightning. It will be equipped with automatic variable rate filter attenuation system. A PC-Camlink frame grabber connects the camera and an onboard computer, and it is responsible for transmission of the images. Furthermore, the camera is preferred over other types of a camera because;

(i) Due to the speed of the train which the camera is mounted, images need to be captured fast, and they are embedded with high shutter speed.
(ii) They have a higher signal-noise ratio which will help reduce the noise on images thereby giving images with high resolutions.
(iii) Redundant images can be eliminated as there is no overlap between successive frames of imagery.

(ii) The Processing Phase

The railway track images are selected from the database and sent to the improved Convolutional Network for semantic and superpixel segmentation.

- Fully Convolutional Network (FCN) Model

Due to no small amount of image data, we use the FCN model to extract and recognise image features efficiently. We also take advantage of the FCN to skip elaborate procedures of feature extraction. The Fully Convolutional Network (FCN) Model will be adopted for crack detection and segmentation. FCN learns a mapping from pixels to pixels, without extracting the region proposals and does not depend on the size of the input image. The FCN network pipeline is an extension of classical Convolutional Neural Network (CNN). The main idea is to make the classical CNN take as input arbitrary-sized images.

As FCNs are capable of learning image features automatically, the raw images are fed directly into the FCN model without further pre-processing. Below are the critical features of FCN architecture:

1. The existing datasets are not large enough to train the FCN model from scratch. Hence, this research work will fine-tune previously trained models such as Visual Geometric Group (VGG-16) through transfer learning.
2. The fully connected layers of VGG16 is converted to fully convolutional layers, using 1×1 convolution which produces a class presence heat map in low resolution.
3. The upsampling of these low-resolution semantic feature maps is done using transposed convolutions (initialised with bilinear interpolation filters).
4. At each stage, the upsampling process is further refined by adding features from coarser but higher resolution feature maps from the lower layer in VGG16.
5. Skip connection is introduced after each convolution block to enable the subsequent block to extract more general, class-salient features from the previously pooled features.

The multinomial logistic loss with a multi class output $y^i \in \{1, \dots, K\}$ for K classes is used to tune and optimize the filters of the convolutional layers where each filter consists of adaptable weights. The training set $\{(x^{(1)}, y^{(1)}), \dots (x^{(m)}, y^{(m)})\}$ with m samples which contains input x and desired output y is given. h_θ describes the class probability:

$$h_\theta(x) = \begin{pmatrix} P(y=1|x;\theta) \\ P(y=2|x;\theta) \\ \vdots \\ P(y=K|x;\theta) \end{pmatrix} = \frac{1}{\sum_{j=1}^{K} \exp(\theta^{(j)T}x)} \begin{pmatrix} \exp(\theta^{(1)T}x) \\ \exp(\theta^{(2)T}x) \\ \vdots \\ \exp(\theta^{(K)T}x) \end{pmatrix}; \qquad (1)$$

Where θ represents the parameters of the model.

$$J(\theta) = -\left(\sum_{i=1}^{m} \sum_{k=1}^{K} I\{y^{(i)} = k\} logP(\, y^{(i)} = k|x^{(i)};\theta\right); \qquad (2)$$

Where I {.} is the “indicator function”, so that

$$I\begin{cases} a\ true\ statement = 1 \\ a\ false\ statement = 0 \end{cases}; \qquad (3)$$

$P(y^{(i)} = k|x^{(i)};\theta)$ represents the probability of a specific class:

$$P(y^{(i)} = k|x^{(i)};\theta) = \frac{\exp(\theta^{(k)T}x^{(i)}}{\sum_{j=1}^{K} \exp(\theta^{(j)T}x^{(i)}}; \qquad (4)$$

The multinominal loss is propagated back through all layers to adapt the FCN model.

3.2 Simple Linear Iterative Clustering (SLIC) Model

The SLIC is an algorithm used to segment superpixels of an image into visually homogeneous regions based on a spatially localized version of k-means clustering. SLIC is efficient and produces regions which adhere superpixel algorithms group pixels into perceptually meaningful atomic regions which can be used to replace the rigid structure of the pixel grid well to edges in the image. A superpixel is a group of pixels which have similar characteristics. It is a colour based segmentation that is useful for image segmentation, it reduces the number of entities to be labeled semantically and enable feature computation on bigger, more meaningful regions. The superpixel should adhere to the following properties;

- It should adhere well to image boundaries.
- When used to reduce computational complexity as a preprocessing step, it should be fast to compute, memory efficient, and simple to use.
- When used for segmentation purposes, it should both increase the speed and improve the quality of the results.

The SLIC algorithm is satisfactory in all regards to these properties, it has been used both in the context of classical image analysis algorithms and in the context of deep learning. It takes two parameters: regionsize: the nominal size of the regions (superpixels) and the regularizer: strength of the spatial regularization.

3.3 Superpixel Semantic Annotation

The semantic segmentation algorithm combines FCN and SLIC. The FCN model extracts the overall shade of objects perfectly but fails to focus on the detailed structures of objects to make the FCN model give a more accurate and detailed description of the target edge. The superpixel segmentation map of an image obtained using SLIC is combined with pixel-level classification map produced by the FCN. This combination is therefore expected to give a revised semantic segmentation of the image as we take the advantage of the model to skip elaborate procedures of feature extraction.

Algorithm 1: A Simple Linear Iterative Clustering Superpixel Segmentation Algorithm
Input: *k, the desired number of approximately equally sized superpixels*
Output: *E ≤ threshold. (E= residual error E between the new cluster center locations and previous cluster center locations)*

Process:

//Initialization
Step 1: Initialize clusters I_K= $[n_k,\ a_k, b_k, c_k, d_k]^T$ by sampling pixels at regular grid steps R.
Step 2: Move cluster centres to the lowest gradient position in a 3 × 3 neighborhood.
Step 3: Set label l(p) = -1 for each pixel p
Step 4: Set distance d(p) = ∞ for each pixel p
Step 5: Repeat
//Assignment
*Step 6: **for** each cluster centre I_K **do***
*Step 7: **for** each pixel p in a 2R × 2R region around I_K **do***
Step 8: Compute the distance D between $I_K\ and\ p$.
*Step 9: **if** D < d(p) **then***
Step 10: set d(p) = D
Step 11: set l(p) = k
*Step 12: **end if***
*Step 13: **end for***
*Step 14: **end for***
//Update
Step 15: Compute new cluster centres.
Step 16: Compute residual error E.

Algorithm 2: Superpixel Semantic Algorithm

Input: $S_p = \{Sp_1, Sp_2, \dots, Sp_{k,} \dots Sp_k\}$
Output: Superpixel semantic annotation result

Process:
Step 1: Obtain an FCN pixel-level classification map
Step 2: Obtain an SLIC superpixel segmentation map.
the collection of superpixel S_p= $\{Sp_1, Sp_2, \dots, Sp_{k,} \dots Sp_k\}$,
the number of semantic categories in superpixel Sp_k *is Z,*
the proportion of pixels of the semantic category c (0,1,...,20),
all the pixels in the superpixels Sp_k *is* Y_t,
Generate superpixel semantic annotation using this four criteria
Loop: ***For*** *k = 1: K*
If *there is no image edge in superpixel* Sp_k *and Z = 1* ***then***
Step 3: Label the superpixel with FCN semantic result
End
If *there is no image edge for superpixel* Sp_k *and Z > 1* ***then***
Step 4: Use t of the largest Y_t *to label the superpixel*
End
If *there is image edge in superpixel* Sp_k *and Z = 1* ***then***
Step 5: Label the superpixel with FCN semantic result
End
If *there is image edge for superpixel* Sp_k *and Z > 1* ***then***
If Y_t*> 80% in superpixel* Sp_k ***then***
Step 6: Use t of the largest Y_t *to label the superpixel*
Else
Step 7: Maintain the FCN semantic segmentation result
End

(iii) Output Phase

The semantic segmentation result obtained for each image indicates whether it has a crack or not. Whenever a crack is being detected in any image, the railway maintenance team would be informed through a Graphical User Interface (GUI). The GUI specifies the location of the crack through the information provided by the Global Positioning System (GPS)-based camera used to capture the images. This will make it easier and faster for the maintenance team to identify exactly where cracks are located when they go to the field for repairs.

4. CONCLUSION

Railway track breakage is an essential factor in railway operation because it guides trains and are subjected to severe contact stresses, each train wheel passage reshapes the railway track due to wear, extreme levels of stress concentration and also induces surface and subsurface fatigue cracks. This study presents an improved method to Railway track breakage detection using Convolutional Neural Network. Several conventional methods former used for Railway track breakage system were discussed. The improved CNN is referred to as Fully Convolutional Network (FCN), and it is combined with a superpixel algorithm called Simple Linear Iterative Clustering (SLIC), which adapts *k*-means clustering approach to generate superpixels efficiently. This work helps is reducing the accident rate caused through the railway track breakage by detecting the breakages on the track.

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