

A Cognitive Rail Track Breakage Detection System Using Artificial Neural Network

Olufunke Rebecca Vincent^{1*}, Yetunde Ebunoluwa Babalola², Adesina Simon Sodiya³, Olusola John Adeniran⁴
¹⁻⁴ *Federal University of Agriculture, Abeokuta, Nigeria*

Abstract – Rail track breakages represent broken structures consisting of rail track on the railroad. The traditional methods for detecting this problem have proven unproductive. The safe operation of rail transportation needs to be frequently monitored because of the level of trust people have in it and to ensure adequate maintenance strategy and protection of human lives and properties. This paper presents an automatic deep learning method using an improved fully Convolutional Neural Network (FCN) model based on U-Net architecture to detect and segment cracks on rail track images. An approach to evaluating the extent of damage on rail tracks is also proposed to aid efficient rail track maintenance. The model performance is evaluated using precision, recall, F1-Score, and Mean Intersection over Union (MIoU). The results obtained from the extensive analysis show U-Net capability to extract meaningful features for accurate crack detection and segmentation.

Keywords – Deep learning, fully convolutional neural network, rail track breakage, U-Net architecture.

I. INTRODUCTION

The developing economies have resulted in an increasing need for railway utilisation because of its advantages over other means of transportation. The benefits of rail transportation include cost efficiency. It is least affected by weather turbulences; traffic congestion is reduced, and it can also serve as an alternative for road transportation. Therefore, various efforts are being made to revive the system currently at a depleted state. Transportation is a vital part of our daily activities; hence, the need for railway transportation cannot be overemphasized.

Rail track breakage is an essential factor in railway operation. Rails guide trains and are subjected to severe contact stresses, and each train wheel passage reshapes the rail tracks due to wear, extreme levels of stress concentration, and induces surface and subsurface fatigue cracks [1]. Recent statistics reveal that approximately 90 % of railway accidents are due to cracks on rails [2]–[4]. These cracks pose severe threats to trains; hence, it is essential to effectively detect the breakage(s) for adequate maintenance and safety purposes. Manual detection of breakage on track is cumbersome and not entirely effective, owing to much time consumption and skilled technicians' requirement [5]. Also, manual inspection is not

possible in some regions, like in deep coal mines, mountain regions, and dense, thick forest regions.

Various advanced methods utilising different sensory technologies have been used for breakage detection. The track circuit is 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 [6]. Track circuit was initially developed for train detection. Still, its ability to detect full traverse breaks in the tracks that would interrupt the current to the receiver makes it suitable for rail track breakage detection. Sensing approaches other than track circuits adopted for broken rail detection are the Non-Destructive Testing (NDT) approaches, such as magnetic field methods, radiography, ultrasound, fibre optics, and wavelets from an accelerometer, strain gauges, and acoustics [7], [8].

Most passengers opt for railway transportation because of the level of trust in their safety compared to other means of transport. Due to the long-term impact of the rail track and train weight, a variety of defects will be formed on the track [9]. Rail accidents are escalating daily due to a lack of adequate maintenance of the tracks. Recent studies have, however, reported accidents in some countries due to derailments, and this should not be overlooked because of the current growth of the railway system. Broken rails are the leading cause of significant derailment accidents [10].

Though various approaches have been used in detecting breakages on the rail track, these approaches need significant improvements. Derailments usually lead to catastrophic consequences like the loss of lives and property, which will significantly affect the economy and the environment [11].

Detecting rail track breakage through manual and semi-automatic inspection is time-consuming, labour-intensive, and wastes a lot of time and resources. At times, complex infrastructure is placed along the railway track, which can hinder train movement at that particular time [12], [13]. Most existing sensory technologies cover a limited distance of inspection at a time [14], [15]. In contrast, the existing computer vision techniques require manual feature extraction from images and cannot effectively handle images with poor quality, low resolution, and noise [12], [16]–[19].

* Corresponding author. E-mail: vincentor@funaab.edu.ng

This study develops a deep learning approach based on an automatic railway inspection model to detect any breakage on a rail track and estimate the severity of damage done. The study uses an improved Fully Convolutional Neural Network for the track breakage detection because recently many deep learning methods have allowed for significant improvement based on artificial intelligence methods [20]. Also, a deep learning model automatically extracts features and classifies the sequences [21]. The rest of this paper is organised as follows. Section 2 presents the literature review, while Section 3 presents the proposed breakage detection model. Section 4 describes the experiments performed and gives the results and evaluation, and Section 5 presents conclusions.

II. LITERATURE REVIEW

The detection of broken rail tracks has been widely studied during the past decade. The future of rail track inspection lies in developing automated rather than manual methods. A critical review of related work that has been used in detecting rail track breakage has shown certain drawbacks.

Table I shows a summary of the existing methods and their weaknesses. Conventional approaches for rail track inspection are mostly semi-automatic, which is time-consuming and labour-intensive. There are also regions where the assessments are not possible. At times, complex infrastructure is placed along the rail track, which can hinder train movement at that particular time [12], [13]. Most existing sensory technologies cover a limited distance of inspection at a time [14], [15]. Existing computer vision techniques have challenges in feature extraction on images obtained from tracks and have poor quality and low resolution [12].

III. THE PROPOSED BREAKAGE DETECTION SYSTEM

This study adopts an improved fully Convolutional Neural Network (FCN) for visual inspection of rail tracks. A *U-Net* model used for image segmentation proposed by [31] has been trained and evaluated with a dataset of rail track images. The dataset and the *U-Net* model are further discussed in the following subsections.

TABLE I
SUMMARY OF RELATED WORK

References	Method	Issues discussed	Strength(s)	Weakness(es)
Singh <i>et al.</i> (2006) [25]	Computer Vision-based inspection	Finding missing clips that have been recently replaced in place of damaged clips	High performance, large area coverage	Clips get broken due to strain
Shah (2010) [26]	Computer Vision-based inspection	Gage detection	Logs the location of the defect. The history of inspection is maintained	Lengthy computation time. Not real-time
Francois (2012) [14]	Guided wave inspection	If wave signals are not received at the receiving station at the required time, an alarm is triggered	Propagates reasonably well in steel rails	Limited distance. Disturbed by the environment
Faghih-Roohi <i>et al.</i> (2016) [23]	Computer Vision-based inspection	Solution to the analysis of image data for the detection of rail surface defects was proposed	Saves time and expenses. Extraction of suitable features	Limited deep networks
Er.Nisthul <i>et al.</i> (2017) [5]	Infrared (IR) Sensor	Automatic railway detection system by integrating an infrared red (IR) and GSM technology	Addition of solar panels to help conserve power. Automatic alert system	Low signal transmission. Vehicle is operated in battery power
Espinosa <i>et al.</i> (2018) [22]	Principal Component Analysis (PCA) technique	Technique designed to identify rail breakages in double-track railway lines based on the analysis of currents	Shorter time for analysing tracks and approximately detecting breakage location	Cannot detect more than a breakage. It is affected by high moisture
Patil <i>et al.</i> (2018) [4]	Ultrasonic-based inspection	Crack detection of distance measurement and encoder and decoder is used to transfer the data through light for communication purposes	Light encoder and decoder. Motor driver for a driverless system	Limited run time due to power source. Neither GSM nor GPS based
Shang <i>et al.</i> (2018) [24]	Computer Vision-based inspection	Novel two-stage pipeline method for rail defect detection by localising and classifying the rail image	Efficient and safer. Strong robustness in detection precision	No guarantee for real-time work
Lang (2019) [27]	Track circuit-based systems	Plurality of sensors installed and the sensors have their respective signal acquisition	Alerting system. Adapted to other railways	Cannot detect slight cracks. Not real-time
Jhadhav <i>et al.</i> (2019) [28]	Ultrasonic-based inspection	Intelligent train tracking and management system. The PIC controller is used to stop the motor driver when the crack is detected	Automatic alerting. Quick response	Semi-automatic Delay of the train
Xing <i>et al.</i> (2019) [29]	Single-mode extraction algorithm (SMEA)	The detection mode, the frequency, and the excitation method were selected through the dispersion curves and modal identification	Precise determination of the rail defect	Limited distance covered by the model per time
Minhas (2020) [30]	Computer Vision-based inspection	Convolutional auto-encoder architecture for anomaly detection that is trained only on the defect-free (normal) instances	Network learned to detect the actual shape of the defects. Automatic extraction	Datasets with uneven illumination were ignored. Results contained noise

A. Dataset

This study builds upon the Type-I Rail Surface Discrete Defects (RSDDs) dataset consisting of 65 samples of rail track images collected by [11]. The original images with dimensions ranging from 160×1000 pixels to 160×1282 pixels have been cropped into smaller patches with 256×256 pixels. Cropping has been done to ensure that all images have a uniform size and aspect ratio. The convolution-based segmentation model adopted in this study requires a square shape input image. After cropping, 118 images have been obtained for the Type-I RSDD dataset.

Furthermore, the datasets have been normalized to ensure that the pixels that make up each input image have a similar data distribution. The significant benefit is a faster convergence when training the segmentation model. Normalisation has been done by subtracting each pixel mean and then dividing the result by the standard deviation. The normalised images have been scaled in the range to have positive pixel values in the range $[0, 1]$.

B. U-Net Model

U-Net is based on the fully connected Convolutional Network. It extracts features of different levels through convolution sequence, Rectified Linear Unit (ReLU) activation function, and max-pooling operation to capture each pixel context. As illustrated in Fig. 1, the U-Net model uses a downsampling (encoding) network to extract meaningful features. In contrast, the features extracted are used to build up a classification map through an upsampling (decoding) network to segmentation of the pixels. The characteristic of U-Net is that the encoding network and the decoding network are mutually mapped.

The downsampling phase of the U-Net uses residual layers, *ResNet*. The *ResNet* architecture is adopted for this study because deep networks are hard to train due to their vanishing gradient problem. As the network goes deeper, its performance starts degrading. The *ResNet* deals with this problem by utilising skip connections to ignore some layers with residual block help. The residual partnerships enable the network to preserve what it has learned by having an identity mapping weight function where the input is equal.

The training of the U-Net model involves forward computation and backward propagation. The forward propagation includes the convolution operations for downsampling, deconvolution operations for upsampling, and the loss function estimation. The multinomial logistic loss with a multi-class output $y^i \in \{1, \dots, K\}$ for K classes has been used to tune and optimise the filters of the convolutional layers where each filter consists of adaptable weights. The multinomial loss is propagated back through all layers to adapt the U-Net model with the Adaptive Moment Estimation (ADAM).

The ADAM algorithm is a first-order gradient-based optimisation of stochastic objective functions, based on adaptive estimates of lower-order moments [32]. It has been used because it is straightforward to implement,

computationally efficient and requires low memory, and is well suited for large problems in terms of data.

IV. EXPERIMENTS AND RESULTS

The results obtained from all the experiments carried out are presented in the following subsections.

A. U-Net Training

The U-Net segmentation model training comes with the challenge of choosing the right values for its hyperparameters. To tackle this problem, eight different experiments have been carried out with varying values for three hyperparameters: learning rate, weight loss, decay, and batch size. Eight different models have been obtained from the experiments.

80 % of the dataset obtained has been used to train each model for 100 epochs. For each epoch, the remaining 20 % has been used to estimate the validation loss.

B. Training Results

Figure 1a shows the training and validation losses for model 1; this experiment has been carried out for the eight models. Figures 1c and 1d show the plot of validation losses of all the models against the number of epochs. It can be observed from the figures that a higher learning rate and weight decay loss have led to model instability during training; as the values become lower, the model becomes more stable. However, having shallow values has slowed down the learning process. It can also be observed that models 5 and 6 have the best loss values from both figures (1c and 1d). As seen in Fig. 1b, model 6 has the overall best performance. The choice of hyperparameter values and the validation loss for each model are shown in Table II.

C. Performance Evaluation

The trained U-Net model performance has been evaluated using the validation set, which is 20 % of the whole dataset. The following metrics have been used: Precision, Recall, *F1*-Score, and Mean Intersection over Union (mIoU). These metrics are beneficial when comparisons are to be made with non-machine learning models.

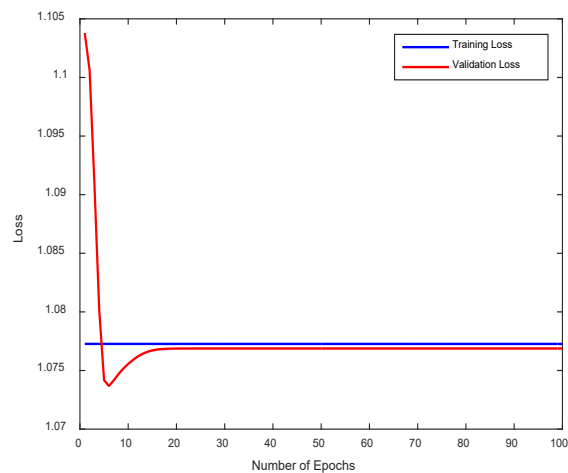


Fig. 1a. Training and validation losses for model 1.

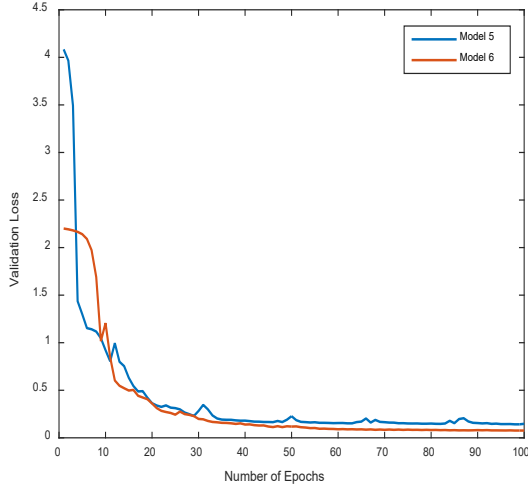


Fig. 1b. Validation losses for models 5 and 6.

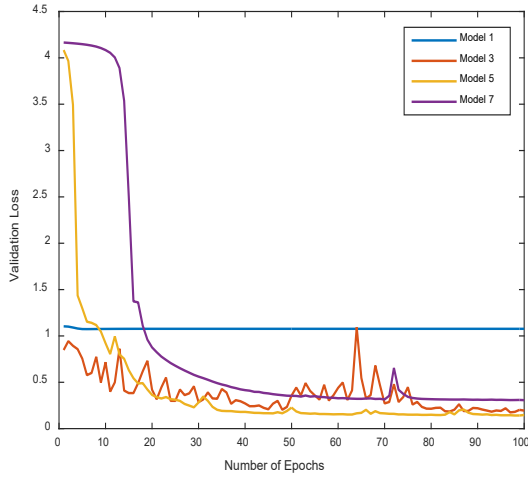


Fig. 1c. Validation losses for models 1, 3, 5 and 7.

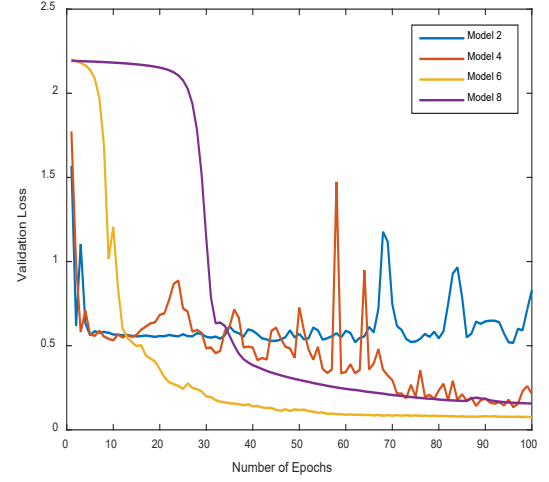


Fig. 1d. Validation losses for models 2, 4, 6 and 8.

(i) Precision is the ratio of correctly predicted positive observations to the total predicted positive observations:

$$\text{Precision} = \frac{TP}{TP+FP} . \quad (1)$$

(ii) Recall measures the ratio of correctly predicted positive observations to observations in the actual class:

$$\text{Recall} = \frac{TP}{TP+FN} . \quad (2)$$

(iii) *F1* score is an overall measure of a model accuracy that combines the weighted average of precision and recall:

$$F1\text{-Score} = 2 \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} . \quad (3)$$

(iv) Intersection over Union (IoU) is used to measure if the image target is detected:

$$\text{IoU} = \frac{p_{ii}}{\sum_{j=0}^k p_{ij} + \sum_{j=0}^k p_{ji} - p_{ii}} , \quad (4)$$

where p_{ii} is the number of true positives, p_{ij} is the number of false positives, p_{ji} is the number of i for each image.

TABLE II
COMBINATION OF HYPERPARAMETER VALUES

Model	Batch size	Learning rate	Weight-decay loss	Minimum validation loss
Model 1	16	0.01	0.01	1.073 679
Model 2	32	0.01	0.01	0.516 874
Model 3	16	0.001	0.001	0.175 315
Model 4	32	0.001	0.001	0.141 778
Model 5	16	0.0001	0.0001	0.135 074
Model 6	32	0.0001	0.0001	0.076 191
Model 7	16	0.00001	0.00001	0.307 249
Model 8	32	0.00001	0.00001	0.156 535

TABLE III
PERFORMANCE COMPARISON FOR ALL THE U-NET MODELS

Model	Precision	Recall	F1-Score	mIoU
Model 1	97.80	63.36	68.66	26.66
Model 2	97.66	63.36	68.65	26.64
Model 3	90.66	90.72	89.05	67.54
Model 4	83.05	87.93	84.47	57.79
Model 5	86.86	92.49	88.11	66.70
Model 6	89.48	93.49	90.06	70.19
Model 7	74.80	69.16	68.11	28.35
Model 8	73.66	70.03	65.26	32.06

(v) Mean Intersection over Union (mIoU) computes the average value of IoU for all the images used for evaluation.

Table III shows the result of the performance evaluation carried out on the models. As expected from the previous validation loss results, model 6 has the best score for all the metrics.

D. Extent of Damage Evaluation

Aside from detecting cracks, it is also essential to estimate the severity of damage on the rail tracks. This study proposes a novel approach to evaluating the extent of the damage:

$$\text{Extent} = \frac{\text{number of pixels with crack}}{\text{total number of pixels}} \times 100. \quad (5)$$

In this study, it has been assumed that the rail tracks can fall under one of the three states at any point in time. The three states are:

(i) No damage: this state is predicted when less than 1 % of the rail track image pixels are classified as being cracked.

(ii) Slightly damaged: this state is predicted when the percentage of pixels classified as cracked is between 0 % and 5 %.

(iii) Damaged: this state is predicted when the percentage of pixels classified as cracked is between 5 % and 50 %.

(iii) Severely damaged: this state is predicted when more than 50 % of the rail track image pixels are classified as being cracked. Fig. 2a shows four samples of original rail track images before damage evaluation, while Fig. 2b shows the segmented rail track images with the extent of damage evaluation. The result will assist the maintenance team in decision making.

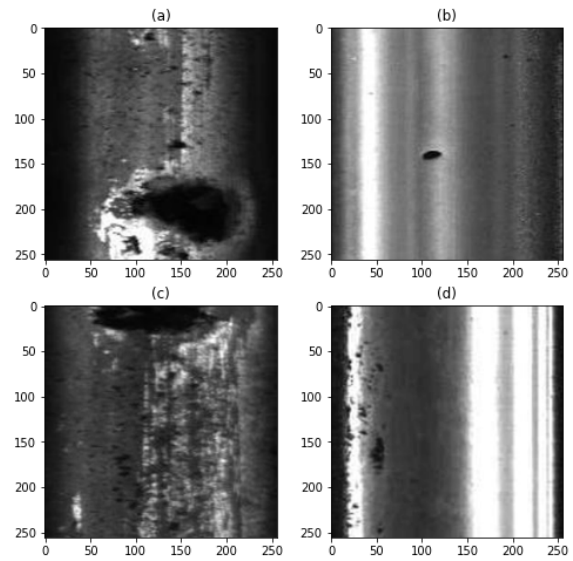


Fig. 2a. Original rail track images.

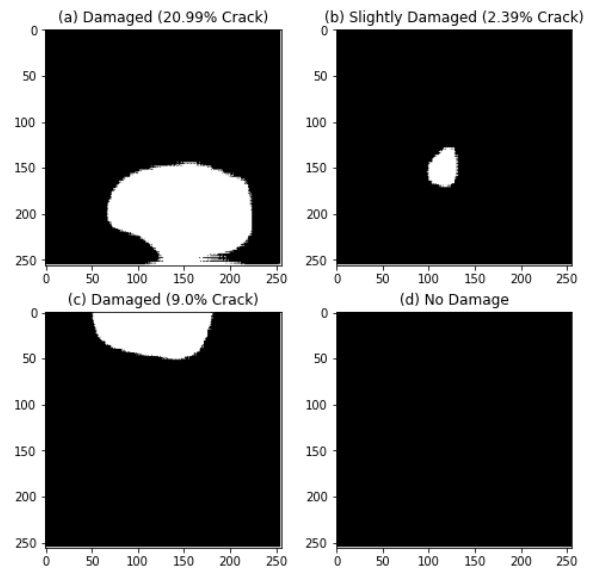


Fig. 2b. Segmented images with the extent of damage evaluation.

V. CONCLUSION

Manual detection of cracks on the rail track is complicated, time-consuming, and always prone to error due to human inconsistency. In this paper, an approach that uses a deep learning model for automatic rail-track inspection has been presented. The model uses *U-Net*, a network based on an extended and modified fully convolutional network. The results obtained from the extensive analysis show *U-Net* capability to extract meaningful features needed for accurate crack detection and segmentation.

The significant contribution of this study is the use of a limited dataset for image segmentation tasks using deep learning and resulting in a good model. Another contribution is also reflected in the automatic detection of the severity of damage done on the track and a framework that balances maximum accuracy with less network complexity. The developed method is designed for rail track breakage detection. It can also be extended to other fault inspection systems like pipeline breakage in the oil and gas industry, fault detection in industrial products, such as fabrics, and fault detection in 3D-seismic volumes for the earth scientists.

In future, the study would be extended in the use of geotagged images to determine the exact geographical location of the cracks. Also, the results of this study indicate that performance depends on hyperparameters. There are several hyperparameters, but we had to choose three random ones, so an efficient means of hyperparameter selection should have been experimented with.

REFERENCES

- [1] W. L. Bayissa and M. Dhanasekar, "High-Speed Detection of Broken Rails, Rail Cracks, and Surface Faults," CRC for Rail Innovation, Brisbane, Australia, 2011.
- [2] C. K. Viswakarma, A. Jain, and L. S. Nayak, "An Intelligent Design to Detect Broken Track for Indian Railway," Excel India Publishers, New Delhi, 2014.
- [3] N. Bhargav, A. Gupta, M. Khirwar, S. Yadav, and V. Sahu, "Automatic Fault Detection of Railway Track System Based on PLC," *International Journal of Recent Research Aspects*, vol. 3, no. 1, pp. 91–94, Mar. 2016.
- [4] B. R. Krishna, D. Seshendra, G. Raja, T. Sudharshan, and K. Srikanth, "Railway Track Fault Detection System by Using IR Sensors and Bluetooth Technology," *Asian Journal of Applied Science and Technology*, vol. 1, no. 6, pp. 82–84, Jul. 2017.
- [5] A. Lakra, V. V. Kumar, V. Dudhani, H. Kabra, and K. M. Vanitha, "Automatic Crack Detection System in Railway Tracks," *Research and Applications: Embedded System*, vol. 1, no. 2, 3, pp. 24–27, 2018.
- [6] X. Liu, M. R. Saat, and C. P. L. Barkan, "Integrated Risk Reduction Framework to Improve Railway Hazardous Materials Transportation Safety," *Journal of Hazardous Materials*, vol. 260, pp. 131–140, Sep. 2013. <https://doi.org/10.1016/j.jhazmat.2013.04.052>
- [7] K. Schwartz, "Development of an Acoustic Broken Rail Detection System," Final Report for High-Speed Rail IDEA Project 42, 2004.
- [8] Z. Jin, Q. Han, K. Zhang, and Y. Zhang, "An Intelligent Fault Diagnosis Method of Rolling Bearings Based on Welch Power Spectrum Transformation with Radial Basis Function Neural Network," *Journal of Vibration and Control*, vol. 26, no. 9–10, pp. 629–642, May 2020. <https://doi.org/10.1177/2F1077546319889859>
- [9] Y. Min, B. Xiao, J. Dang, B. Yue, and T. Cheng, "Real-Time Detection System for Rail Surface Defects Based on Machine Vision," *EURASIP Journal on Image and Video Processing*, vol. 2018, article number 3, Jan. 2018. <https://doi.org/10.1186/s13640-017-0241-y>
- [10] F. Espinosa, A. Hernandez, M. Mazo, J. Urena, M. C. Perez, J. A. Jimenez, I. Fernandez, J. C. Garcia, and J. J. Garcia, "Detector of Electrical Discontinuity of Rails in Double-Track Railway Lines: Electronic System and Measurement Methodology," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 4, pp. 743–755, Apr. 2017. <https://doi.org/10.1109/TITS.2016.2586538>
- [11] J. Gan, Q. Li, J. Wang, and H. Yu, "A Hierarchical Extractor-Based Visual Rail Surface Inspection System," *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7935–7944, Dec. 2017. <https://doi.org/10.1109/JSEN.2017.2761858>
- [12] C. Tastimur, H. Yetis, M. Karaköse, and E. Akin, "Rail Defect Detection and Classification with Real-Time Image Processing Technique," *International Journal of Computer Science and Software Engineering*, vol. 5, no. 12, pp. 283–290, Dec. 2016.
- [13] D. Nagdevte, M. Zakir, A. Muley, and A. H. Shelar, "Detection of Crack in Rail Road Using Ultrasonic and PIR Sensor," *International Research Journal of Engineering and Technology*, vol. 4, no. 1, pp. 1762–1764, Jan. 2017.
- [14] S. Alahakoon, Y. Q. Sun, M. Spiriyagin, and C. Cole, "Rail Flaw Detection Technologies for Safer, Reliable Transportation: A Review," *Journal of Dynamic Systems, Measurement, and Control*, vol. 140, no. 2, article number 020801, Feb. 2018. <https://doi.org/10.1115/1.4037295>
- [15] F. Espinosa, A. Hernández, M. Mazo, J. Ureña, M. C. Pérez, J. A. Jiménez, I. Fernández, J. C. García, and J. J. García, "Detector of Electrical Discontinuity in Double-Track Railway Lines: Electronic System and Measurement Methodology," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 4, pp. 743–755, Apr. 2017. <https://doi.org/10.1109/TITS.2016.2586538>
- [16] C. Taştımur, M. Karaköse, and E. Akin, "A Vision-Based Condition Monitoring Approach for Rail Switch and Level Crossing Using Hierarchical SVM in Railways," *International Journal of Applied Mathematics, Electronics and Computers*, vol. 4, pp. 319–325, Dec. 2016. <https://doi.org/10.18100/ijamec.270634>
- [17] L. Chen, Y. Liang, and K. Wang, "Inspection of Rail Surface Defect Based on Machine Vision System," in *2nd International Conference on Information Science and Engineering*, Dec. 2010, pp. 3793–3796. <https://doi.org/10.1109/ICISE.2010.5691348>
- [18] V. R. Vijaykumar and S. Sangamithirai, "Rail Defect Detection Using Gabor Filters with Texture Analysis," in *3rd International Conference on Signal Processing, Communication and Networking*, Mar. 2015. <https://doi.org/10.1109/ICSCN.2015.7219838>
- [19] H. Trinh, N. Haas, Y. Li, C. Otto, and S. Pankanti, "Enhanced Rail Component Detection and Consolidation for Rail Track Inspection," in *2012 IEEE Workshop on the Applications of Computer Vision*, Jan. 2012, pp. 289–295. <https://doi.org/10.1109/WACV.2012.6163021>
- [20] P. Duda, M. Jaworski, A. Cader, and L. Wang, "On Training Deep Neural Networks Using a Streaming Approach," *Journal of Artificial Intelligence and Soft Computing Research*, vol. 10, no. 1, pp. 15–26, Jan. 2020. <https://doi.org/10.2478/jaiscr-2020-0002>
- [21] M. H. P. da Cruz, P. T. M. Saito, A. R. Paschoal, and P. H. Bugatti, "Classification of Transposable Elements by Convolutional Neural Networks," in *Artificial Intelligence and Soft Computing. ICAISC 2019*, L. Rutkowski, R. Scherer, M. Korytkowski, W. Pedrycz, R. Tadeusiewicz, J. Zurada J., Eds. Lecture Notes in Computer Science. Springer, Cham, 2019, vol. 11509, pp. 157–168. https://doi.org/10.1007/978-3-030-20915-5_15
- [22] F. Espinosa, J. J. García, A. Hernández, M. Mazo, J. Ureña, J. A. Jiménez, I. Fernández, C. Pérez, and J. C. García, "Advanced Monitoring of Rail Breakage in Double-Track Railway Lines by Means of PCA Techniques," *Applied Soft Computing*, vol. 63, pp. 1–13, Feb. 2018. <https://doi.org/10.1016/j.asoc.2017.11.009>
- [23] H. Yuan, H. Chen, S. Liu, J. Lin, and X. Luo, "A Deep Convolutional Neural Network for Detection of Rail Surface Defect," in *2019 IEEE Vehicle Power and Propulsion Conference*, Oct. 2019. <https://doi.org/10.1109/VPPC46532.2019.8952236>
- [24] A. K. Singh, A. Swarup, A. Agarwal, and D. Singh, "Vision Based Rail Track Extraction and Monitoring through Drone Imagery," *ICT Express*, vol. 5, no. 4, pp. 250–255, Dec. 2019. <https://doi.org/10.1016/j.icte.2017.11.010>
- [25] L. Shang, Q. Yang, J. Wang, S. Li, and W. Lei, "Detection of Rail Surface Defects Based on CNN Image Recognition and Classification," in *20th International Conference on Advanced Communication Technology*, Mar. 2018, pp. 45–51. <https://doi.org/10.23919/ICACT.2018.8323642>

- [26] E. Resendiz, J. M. Hart, and N. Ahuja, "Automated Visual Inspection of Railroad Tracks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 751–760, Jun. 2013. <https://doi.org/10.1109/TITS.2012.2236555>
- [27] A. Malejafarian, E. O'Brien, P. Quirke, and C. Bowe, "Railway Track Monitoring Using Train Measurements: An Experimental Case Study," *Applied Sciences*, vol. 9, no. 22, article number 4859, Nov. 2019. <https://doi.org/10.3390/app9224859>
- [28] M. Pathak, S. Alahakoon, M. Spiragin, and C. Cole, "Rail Foot Flaw Detection Based on a Laser-Induced Ultrasonic Guided Wave Method," *Measurement*, vol. 148, article number 106922, Dec. 2019. <https://doi.org/10.1016/j.measurement.2019.106922>
- [29] B. Xing, Z. Yu, X. Xu, L. Zhu, and H. Shi, "Research on a Rail Defect Location Method Based on a Single-Mode Extraction Algorithm," *Applied Sciences*, vol. 9, no. 6, article number 1107, 2019. <https://doi.org/10.3390/app9061107>
- [30] X. Chen, Z. Wang, Z. Zhang, L. Jia, and Y. Qin, "A Semi-Supervised Approach to Bearing Fault Diagnosis under Variable Conditions Towards Imbalanced Unlabeled Data," *Sensors*, vol. 18, no. 7, article number 2097, Jul. 2018. <https://doi.org/10.3390/s18072097>
- [31] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, N. Navab, J. Hornegger, W. Wells, A. Frangi, Eds. Lecture Notes in Computer Science. Springer, Cham, 2015, vol. 9351, pp. 234–241. https://doi.org/10.1007/978-3-319-24574-4_28
- [32] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," arXiv preprint arXiv:1412.6980, 2014. [Online]. Available: <https://arxiv.org/abs/1412.6980>

Olufunke Rebecca Vincent is an Associate Professor of Computer Science. She obtained a PhD degree in Computer Science in 2010 after completing her fieldwork with the Computational Intelligence Group, Clausthal University of Technology, Germany. She did a Post-Doctoral Fellowship in Germany in 2014. She has visited several international academic institutions for training, workshops, conferences, and research and won national and international recognitions. She is a Fellow of Nigeria Computer Society, Computer Professional Registration Council of Nigeria and a member of IEEE. Her research areas include Computational and Artificial Intelligence, Images and Vision, and e-Commerce Security. E-mail: vincentor@funaab.edu.ng

Yetunde Ebunoluwa Babalola is holds a Master degree in Computer Science. She obtained her Bachelor of Science degree in Computer Science at the Federal University of Agriculture, Abeokuta. She has published three conference proceedings and attended four academic conferences. She is a member of the Nigerian Computer Society and the Computer Professional Registration Council of Nigeria.

Adesina Simon Sodiya is a Professor of Computer Science and Information Security, currently in the Department of Computer Science, University of Agriculture, Abeokuta, Ogun state, Nigeria. He completed his PhD in Computer Science in 2004 with a focus on Information Security. He has taught courses in Information Security and other areas of Computer Science at undergraduate and postgraduate levels. Sodiya A. S. is a fellow and President of Nigeria Computer Society.

Olusola John Adeniran is currently a Professor at the Department of Mathematics, Federal University of Agriculture, Abeokuta, Nigeria. His Area of specialization is Non-Associative Algebraic Systems – an area which has a lot of applications in Coding and Cryptology/Cryptography. He has been involved in a lot of in Computer Science. His publications are in both Theory and Applications of Algebraic Systems.