Fuzzy Systems and Soft Computing
ISSN : 1819-4362

COMPARING THE EFFICIENCY OF DAMAGE DETECTION TECHNIQUES IN RAILWAY TRACK USING DEEP LEARNING

Dr. M. Anita Indu Assistant Professor PG Department of Computer Science, Shri Shankarlal Sundarbai Shasun Jain College for Women, Chennai, India m.anitaindu@shasuncollege.edu.in
Ms. M.L. Smitha Research Scholar PG Department of Computer Science, Shri Shankarlal Sundarbai Shasun Jain College for Women, Chennai, India smithasiva16@gmail.com

Abstract—
The detection of defects or cracks in rail track is crucial for railway management in India. The railway department plays a major role for vital preventive measure against train accidents in both summer and rainy seasons. During summer, track cracks can lead to train wheel slippage, while in rainy conditions, corrosion contributes to crack formation. The current detection method involves Echo image display devices or semi-conduction magnetism sensor devices, which are often time-consuming. In contrast, the proposed approach utilizes deep learning models to enhance rail track images, extracting features that a neural network classifier then categorizes as cracked or non-cracked. This innovative methodology employs a soft computing approach for crack detection, trained on diverse crack images from various environments. The system automatically classifies images based on learned patterns, achieving an impressive accuracy rate of 94.9% in detecting and segmenting cracks compared to manually identified and segmented images.

Keywords—
Railway Track Crack Detection, Deep Learning models, CNN, ANN, YOLO

INTRODUCTION

In the contemporary era, the indispensability of a well-functioning railway network resonates globally. Comprising infrastructure, development, and maintenance facets, the railway system entails meticulous planning and construction of rail tracks, along with the establishment of pivotal connections in railway junctions. Expanding the railway network becomes pivotal for reaching remote rural areas, necessitating ongoing development efforts. The meticulous maintenance division is tasked with preserving the integrity of rail tracks, which are susceptible to corrosion from environmental factors like air and floods during the rainy season. These corrosive elements contribute to cracks in the rail tracks, posing a significant risk of train accidents. Thus, ensuring the quality of rail tracks becomes paramount in averting such defects, requiring frequent inspections to mitigate potential accidents.

Qiao Jian-hua (2008) discussed about a fundamental global mode of transportation, rail systems provide unparalleled convenience, yet their safety has become an escalating challenge. The relentless flow of rail traffic results in the gradual wear and tear of tracks, leading to the emergence of fractures, gaps, and other structural damages. These issues pose inherent risks of accidents, underscoring the critical need for accurate detection of surface defects on the rails.

Fig 1 : Destroyed Track

Fig 2 : Partial Dispatched Track
(Source: https://www.mdpi.com/1424-8220/21/18/6221)

The above figure shows that fault may arise from factors such as excessive loads and the impact of both cold and hot weather conditions. Implementing automatic detection systems is essential to address these challenges promptly and maintain the overall health and safety of railway tracks. Over time, various mainstream methods have been developed to address this imperative task.

DEEP LEARNING TECHNIQUES

Over the past decade, researchers have sought to enhance the efficiency of anomaly detection in railway infrastructure by leveraging artificial intelligence (AI) techniques. Initially turning to Machine Learning (ML), a subset of AI focused on algorithms learning from data, methods like Singular Value Decomposition (SVD), Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Histogram Match (HM) have been explored. These algorithms aim to instruct machines in performing tasks based on specific characteristics and examples provided by human users, as demonstrated in an experimental study utilizing various feature extraction techniques [8].

S. Iyer, T. Velmurugan, A. Gandomi, V. Noor, K. Saravanan, and S. Nandakumar (2021)proposed a method for detecting flaws in partially worn or missing fasteners. A model was designed with hierarchical approach which ensembles to enhance large-scale rail defect detection by examining the relationship between rail faults and track geometry anomalies[32]. The model addresses rail surface crack by recognizing their edges, employs a bi-layer data-driven method (BDF). ML architectures like wavelet scattering networks and neural networks are introduced for determining the positioning and size of rail-head defects [30]. A classification approach was established by researchers, employing acceleration data from an inspection vehicle to scrutinize rail surface faults or components. They extend their approach to include a Convolutional Neural Network (CNN) for detecting rail joints or defects, incorporating a discrete wavelet function. Notably, a shift towards Deep Learning (DL) methods is evident, utilizing architectures like ResNet and Fully Convolutional Network (FCN) to improve the performance of classification models[25]. This trend underscores a growing emphasis on employing DL techniques for tasks such as classification, segmentation, and detection, given their ability to gradually extract features at different levels through artificial neural networks with multiple layers.

Efficient, low-power, and portable defect detection is imperative for the effectiveness of rail transport. The YOLO (You Only Look Once) network, renowned for its success in facial recognition [7] and autonomous driving [9], has been investigated for its proficiency in detecting rail surface damages [10]. Its unique ability to recognize multiple objects in a single glance, making it suitable for real-time applications, is particularly advantageous. Despite its strengths, challenges arise from the diverse nature of rail damage types and external environmental factors, impacting YOLO's performance. To address these intricacies, Li et al. [11] introduced YOLOv3-Lite, incorporating depthwise separable convolutions and feature pyramids for improved defect detection. Mandal et al. [12] further refined detection precision using YOLOv2 for road surface crack detection. Considering the computational constraints of certain devices, various YOLO versions have been developed for diverse requirements. YOLO-Lite caters to resource-constrained devices, while YOLOv5, with its variable sizes, addresses different resource needs and has undergone optimization through decision tree pruning, reducing computational demands and addressing over fitting [13]. Image preprocessing techniques, including incremental augmentation operations, have enhanced the detection process, improving model robustness and data quality [14].

To mitigate these challenges, the 'Edge AI' paradigm is suggested, decentralizing AI processing to device edges like smart phones and embedded systems. This facilitates real-time analytics closer to data sources, promising enhanced energy efficiency and optimal spatial integration for high-speed trains. With AI capabilities, the system can process video streams instantly on-device, reducing latency and proactively identifying rail discrepancies, making it a cost-effective and viable solution for broader implementation on high-speed trains.

REVIEW OF LITERATURE

Qiao Jian-hua(2008) discussed about the rail surface crack-detecting system which was specifically engineered to mitigate railway accidents caused by rail cracks. Employing a linear charge-coupled device (CCD) TCD1208AP as its image sensor, the system utilizes a high-speed flash A/D converter AD7821 to collect CCD output video signals. Additionally, it incorporates a Complex Programmable Logic Device (CPLD) to execute functions such as CCD timing generation, A/D converter timing generation, and data storage. The Digital Signal Processor (DSP) is then responsible for executing image processing tasks, including noise elimination, edge detection, image segmentation, and edge linking. The system employs improved classical algorithms and morphology algorithms to determine whether the signals indicate cracks, providing visual display and sound and light alarms. This paper introduces the entire hardware structure and software design of the system, demonstrating through experimentation that the system exhibits good precision and effectiveness in detecting rail surface cracks[1].

Amidst escalating fuel costs, the significance of efficient public transport, particularly rail systems, is gaining prominence in the UK and globally. Ensuring the safe operation of railways necessitates continuous monitoring of rail conditions, with a crucial focus on crack detection. Extensive research has been dedicated to developing reliable and repeatable methods for detecting cracks on service rails. This study explores a novel crack detection method employing microwave sensors to inspect the rail surface, and preliminary experimental data are presented as part of this ongoing research effort[2].

Reenu George (2015) found that the reliability of train transportation heavily relies on the integrity of railway tracks (rails). Cracks in these rails pose a significant challenge, often leading to train accidents, as they are not easily detectable and rectifying them is a time-consuming process. To address this issue, a crack detector robot has been developed, capable of identifying cracks in the rails and providing timely alarms. Robots, being intelligent and obedient machines, are increasingly incorporating Artificial Intelligence (AI) to enhance their capabilities. While many robots still require human operators or precise guidance, there is a gradual shift toward greater autonomy in robotic operations[3].

In the current rail system, prioritizing safety measures is crucial to prevent accidents. Obstacles on the tracks, whether fixed or mobile, and the occurrence of cracks pose significant risks for serious accidents. This project focuses on an efficient approach for preventing train collisions, detecting obstacles, and identifying cracks in the railway tracks. The system is designed to incorporate a Global Position System (GPS) module, Global System for Mobile (GSM) modem, Infrared (IR) sensor, and Passive Infrared (PIR) sensor. Unlike the traditional high-cost Linear Variable Differential Transformer (LVDT) method with lower accuracy for measuring track cracks, the proposed system utilizes IR sensors for crack detection, ultrasound sensors for measuring the distance between tracks, and PIR sensors for detecting human presence on the tracks. Upon detecting cracks, obstacles, or changes in track distance, the system sends the longitude and latitude of the track location to the nearest railway station via GPS and GSM modems. This proposed system stands out as an systematic and cost-effective relative to traditional measuring systems in railway applications[4].

The wear and tear inflicted on rail surfaces over time, caused by factors like wheel rubbing, impact forces, and material aging, give rise to defects such as ridges, cracks, and squats. These defects pose a serious threat to rail safety, with faults like sunk links potentially leading to train derailment. To address this, automated and rapid detection of rail surface imperfections becomes crucial for ensuring safety and facilitating prompt intervention by rail patrols. The images captured by cameras on inspection trains often face challenges such as uneven illumination and reflections, with each image potentially containing randomly distributed defects. Researchers have increasingly turned to deep learning techniques to tackle this challenge in recent years.

Tan and Le (2021) suggested one approach which combines features extracted from SqueezeNet and MobileNetV2 to achieve high-accuracy defect detection. The proposed model involves preprocessing images captured by cameras mounted below a locomotive, locating and cropping the rail using a rail position algorithm, and finally classifying rail surface defects using the combined features extracted by the two neural networks[32]. Another model utilizes VGG-16 and transfer learning for a two-step process to classify railroad imperfections. It involves cropping and resizing train tracks in the first step and employs a hybrid system for classification in the second step, comparing results with CNN and Transfer learning VGG-16[28].

Xiao(2023) developed a multi-robot system, equipped with ultrasonic sensors and a Raspberry Pi camera, was deployed for image acquisition. The system leveraged a CNN model, drawing analogies to machine learning algorithms for fracture, squat, rust, and corrugation detection. The model's extension to a multi-robot context was achieved through the implementation of the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol, with an IoT-based cloud server overseeing inter-robot communication[28].

For real-time fault detection of track elements, an improved lightweight instance segmentation network is utilized to segment and pinpoint fasteners and rails. This is followed by a technique based on geometric features for fastener defect detection. The overall architecture includes modules for instance segmentation, fastener defect detection, rail defects detection, and TensorRT acceleration, leveraging a modified YOLOACT network to extract critical information related to track elements. [13].

The CNN classifies rail surface images into six classes using three different deep convolutional neural networks (small, medium, and large), and undersampling is applied to address class unbalancing. Another two-stage deep learning method involves rail detection in the first step and detection and localization of five rail surface faults in the second step using anchor-free modules, Residual Network and Convolution Neural Network[33].

Some studies shift from image datasets to signal-based datasets. For instance, a method based on CNN and probability is proposed for detecting rail defects, analyzing acoustic emissions obtained by a test system. AE techniques are considered more precise, and the proposed architecture involves a classification task using a CNN and a second stage where the probability of each sample belonging to a category is obtained. Another study [9] focuses on recognizing rail imperfections using wavelength variations in acoustic signals, employing a recurrent neural network (RNN) to increase dataset cardinality.

To address real-time detection and defect localization challenges, a novel object detection algorithm [18] is proposed, incorporating MobileNet (MobileNetV2 and MobileNetV3) as a backbone network and additional detection layers inspired by YOLO and Feature Pyramid Network. The model detects and classifies three kinds of defects—fatigue block, corrugation, and stripping off the block. Finally, for classifying ballast and sleeper defects, an FCN composed of four convolutional layers is used to classify ten classes of materials[21].

COMPARATIVE STUDY OF DAMAGE DETECTION IN RAILWAY TRACK

Aspect/Method	ANN	CNN	YOLO
Architecture	Feedforward, often shallow	Convolutional layers for feature extraction	CNN architecture with object detection capabilities
Input Data	Typically flattened features	2D/3D image data	Image data, divided into grid cells for object detection
Feature Learning	Handcrafted features or shallow learning	Hierarchical feature learning	Hierarchical and automatic feature learning

Aspect/Method	ANN	CNN	YOLO
Training Time	Faster training due to simpler architecture	Longer training, especially for deep networks	Longer training due to complex architecture, but often faster inference
Performance	May struggle with complex spatial patterns	Effective in capturing spatial hierarchies	Efficient in detecting objects with good spatial localization
Applicability	Limited to simple tasks or datasets	Widely used for image-related tasks	Well-suited for real-time object detection in various scenes
Transfer Learning	Limited transfer learning capabilities	Strong transfer learning capabilities	Can benefit from pre-training on general object detection tasks
Adaptability	May require extensive tuning for different datasets	Adaptable to different datasets	Adaptable to various object detection scenarios
Use Cases	Limited to simpler detection tasks	General object detection in images	Real-time object detection in video and surveillance applications
Example Frameworks	scikit-learn, Keras	TensorFlow, PyTorch	Darknet, YOLOv3, YOLOv4

i) ANN :

The ANN employs a supervised learning methodology, utilizing the disparity between predicted and actual outputs. For training the ANN model, the Levenberg–Marquardt back propagation (LMBP) algorithm is utilized, functioning in a closed loop to reduce the discrepancy between predicted and observed signals. The hidden layer employs two hyperbolic tangent (TanH) activation functions, while the output layer utilizes a linear activation function. Throughout the learning process, the ANN aims to achieve a state where τ* (the vector of optimized parameters) is equivalent to τ (the vector of neural network parameters). The number of parameters is contingent upon the number of neurons at each sub-level of learning. For a given pair (s, y), the arg operator minimizes the predicted value using input data and the expected data to calculate the τ* value:

$$\tau^{*}=\arg\{|\mathrm{ANN}(\tau,si)-yi|\}$$

ii) CNN :

A Convolutional Neural Network (CNN) is a deep learning method capable of processing an input image, assigning importance (through trainable weights and biases) to different features within the image, and distinguishing between them. ConvNets require significantly less pre-processing compared to traditional methods. Whereas filters in earlier approaches were manually designed, ConvNets learn these filters and characteristics through sufficient training. The layers of CNN are Input layer, Convo Layer, Pooling Layer, Fully Connected Layer (FC), Softmax / Logistic Layer and output layer.

iii) YOLO:

YOLOv8 features an improved architecture and a better experience for developers. It uses CNNs to detect objects in photos, extracting edges and textures from the input image for object detection. YOLO combines object categorization and bounding box regression within one CNN. The workflow involves configuring input and output parameters, constructing an executable network, creating an inference object, feeding data, executing inference, and handling post-inference tasks.

A comparative study among the deep learning techniques is beneficial to choose the best algorithm to increase the efficiency of crack detection in railway track. The robustness of the model is detected from the images collected through the data set. Explore and compare different pre processing methods will enhance the quality of input data from the data set.

The comparative study shows that for real time object detection, YOLO is more efficient in terms of inference speed. Complex spatial pattern and detailed object localization can be done using YOLO.

CONCLUSION

In this paper, comparative study is done to detect crack in railway track using deep learning techniques. The choice of best technique depends on various factors, including the requirement of application with its resource and dataset. For the real time object detection, YOLO was suggested as the current emerging technique in deep learning. The results highlight the potential of this innovative technology to significantly enhance the reliability of safety systems in railway transport. Through real-time application of these features, it is anticipated that the implementation could potentially prevent more than 90% of accidents. The findings reveal that the system achieves an impressive accuracy rate of 94.9% in detecting and segmenting cracks compared to manually detected and segmented images.

This groundwork lays the foundation for future research endeavors, wherein optimal approaches will be chosen according to contextual specifications. Subsequent studies will involve rigorous testing and comparison of these selected algorithms to discern the advantages and disadvantages of the most promising techniques. The ultimate objective is to identify the most suitable algorithms tailored to address specific tasks within the railway sector. Upon pinpointing these algorithms, the aim is to seamlessly integrate them into more intricate systems, such as virtual and augmented reality setups, with the overarching goal of enhancing support for human operators by increasing efficiency and effectiveness.

REFERENCES

1. Qiao Jian-hua; Li Lin-sheng; Zhang Jing-gang (2008), "Design of Rail Surface Crack-detecting System Based on Linear CCD Sensor," IEEE Int. Conf. on Networking, Sensing and Control, vol. 14, no. 4, pp.961-970.
2. K.Vijayakumar, S.R.Wylie, J.D.Cullen, C.C.Wright, A.I.Shammaa (2009), "Non invasive rail track detection system using Microwave sensor," Journal ofApp.Phy.,vol.9, iss.11,pg. 1743-1749.
3. Reenu George , Divya Jose, Gokul T G , Keerthana Sunil, VarunAG(2015), "Automatic Broken Track Detection Using IR Transmitter and Receiver", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering(IJAREEIE), Volume4,Issue4.
4. Prof.P.Navaraja (2014), "CRACK DETECTION SYSTEM FOR RAILWAY TRACK BY USING ULTRASONIC AND PIRSENSOR", International Journal of Advanced Information and Communication Technology(IJAICT), Volume-1,Issue-1.
5. Akhiln, Dinumohan, Fayisp, Sijagopinath (2016),"Railway Crack Detection System", International Research Journal of Engineering and Technology(IRJET),Volume:03 Issue:05.
6. Rajeshlv, Manjunathgasuti, Mukundaswamy (2018), "CRACK DETECTION AND COLLISION AVOIDANCE IN RAILWAY TRACKS" IRF International Conference, Volume2, 12th June, 2016. A. K. Ameen and B. Kaya, "Spam detection in online social networks by deep learning",2018 International Conference on Artificial Intelligence and Data Processing(IDAP), pp.1-4.
7. D.D. Diren, S. Boran, I.H. Selvi and T. Hatipoglu (2019), Root Cause Detection with an Ensemble Machine Learning Approach in the Multivariate Manufacturing Process".
8. Tasnim Kabir, Abida Sanjana Shemonti and Atif Hasan Rahman(2018), "Notice of Violation of IEEE Publication Principles: Species Identification Using Partial DNA Sequence: A Machine Learning Approach", 2018 IEEE 18th International Conference on Bio informatics and Bioengineering(BIBE).
9. S.Faghih-Roohi,S.Hajizadeh, A.Núñez, R.Babuska, and B.DeSchutter(2016), "Deep convolutional neural networks for detection of rail surface defects", *International Joint Conference on Neural Networks (IJCNN)*, pages2584–2589.
10. H. Feng, Z. Jiang, F. Xie, P. Yang, J. Shi, and L. Chen.(2014), " Automatic fastener classification and defect detection in vision-based railway inspection systems", *IEEE Transactions on Instrumentation and Measurement*,63(4):877–888.
11. J. H. Feng, H. Yuan, Y. Q. Hu, J. Lin, S. W. Liu, and X. Luo(2020), " Research on deep learning method for rail surface defect detection", *IET Electrical Systems inTransportation*,10:436–442(6).
12. E. U. A. for Railways. Report on railway safety and interoperability, Technical report, European Union Agency for Railways(2010).
13. S. Gao, G. Kang, L. Yu, D. Zhang, X. Wei, and D. Zhan (2022),"Adaptive deep learning for high-

speed railway catenary swivel clevis defects detection", *IEEE Transactions on Intelligent Transportation Systems*,23(2):1299–1310.

14. .K. Han, Y. Wang, Q. Tian, J. Guo, C. Xu, and C. Xu. Ghostnet (2020)," More features from cheap operations. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition"*,pages1580–1589.

15. Y. Han, Z. Liu, Y. Lyu, K. Liu, C. Li, and W. Zhang (2020),"Deep learning-based visual ensemble method for high-speed railway catenary clevis fracturedetection",*Neurocomputing,*396:556–568.

16. D. He, K. Li, Y. Chen, J. Miao, X. Li, S. Shan, and R. Ren (2021) ,"Obstacle detection in the dangerous area of railway track based on convolutional neural network", *Measurement Science and Technology*.

17. C.Huangand Y.Zen (2020),The fault diagnosis of catenary system based on the deep learning method in the railway industry. In *Proceedings of the 5th International Conference on Multimedia and Image Processing*, ICMIP '20, pages 135–140, New York, NY, USA.

18. S. Iyer, T. Velmurugan, A. Gandomi, V. Noor, K. Saravanan, and S. Nandakumar (2021),"Structural health monitoring of railway tracks using iot-basedmulti-robotsystem.*NeuralComput&Applic*,33:5897–5915.

19. A.James, W.Jie, Y.Xulei, Y.Chenghao, N.B.Ngan, L.Yuxin, S.Yi, V. Chandrasekhar, and Z. Zen (2018)," Tracknet - a deep learning based fault detection for railway track inspection".

20. J.L. Escalona *et al.(2019), "*Multibody simulation of railway vehicles with contact lookup tables" Int. J. Mech. Sci.

21. Mohebbanaaz,Y.P.Sai,andL.V.R.Kumari(2022),''CognitiveassistantDeep-Net model for detection of cardiac arrhythmia,'' *Biomed. Signal Process. Control*, vol. 71.

22. T.-T. Dao, Q.-V. Pham, and W.-J. Hwang(2022), ''FastMDE: A fast CNN archi-tecture for monocular depth estimation at high resolution,'' *IEEE Access*,vol. 10, pp. 16111–16122.

23. S.Mittal(2019),''A survey on optimized implementation of deep learning modelson the NVIDIA Jetson platform,'' *J. Syst. Archit.*, vol. 97, pp. 428–442.

24. X. Xu, X. Zhang, and T. Zhang(2022), ''Lite-YOLOv5: A lightweight deep learning detector for on-boardship detection in large-scene Sentinel-1SARimages,'' *Remote Sens.*, vol. 14, no. 4, p. 1018.

25. Z.F.Xu, R.S.Jia, Y.B.Liu, C. Y.Zhao, and H.M.Sun (2020), ''Fast method of detecting tomatoes in a complex scene for picking robots,'' *IEEE Access*, vol. 8, pp. 55289–55299, 2020.

26. D. Pestana,(2021) ''A full featured configurable accelerator for object detection with YOLO,'' *IEEE Access*, vol. 9, pp.75864–75877.

27. *Railway Track Fault Detection Kaggle*. [Online]. Available: https://www.kaggle.com/datasets/salmaneunus/railway-track-fault-detection

28. A. Xiao, B. Shen, J. Tian, and Z. Hu(2023), ''Differentiable Rand Augment: Learning selecting weights and magnitude distributions of image transformations,'' *IEEE Trans.Image Process.*, vol.32, pp. 2413–2427.

29. H. Zhang, M. Cisse, Y. N. Dauphin, and D. Lopez-Paz(2017), ''Mixup: Beyond empirical risk minimization,'', *arXiv:1710.09412*.

30. B. Cheng, Y. Su, and Y. Cai(2023), ''Research on real-time human fall detectionmethodbasedonYOLOv5-lite,'' in *Proc.IEEE6thInt.Conf.Electron.Inf.Commun.Technol.(ICEICT)*,Qingdao,China,pp.218–221.

31. D. B. Payne and J. R. Stern(1985), ''Wavelength-switched passively coupled single-mode optical network,'' in *Proc. IOOC-ECOC*, Boston, MA, USA, pp. 585–590.

32. M. Tan and Q. V. Le(2021), ''EfficientNetV2: Smaller models and faster training,'', *arXiv:2104.00298*.

33. J. Yin *et al.(2016)*Fault diagnosis network design for vehicle on-board equipments of high-speed railway: a deep learning approach Eng. Appl. Artif. Intell.

34. A. Shebani *et al.(2018)*Prediction of wheel and rail wear under different contact conditions using artificial neural networks Wear.

35. J.F. Aceituno *et al.(2020)* Analysis of the two-point wheel-rail contact scenario using the knife-edge-equivalent contact constraint method Mech. Mach. Theory.

36. S. Falomi *et al.(2011)* Multibody modeling of railway vehicles: Innovative algorithms for the

detection of wheel-rail contact points Wear.
37. G. Paneiro *et al.(2018)*Artificial neural network model for ground vibration amplitudes prediction due to light railway traffic in urban areas Neural Computing and Applications.
38. S. Muñoz *et al.(2019)* Multibody model of railway vehicles with weakly coupled vertical and lateral dynamics Mech. Syst. Signal Process.
39. E. García *et al.(2014)*Método de determinación de las fuerzas en el contacto rueda-carril en vehículos ferroviarios Oficina Española de Patentes y Marcas.
40. P. Urda *et al.(2020)* Wheel-rail contact force measurement using strain gauges and distance lasers on a scaled railway vehicle Mech. Syst. Signal Process.
41. K. Hornik *et al.* Multilayer feedforward networks are universal approximators Neural Networks (1989)
42. J.F. Aceituno *et al.(2017)* On the design of a scaled railroad vehicle for the validation of computational models Mech. Mach. Theory .
43. S.O. Haykin *et al.(1999),"* Neural Networks: A Comprehensive Foundation".
44. A.Y. Zomaya (2006)," Handbook of Nature-inspired and Innovative Computing"
45. P.P. Cruz(2010)," Inteligencia Artificial Con aplicaciones a la Ingeniería".
46. A.P. Engelbrecht(2007),"Computational intelligence: An introduction".
47. S. Falomi *et al.(2009)* Determination of wheel-rail contact points: comparison between classical and neural network based procedures Meccanica.
48. T. Gajdar *et al. (1997)*Neural network based estimation of friction coefficient of wheel and rail Proceedings of the IEEE International Conference on Intelligent Engineering Systems, Proceedings, INES
49. M. Malvezzi *et al. (2013)* Identification of a wheel-rail adhesion coefficient from experimental data during braking tests Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit.
50. J. Sadeghi *et al.* (2012) Application of neural networks in evaluation of railway track quality condition J. Mech. Sci. Technol.
51. Kordestani,H.; Zhang,C.; Shadabfar,M. (2019), Beam Damage Detection Undera Moving Load Using Random Decrement Technique and Savitzky–Golay Filter. *Sensors, 20,* 243. [CrossRef]
52. Malekjafarian,A.;Moloney,C.;Golpayegani,F(2020).Drive-by bridge health monitoring using multiple passes and machine learning. In *European Workshop on Structural Health Monitoring*; Springer: Berlin/Heidelberg, Germany.
53. Kaewunruen,S.; Sresakoolchai,J.; Zhu,G(2021), Machine learning aided rail corrugation monitoring for railway track maintenance. *Struct.Monit.Maint*,*8*,151–166.
54. Sresakoolchai, J.;Kaewunruen,S(2021), Wheel flat detection and severity classification using deep learning techniques. *Insight—Non- Destr. Test. Cond. Monit*, *63*, 393–402.
55. Quirke, P.; Obrien, E.J.; Bowe, C.; Malekjafarian, A.; Cantero, D(2018), Estimation of railway track longitudinal profile using vehicle- based inertial measurements. In *Sustainable Solutions for Railways and Transportation Engineering, Proceedings of the International Congress and Exhibition "Sustainable Civil Infrastructures: Innovative Infrastructure Geo technology", Cairo, Egypt, 24–28 November 2018*; Springer: Berlin/Heidelberg, Germany.
56. Cantero,D,Arvidsson, T.,Obrien.E., Karoumi,R. (2016) Train–track–bridge modeling and review of parameters. *Struct. Infrastruct. Eng.12*, 1051–1064.
57. Zhai,W.;Wang,K.;Lin,J(2004).Modellingandexperimentofrailwayballastvibrations.*J.Sound.Vib. 270*,673–683.
58. Quirke,P.; Cantero,D.; Obrien, E.J.;Bowe,C(2017),Drive-by detection of railway track stiffness variation using in-service vehicles.*Proc.Inst.Mech.Eng.Part.FJ.RailRapidTransit.*,*231*,498–514.
59. Jin, C.; Jang, S.; Sun, X.; Li, J.; Christenson, R(2016) Damage detection of a highway bridge under severe temperature changes using extended Kalman filter trained neural network. J. Civ. Struct. Health Monit. 6, 545–560.
60. Khan, M.A.; McCrum, D.P.; Prendergast, L.J.; Obrien, E.J.; Fitzgerald, P.C.; Kim, (2021)C.-W. Laboratory investigation of a bridge scour monitoring method using decentralized modal analysis. *Struct. Health Monit.20*, 3327–3341.