AI Based Acoustic Wave Monitoring of Rail Defects

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ABSTRACT: Rail is one of the most energy efficient and economical modes of transportation. Regular rail- way track health inspection is an essential part of a robust and secure train operation. Delayed investigations and problem discoveries pose a serious risk to th e safe functioning of rail transportation. The traditional method of manually examining the rail track using a railway cart is both inefficient and susceptible to mistakes and biasness. It is imperative to automate inspection in order to avert catastrophes and save countless lives, particularly in zones where train accidents are numerous. This research develops an Internet of Things (IoT)-based autonomous railway track fault detection scheme to enhance the existing railway cart system to address the aforementioned issues. In addition to data collection on Pakistani railway lines, this work contributes significantly to railway track fault identification and classification based on acoustic analysis, as well as fault localization. Based on their frequency of occurrences, six types of track faults were first targeted: wheel burnt, loose nuts and bolts, crash sleeper, creep, low joint, and point and crossing. Support vector machines, logistic regression, random forest, extra tree classifier, decision tree classifier, multilayer perceptron and ensemble with hard and soft voting were among the machine learning methods used. The results indicate that acoustic data can successfully assist in discriminating track defects and localizing these defects in real time. The results show that MLP achieved the best results, with an accuracy of 98.4 percent.

I. INTRODUCTION

Railways are a country's lifeline, particularly in developing nations, serving the public's transportation requirements as well as being the backbone of trade and supply lines. The railway market has strengthened over time, providing better opportunities for the public and the country's economy. Rail is one of the most energy efficient modes of transportation, accounting for 8% and 9% of global passenger and freight transit respectively, while consuming only 3% of total trans- portation energy [1]. Rail uses 12 times less energy and produces 711 times fewer Greenhouse Gases (GHGs) per passenger kilometer travelled than private automobiles andairlines, making it the most efficient means of motorized passenger transportation. Aside from shipping, freight rail is the most energy efficient and low carbon mode of transportation [1]. However, high performance railway operations must be provided to ensure the continuous running of railway trains and the safety of passengers. Railway infrastructure plays a vital role in modern transportation, necessitating continuous monitoring to ensure safety, efficiency, and reliability. Among the various types of rail defects, issues like cracks, fractures, and wear present significant risks, potentially leading to catastrophic failures if undetected. Traditional inspection methods, though effective, are often labor-intensive, time-consuming, and limited in predictive capabilities. Recent advancements in Artificial Intelligence (AI) and acoustic wave sensing offer a transformative approach to rail defect detection and prediction. Acoustic wave-based systems can detect anomalies in real-time by analyzing sound wave propagation through the rail material.

AI algorithms, particularly machine learning and deep learning models, enhance this process by learning from vast datasets to identify subtle patterns associated with early- stage defects, material fatigue, and wear progression.

This AI-based acoustic monitoring system not only detects visible and subsurface defects such as cracks and fractures but also predicts rail wear trends and evaluates overall rail quality. By integrating additional parameters—such as vibration, temperature, and load—into the analysis, the system achieves comprehensive and intelligent rail health monitoring. This leads to improved maintenance planning, reduced operational costs, and enhanced safety across railway networks.

The general public, commuters, and tourists all travel by train, and their safety is compromised if railway tracks are unfit for day-to-day operations. Similarly, freight safety and dependability are critical components of the supply chain, necessitating fault-free and fault tolerant railway tracks. Because mechanical and physical wear and tear can develop over time, regular inspections are essential to reduce train derailing incidents. Rail freight traffic increased interna- tionally between 2018 and 2019, with Europe and Turkey human examination is prone to mistakes, and manual inspection is time consuming and can be biased. In Pakistan, a railway cart is currently utilized for track inspection, with human specialists manually

inspecting the track and determining where repairs are required. An automated railway track fault detection system would reduce human error, provide greater inspection ranges and accuracy and reduce overall labor costs.

and comprehensive diagnostics.

handling around 3.1 trillion-ton kilometers in 2019, ranking slightly lower than Asia/Oceania/Middle East, which han- dled over 3.5 trillion-ton kilometers of freight by rail in the same year [2]. Each year, China, and India service approx- imately 773 and 770 billion passenger kilometers, respec- tively. Russia (175.8 billion), France (88.3 billion), Germany (77 billion),

Ukraine (53.1 billion), and the United Kingdom (51.8 billion), are among the other nations with significant rail passenger traffic [3]. Pakistan is also a country where many people prefer traveling by rail, with an anticipated 70 million people reported to travel by train between 2018 and 2019 [4]. Pakistan railways (PR) has earned 48.652 billion Pakistani Rupee (PKR) from its operation between 2020 and 2021 [5]. Although railway is a well-known mode of trans- portation throughout the country, the sad reality is that it does not nearly match global standard requirements.
To achieve high accuracy in defect detection and predictive maintenance, machine learning (ML) and deep learning (DL) techniques are employed alongside advanced acoustic emission (AE) monitoring. Techniques such as Support Vector Machines (SVM), Random Forests (RF), and k- Nearest Neighbors (k-NN) are effective for classifying different types of defects based on extracted acoustic features. For more complex pattern recognition, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are used to analyze time-series acoustic data for fault diagnosis and wear prediction.

Acoustic wave monitoring involves the use of piezoelectric sensors or ultrasonic transducers, which capture stress waves generated by defects like micro-cracks or material discontinuities. These acoustic signals are processed using techniques such as Short-Time Fourier Transform (STFT), Wavelet Transforms, and Fast Fourier Transform (FFT) to extract relevant features like signal amplitude, frequency content, and energy distribution. The extracted features are then fed into AI models trained on labeled datasets to classify rail conditions and forecast degradation trends.

By leveraging this AI-acoustic synergy, rail inspection systems can achieve real-time, non-destructive, and automated rail health monitoring, enabling proactive maintenance and extending the lifespan of railway infrastructure. Extended Introduction infrastructure. Extended Introduction With increasing demand on rail networks worldwide, ensuring the structural integrity manual and visual maintenance and extending the lifespan of railway infrastructure. Extended Introduction With increasing demand on rail networks worldwide, ensuring the structural integrity of railway tracks has become more critical than ever. Failures such as fatigue cracks,
transverse fractures, head checks, and progressive rail wear not only degrade rail performance but also pose significant safety hazards. While manual and visual inspections are commonly practiced, their intermittent nature and dependence on human judgment limit early defect detection

AI-driven acoustic wave monitoring is emerging as a next-generation solution, offering continuous, data-rich insights into rail conditions. This system capitalizes on the fact that different defects alter the propagation behavior of stress waves in unique ways. AI models, particularly those based on self-learning neural networks, can be trained to recognize these subtle wave pattern shifts long before visible damage occurs.

In this advanced monitoring approach, smart sensor arrays are deployed along track sections, continuously capturing acoustic signals generated by both train-wheel interactions and intrinsic rail vibrations. The innovation lies not just in sensing, but in how adaptive AI algorithms interpret these complex acoustic signatures. For instance, autoencoders and attention-based neural networks are now being explored for their ability to highlight early deviations from healthy rail behavior without requiring extensive labeled data.

Beyond detecting cracks and wear, AI-acoustic systems are being developed to infer track stiffness variation, fastening system condition, surface contamination, and even temperature-induced stress fluctuations. Integrating this sensor data with train speed, axle load, and environmental parameters enables a truly holistic diagnostic and prognostic platform.

This synergy between AI and acoustic wave mechanics marks a shift from reactive maintenance to predictive, condition-based rail asset management, reducing downtime, improving safety margins, and extending asset lifecycle— essential for modern rail infrastructure resilience. handling around 3.1 trillion-ton kilometers in 2019, ranking slightly lower than Asia/Oceania/Middle East, which han- dled over
3.5 trillion-ton kilometers of freight by rail in the same year [2]. Each year, China, and India service approx- imately 773 and 770 billion passenger kilometers, respec- tively. Russia (175.8 billion), France (88.3 billion), Germany (77 billion), Ukraine (53.1 billion), and the United Kingdom (51.8 billion), are among the other nations with significant rail passenger traffic [3]. Pakistan is also a country where many people prefer traveling by rail, with an anticipated 70 million people reported to travel by train between 2018 and 2019 [4]. Pakistan railways (PR) has earned 48.652 billion Pakistani Rupee (PKR) from its operation between 2020 and 2021. Although railway is a well-known mode of trans- portation throughout the country, the sad reality is that it does not nearly match global standard requirements. Cracks, creep, loose fittings, crash sleeper, ballast, discontinuity, missing nuts and bolts, and wheel burnt are some of the key issues. A lack of regular visible maintenance, preemptive inspec- tions, delayed problem detection, all generate severe concerns about the security of rail transit operations in Pakistan. As a result, numerous and severe incidents have occurred in recent years, resulting in significant human and financial damage. According to PR’s yearly reports [6], 127 incidents occurred between 2013 and 2020 due to derailing and track defects

Railway tracks require regular and adequate maintenance and if neglected, has a significant influence on the railway network [7]. To mitigate potential negative effects, the viabil- ity of a low-cost automated conventional cart system capa- ble of monitoring the health of the railway track must be developed and evaluated in order to aid the regularly required, efficient and accurate diagnosis, track repairs and to minimize the possibility of accidents. Railway track condition monitor- ing, where railway tracks are regularly monitored to locate and fix faults, is critical for the ongoing running of railway traffic with a greater degree of safety and dependability. How- ever, monitoring hundreds of thousands of miles of railway track necessitates a significant investment in both money and labor making it unlikely. Additionally, human examination is prone to mistakes, and manual inspection is time consuming and can be biased. In Pakistan, a railway cart is currently utilized for track inspection, with human specialists manu- ally inspecting the track and determining where repairs are required. An automated railway track fault detection system would reduce human error, provide greater inspection ranges and accuracy and reduce overall labor costs. The Internet of Things (IoT) has changed the way we interact with our environment. Smart cities, smart homes, pollution manage- ment, energy conservation, smart transportation, and smart industries are applied examples of IoT driven developments. IoT is the also used for data acquisition and telemonitoring in real time. This study presents and proposes an IoT based smart automated cost-effective track conditions inspection approach. Common track faults such as low joint, wheel burnt, creep, crash sleeper, loose nuts and bolts, and point and crossing are investigated with results presented in this study.

The rest of the paper is organized as follows. Section 2 pro- vides a summary of other studies on locating such faults in railway tracks. Section 3 presents the data gathering techniques, data collection device, and proposed study approach. Section 4 provides the results and discussions, while Section 5 has the conclusion.

II. LITERATURE REVIEW

The key motive for inspecting railway lines is for predictive maintenance, problem identification and to ultimately mini- mize the possibility of train accidents. Periodic and frequent railway line examination is critical. Human inspection of hun- dreds of thousands of miles of track is time-consuming, labor-intensive, and susceptible to human error. Due to human error, manually driven systems are insufficient to monitor the health of tracks routinely, reliably, frequently, and universally; thus, automatic identification and monitoring of track faults/cracks is vital. As a result, several automated systems have been developed to reduce efforts and boost the efficiency. Non-destructive evaluation (NDE) techniques such as electromag- netic approaches (Eddy current testing [8], magnetic flux leakage (MFL) testing [9], guided wave-based systems (ultra- sonic testing [9], [10], guided wave detection [11]), vision based systems, IoT based system and acoustic based systems have been employed for rail track inspection. More informa- tion on the tools and procedures used for rail track inspection is provided in [8] and [11]. The literature is categorized by electromagnetic, guided, computer vision. IoT and acoustic based approaches below.

A. ELECTROMAGNETIC APPROACHES

The concept of a train-based differential eddy current (EC) sensor system for fastener detection was presented in [12]. The sensor operates via electromagnetic induction, in which an alternating-current carrying coil generates an EC on the rail and other electrically conductive material in the area, and a pick-up coil measures the returning field. The results of both field measurements and lab testing show that the suggested approach can detect an individual fastening system from a height of 65mm above the rail. A time domain feature of the measurement signal was also used to detect missing clamps within a fastening system.

The performance of a machine learning method to iden- tify and analyze missing clamps within a fastening system, as evaluated by a train-based differential eddy cur- rent sensor, was examined in [13]. This study investigated six classifi- cation algorithms, with KNN being the highest performing model achieving precision and recall of 96.64 % and 95.52 %, respectively.

A typical excitation coil (EC) sensor to simulate rail crack detection presented by [14] and [15]. The alternating current (AC) bridge was included into the EC system by [16] to balance the large baseline signal. The sensor comprised an excitation coil and two detection coils combined to produce a three-winding transformer. In [17] the authors employed a differential pulse ECT sensor two detection coils to measure the plate thickness of various materials. An excitation coil and two hall sensors were used in another differential ECT probe [17]. The detected pulse's characteristics, peak value, and time to zero were extracted for thickness description.

A sensitive magnetic induction head-based magnetic flux leakage (MFL) technique was developed [18], [19]. To mea- sure the change in magnetic flux detected in a magnetic core with an open gap, an induction coil was connected. The maximum sensitivity, however, was attained when the distance was roughly equal to the fracture width. It is very dependent on the orientation of the sensor.

An MFL based multi-sensor technique, with a primary sensor and four auxiliary sensors positioned in the detecting direction was presented [20]. First, the root mean square (RMS) of the primary sensor signal's x- component was deter- mined. The relative values of the sensors signal indicated faults in the data set greater than the threshold. The appropri- ate distances between these sensors were determined based on the magnitude of a flaw and the lift-off [20]. Finite ele- ment modelling and practical investigations demonstrate that this technology. A technique for detecting the components perpendicular to the steel surface using a sensor probe consisting of a semi-circular yoke with induction coils at each end and a gradiometer with two anisotropic magnetic resistance sen- sors was proposed by [21].

In [22] the authors suggested a quantitative technique based on the Pulsed MFL method to investigate the effect of sensor lift-off on magnetic field distribution, which impacts the detection capabilities of var- ious damages. The approach employs a ferromagnetic one to direct additional magnetic flux to seep out. A ferrite is added to a LMF sensor to minimize the reluctance to raise the magnetic strength above the faults in order to detect minor imperfections in the rail surface [23]. A magnetic sensor prototype was built utilizing the best parameters determined by numerical parametric research [24].

B. GUIDED WAVE SYSTEMS

A non-destructive defectoscopic approach, or more precisely an ultrasonic test, conducted using the DIO 562 instrument, which also incorporated measurement data processing was proposed in [25]. During an ultrasonic examination, the equipment replicated the form of the rails. The measurement was evaluated using the PC and the specialist programme DIO 2000.

In [26], the authors, introduced a contact-free rail diag- nosis method based on ultrasound. The non-ablative laser sources were used to generate waves. Echo reception was accomplished using rotational laser vibrometry that measured angular velocity, elastic deformation, and rail angular dis- placement. The detection of rail defects was tracked using unique ultrasonic wave signal-based markers.

To achieve visual identification of the oblique fracture on the railhead surface, a quantitative detection approach.

integrating non-contact laser ultrasonic testing technology and variational mode decomposition (VMD) was presented in [27]. All scanning signals were preliminarily filtered using Wigner time-frequency distribution and fir1 filtering. VMD was also used to divide the signal into several intrinsic mode functions (IMF). The ideal IMF component was chosen based on the correlation coefficient (C) and SNR characteristics between different IMF components and the original sig- nal. Finally, the time-domain and temporal features of sig- nals were used to realize visual crack-induced surface wave energy using ultrasonic propagation pictures.

C. COMPUTER VISION BASED SYSTEMS

Computer vision-based track detection is gaining greater attention. Drones, rather than a moving cart, might enable cost-effective track inspection. An innovative method for calculating gauge measurement using drone footage was proposed by [28]. Track health was evaluated using com- puter vision algorithms from drone data. For data collection, a Da-Jiang Innovations (DJI) Phantom 3, equipped with a 4k camera and Sony sensors was employed. The images were transformed into hue, saturation, and value (HSV) color space to lessen the impact of changing weather conditions on lighting, and then a Gaussian smoothing filter was applied to reduce noise. Because railway tracks have a purple/pinkish hue, all colors between cyan and magenta were separated using various threshold masks to achieve track recogni- tion. Morphological techniques were employed to delete any linked pixels below a certain threshold value, and then a Canny edge detector was utilized to achieve precise results. The study presented by [29] used a camera taking images at

30 frames per second, to conduct a computer vision exper- iment. It was placed on a locomotive with the aim to provide a continuous steady image for real-time railway track fault identification. On the Image net dataset, the Inception V3 model was used to tune for binary class classification. The model generalized effectively on actual vegetation pictures for vegetation overgrowth. A sun kink classifier had a 97.5 % accuracy in classifying professionally produced sun kink videos. The study [30] proposed a visual based track inspec- tion system (VTIS) system employing TrackNet, a multi-phase deep learning-based rail surface anomaly detection and classification approach.

A vision-based system for track inspection and defect identification was presented by [31]. A Gabor filter was used to breakdown the input picture, and texture char- acteristics retrieved using segmentation-based fractal tex- ture examination. The track defects were classified using the AdaBoost classifier. The study by [32] proposed a vision-based autonomous rail inspection system employing the structured topic model (STM) to detect the presence (or absence) of sleepers or fasteners by evaluating real-time pictures captured by a digital camera, positionedbeneath. videos. The scope of [33] was limited to the localization of rail problems, ballast, tie and tie plate, and spikes, tie plate holes, and anchors.

Deep convolutional neural network (DCNN) based cas- cade learning embedded vision inspection technique for rail fastener detection was presented in [34]. The two phases of the proposed technique were region location and defect detection. Initially, a modified Single Shot multibox Detec- tor (SSD) model was used to identify the fastener locations within the collected railway images. To identify faulty fas- teners, a key component identification approach based on an enhanced Faster Region Convolutional Neural Network (RCNN) was used. Extensive trials were carried out to show the effectiveness of the suggested method. The results of the experiments indicated that the suggested technique achieved an average precision of 95.38% and an average recall of 98.62%.

A vision-based rail track inspection system was presented in [35]. Yolo v3 was implemented and trained as the deep learning model, and subsequently, the accuracy and recall rates of damaged fasteners on the test dataset were validated. In the study, a GoPro motion camera, mounted on rail main- tenance vehicle was used to collect and record a total of 20 kilometers of track fastener images. The accuracy and recall rates for faulty fasteners detection were 89% and 95%, respectively .

III. METHODOLOGY

This section describes the dataset acquisition technique and machine learning algorithms used for classification, along with the proposed methodology. All IoT systems have the fol- lowing generic architecture, as shown in Figure 2. A frame- work capable of detecting, responding, and acting/reacting whenever it is exposed to a change or stimulus from a situation in which it is kept without the

MFCC features were used to conduct two tests: one for fault detection and one for fault classification on the entire dataset, achieving an accuracy of 94.1%. An autonomous railway track fault detection system which could identify three types of faults: normal track, wheel burnt, and superel- evation using acoustic analysis was presented in [49]. MFCC features were extracted from the audios of faults and fed into support vector machine (SVM), logistic regression (LR), multilayer perceptron (MLP), convolutional neural network (CNN), decision tree (DT), and random forest (RF) mod- els for classification. In terms of accuracy, the DT and RF models outperform the others. Both algorithms showed 97% accuracy in detecting the aforementioned faults. A railway track inspection system combining standard acoustic meth- ods with deep learning models to improve performance was presented by [50].

The system employed two CNN mod- els, convolutional 1D and convolutional 2D, as well as one recurrent neural network (RNN) model, and a long short- term memory (LSTM). Furthermore, the model reported 94.9%, 96.5%, and 93.3% accuracy on Conv1D, Conv2D, and LSTM, respectively.Using acoustic emission (AE) monitoring data and knowl- edge transferred from an acoustic-related database, study presented in [51] described a unique transfer learning method for assessing the structural states of rail tracks. In particular, the proposed CNN model (NA-AE) transferred lower-layer knowledge from a pre-trained AudioSet model to extract the acoustic-specific features of the time–frequency spec- trograms from over two months of acoustic emission (AE) monitoring data, collected from an in- service point rail; only the higher layers of the proposed model required training. Testing results indicates that the proposed model NA-AE performed well on the rail condition assessment task, based on AE data, with a high macro-F1 score of 97.5 percent and converge in 100s.
A nondestructive single-sensor AE method to detect and localize cracks in steel rail tracks under stress was presented in [52]. AE signals were recorded by the AE sensor and con- verted to digital data by the AE collection module. The dig- ital data were denoised to eliminate ambient and wheel/rail contact sounds, and the denoised data were processed and categorized to pinpoint fractures in the steel rail using a deep learning algorithmic model. The computational model was trained and validated using AE signals of pencil lead breaks at the head, web, and foot of steel rail. The deep learning-based AE method was also implemented on-site in order to detect cracks in the steel rail, with an accuracy of 78%, 80%, and 74% in the rail head, web, and foot, respectively.This technology enhances rail safety by enabling early detection of defects, reducing the risk of accidents and injuries. It also optimizes maintenance by providing data-driven insights, allowing rail operators to schedule repairs and replacements proactively. This approach minimizes downtime, reduces costs, and improves overall rail network efficiency. The integration of AI and acoustic wave monitoring revolutionizes rail maintenance, enabling more efficient and effective.

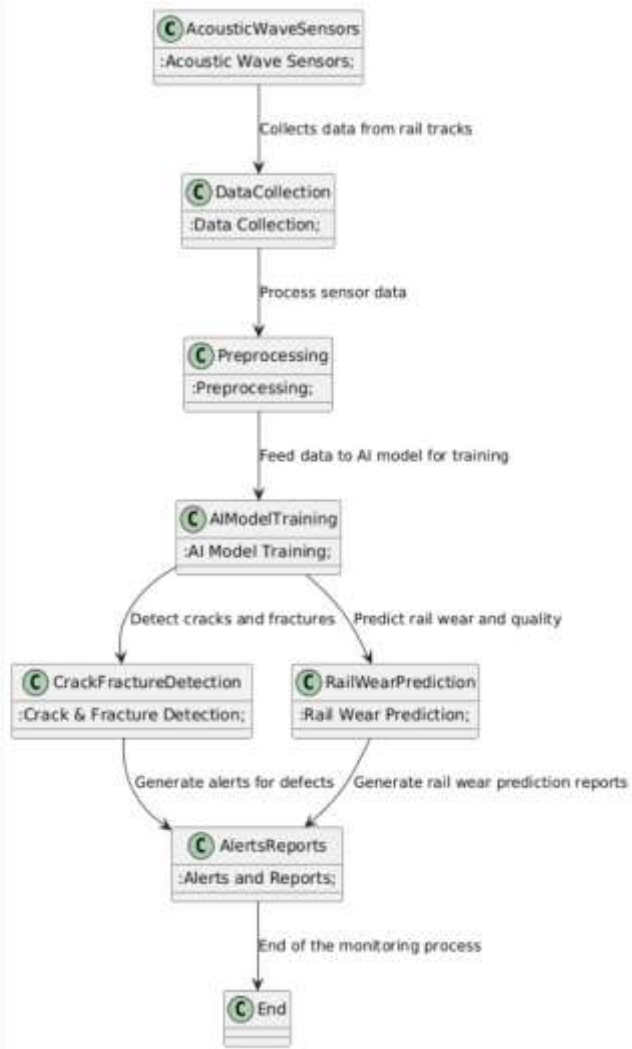

Fig. 1 System flow Diagram

This system flow diagram represents an AI-based rail track monitoring system that leverages acoustic wave sensors to ensure the safety and longevity of railway infrastructure. The process begins with the collection of acoustic data from rail tracks, which is then processed and preprocessed to remove noise and prepare it for analysis. The preprocessed data is used to train an AI model, enabling it to recognize patterns associated with rail defects.
1. Crack and Fracture Detection – Identifies potential structural issues that could lead to accidents if left unaddressed.
2. Rail Wear Prediction – Estimates the level of wear and degradation of the rails over time.
AI-based acoustic wave monitoring is an emerging technology for detecting and predicting rail defects such as cracks, fractures, and wear. By integrating acoustic emission (AE) sensors with machine learning algorithms, this approach offers real-time, non-destructive assessment of rail health.

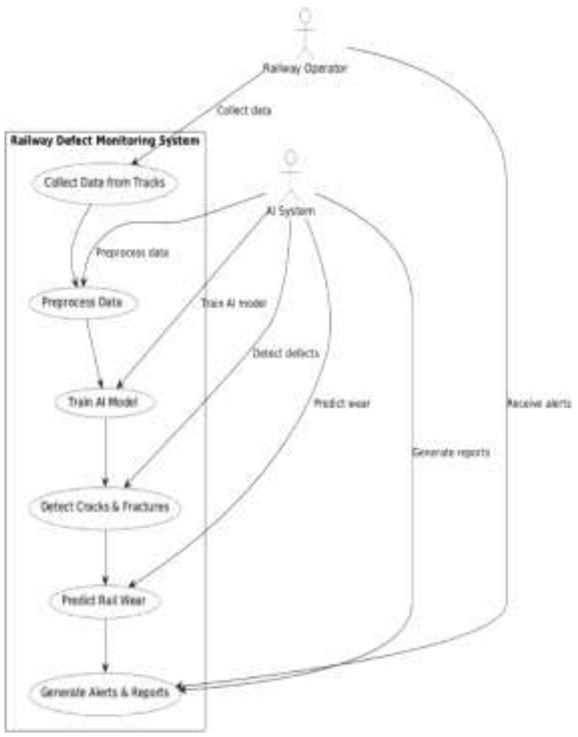

Fig 2 : Use case Diagram

The use case diagram depicts a Railway Defect Monitoring System that utilizes AI to detect and predict railway track issues, including cracks, fractures, and rail wear. The system interacts with two main actors: the Railway Operator and the AI System. Actors Involved:

1. Railway Operator: Responsible for initiating and managing the data collection process. Monitors the results and receives alerts and reports from the AI system.
2. AI System: Performs core functions like training AI models, detecting defects, and predicting rail wear.

System Use Cases:

1. Collect Data from Tracks: Data from railway tracks is collected using sensors or monitoring devices.

CONCLUSION

The AI-based acoustic wave monitoring system for rail defects is a cutting-edge technology that detects cracks, fractures, and predicts rail wear and quality. By utilizing advanced signal processing and machine learning algorithms, this system provides real-time monitoring and analysis of rail conditions. Acoustic sensors detect anomalies in the rail structure, while AI algorithms interpret the data to identify potential defects.

This technology enhances rail safety by enabling early detection of defects, reducing the risk of accidents and injuries. It also optimizes maintenance by providing data- driven insights, allowing rail operators to schedule repairs and replacements proactively. This approach minimizes downtime, reduces costs, and improves overall rail network efficiency.

The integration of AI and acoustic wave monitoring revolutionizes rail maintenance, enabling more efficient and effective monitoring of rail infrastructure. Rail operators can improve safety, reduce costs, and enhance performance. With its potential to transform the rail industry, this technology is poised to play a critical role in shaping the future of rail transportation. By adopting AI-based acoustic wave monitoring, rail operators can ensure safer, more reliable, and more efficient rail networks. This innovative solution is a significant step forward in rail maintenance and safety.

REFERENCES

[1] IEA. (2022). Rail. Accessed: Apr. 30, 2022. [Online]. Available: https://www.iea.org/reports/rail

[2] E. B. Salas. (2022). Global Rail Freight Traffic Between 2018 and 2019. Accessed: Apr. 30, 2022. [Online].Available:https://www.statista.com/statistics/26 3543/global-performance-in-rail-freight-services- byregion/

[3] A. Pariona. Highest Railway Passenger Traffic In The World. Accessed: Apr. 30, 2022. [Online]. Available: https://www.worldatlas.com/articles/ highest-railway-passenger-traffic-in-the-world.html

[4] N. Qureshi, ‘‘Pakistan railways achieves record income in 2018–19,’’ Int. Railway J., Aug. 2019. Accessed: Apr. 13, 2022.

[5] D. Burroughs. Pakistan Records U.S. 1.13bn in Revenue Over Four-Year Period. Accessed: Apr. 13, 2022. [Online]. Available: https://www. railjournal.com/financial/pakistan-records-us-1-13bn-in-revenue-overfour-year-period/

[6] A. Majeed. Train Accident. Accessed: Apr. 13, 2022. [Online]. Available: https://archive.pakistantoday.com.pk/tag/train-accident/

[7] T. Asada, C. Roberts, and T. Koseki, ‘‘An algorithm for improved performance of railway condition monitoring equipment: Alternating-current point machine case study,’’ Transp. Res. C, Emerg. Technol., vol. 30, pp. 81–92, May 2013.

[8] M. P. Papaelias, C. Roberts, and C. L. Davis, ‘‘A review on non-destructive evaluation of rails: State-of-the- art and future development,’’ Proc. Inst. Mech. Eng. F, J. Rail Rapid Transit, vol. 222, no. 4, pp. 367–384, 2008.

[9] F. Wu, Q. Li, S. Li, and T. Wu, ‘‘Train rail defect classification detection and its parameters learning method,’’ Measurement, vol. 151, Feb. 2020, Art. no. 107246.

[10] W. Chen, W. Liu, K. Li, P. Wang, H. Zhu, Y. Zhang, and C. Hang, ‘‘Rail crack recognition based on adaptive weighting multi-classifier fusion decision,’’ Measurement,