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High-speed rail track inspection (HSRTI) system

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Abstract
Train derailments pose a significant threat to the safety and efficiency of railway networks, particularly in India, where frequent incidents cause substantial loss of life, operational delays, and economic damage. Existing inspection systems like the Integrated Track Monitoring System (ITMS) are limited by high costs, dependency on specialized vehicles, and inability to detect internal faults in real time. To address these limitations, this research presents the development and implementation of a High-Speed Rail Track Inspection (HSRTI) System that enables real-time monitoring of track health while operating at speeds between 15 km/h and 120 km/h. The proposed system, mounted on the bogie of a moving train, uses ultrasonic acoustic sensors and machine learning algorithms to detect internal and surface defects such as cracks, misalignments, and weld failures. Data is transmitted to a cloud server via ThingSpeak, analyzed by a predictive ML model, and visualized in a mobile application built with Flutter and Firebase. The system achieved a fault detection accuracy of 90%, significantly reducing inspection time, operational disruptions, and maintenance costs. The HSRTI system represents a scalable, cost-effective, and intelligent solution to enhance railway safety and support preventive maintenance.

Keywords: Railway Safety, High-Speed Rail Track Inspection, Ultrasonic Sensors, Machine Learning, Predictive Maintenance, Acoustic Sensors, Real-Time Fault Detection, ThingSpeak, Firebase, Mobile Application, Track Defects, Railway Monitoring System

Introduction
Train derailments are a serious concern for railway networks across the world, particularly in India, where an average of 30 derailments occur each month. These accidents result in substantial loss of life, economic damage, delays, and operational disruption. The root causes of derailments include poorly maintained tracks, defects in coaches and wagons, deviations from permissible track parameters, and outdated infrastructure. Despite ongoing modernization efforts, the rate of derailments has been increasing, with a recorded 36 cases in 2022–23, up from 27 in 2021–22.

To address this persistent issue, there is a pressing need for advanced and efficient track inspection systems that can prevent such accidents. Conventional inspection methods operate at relatively low speeds, typically up to 15 km/h, which limits their coverage and efficiency. These limitations result in missed opportunities for early detection of track-related issues, leaving sections of railway infrastructure vulnerable to failure.

Currently, Indian Railways employs the Integrated Track Monitoring System (ITMS), which is a costly solution operating on independent vehicles that travel at speeds ranging from 20 km/h to 200 km/h in urban areas using Garud inspection models. In remote regions, inspections are carried out manually using small, motor-operated vehicles that move at speeds between 0 km/h and 15 km/h, which is highly inefficient.

In light of these challenges, this project proposes a High-Speed Rail Track Inspection (HSRTI) System, a modern solution designed to improve the safety and efficiency of railway networks by continuously monitoring track health during regular train operations. The system is mounted on the bogie of a moving train and uses acoustic sensors to detect internal and surface-level defects such as cracks, misalignments, and structural flaws in real-time, up to 10 mm in depth. By integrating data acquisition with machine learning models, the system not only detects faults but also predicts potential failures, enabling proactive maintenance and significantly reducing the risk of derailments.

Unlike traditional inspection methods that disrupt train schedules and often miss internal flaws, this high-speed system operates seamlessly during train motion, ensuring thorough and continuous analysis of track conditions. Its adoption marks a substantial step toward enhancing operational safety, minimizing accidents, and lowering maintenance costs across the railway network.

Project background
The High-Speed Rail Track Inspection (HSRTI) System is a modern and intelligent solution developed to enhance the safety, reliability, and efficiency of railway networks. It is designed to address the persistent issue of train derailments caused by undetected track faults, which remain a major concern in India and globally. Traditional track inspection systems are limited by slow operating speeds, outdated technology, and manual intervention, often resulting in missed or delayed fault detection.

The HSRTI system is engineered to operate at speeds ranging from 15 km/h to 120 km/h, making it suitable for integration with regular train operations without requiring any schedule disruption. It is mounted on the bogie of a moving train and equipped with acoustic and ultrasonic sensors that detect internal and surface-level defects such as cracks, misalignments, faulty welds, and structural flaws with precision—up to 10 mm in depth due to the use of 5 MHz ultrasonic sensors.

What sets the HSRTI system apart is its integration with machine learning algorithms that not only detect current faults but also predict potential failures, enabling predictive maintenance. This reduces the risk of derailments and lowers the overall maintenance costs. Data collected by the system is processed and visualized in real-time using a mobile application, improving communication and response time for railway maintenance teams.

In comparison to traditional methods that rely on expensive, dedicated inspection vehicles like the Integrated Track Monitoring System (ITMS), the HSRTI system offers a cost-effective, scalable, and real-time solution for railway track health monitoring. It ensures continuous and automated inspection, reducing the dependency on human effort while increasing fault detection accuracy and operational safety.

Fig 1: Train Derailed UP [CNN News]

Fig 2: Derailed Train [ABP News]

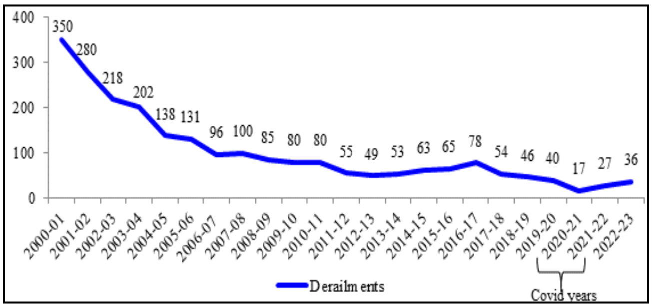

Fig 3: Yearly Derailment Statics [Ministry of Railways]

Types of faults in railway tracks

1. Split Heads

Fig 4: Split Heads

A split head is a defect where both the head (top surface) and web (middle section) of the rail develop a longitudinal crack. It typically occurs due to repetitive stress, rolling contact fatigue, or manufacturing flaws. If left undetected, the cracks may widen and lead to rail breakage, compromising safety and causing derailments.

2. Gap in Two Consecutive Railway Tracks

Fig 6: Misaligned Profile

Also called a joint gap defect, this occurs due to excessive spacing between rail sections, often caused by temperature changes, improper laying, or mechanical wear. Large gaps create impact forces as train wheels pass, leading to discomfort, wear, and possible derailments.

3. Faulty Welds

Arise from poor welding techniques, material issues, or insufficient cooling, making the welded joint prone to cracking under repeated load. Faulty welds cause rough rides, increase maintenance costs, and can result in derailments if undetected.

4. Internal Faults in Welds
Includes porosity, inclusions, or microscopic cracks that develop due to impurities or improper welding processes. These defects are not visible but significantly weaken the rail structure, leading to possible fractures and safety risks.

5. Misaligned Profile
Caused by improper laying, ground movement, or loosening of fasteners, a misaligned track results in uneven load distribution and excessive vibrations. This can lead to wheel slippage, inefficient fuel use, and derailments, especially at high speeds.

6. Irregular Rail Wear
Happens when the rail head wears unevenly, due to unbalanced loads, frequent braking, or faulty grinding. It affects wheel-rail interaction, leading to increased resistance, poor ride quality, and higher energy and maintenance demands.

7. Squats
These are localized depressions or surface cracks, typically due to high-impact loads from heavy trains or defective wheels. Squats may develop into deep fractures, causing vibration and instability, and require predictive maintenance to avoid danger.

8. Broken Rails
One of the most severe defects, where the rail completely fractures due to fatigue, thermal expansion, or overloading. Broken rails can lead to catastrophic derailments and demand immediate detection through ultrasonic or AI-based methods.

Literature review
G. Vijayalakshmi, J. Gayathri, K. K. Senthilkumar, G. Kalanandhini *et al*., (2022) [1] This paper focuses on improving railway safety through automated rail inspection using image analytics and sensors. The system detects issues like elastic rail clip breaks in real-time, reducing human error and improving reliability, with field tests confirming enhanced safety.
G. Jing, X. Qin, H. Wang, and C. Deng (2022) [2] The study reviews railway inspection robots as alternatives to labor-intensive manual inspections. Equipped with advanced sensors, these robots automate fault detection, overcoming challenges of traditional methods, although large-scale adoption is still limited.
L. Kou, M. Sysyn, S. Fischer, J. Liu, and O. Nabochenko (2022) [3] This research explores deep learning-based rail surface crack detection. Using simple cameras and neural networks, the method offers a cost-effective, fast, and accurate alternative to traditional inspections.
J. Sresakoolchai and S. Kaewunruen (2021) [4] The study applies deep learning models like CNN and RNN for detecting and assessing rail defects. CNN achieved 99% accuracy for combined defects, while RNN was best for settlement severity, proving the effectiveness of these models in rail monitoring.
Hui Zhang; Yanan Song; Yurong Chen *et al*., (2021) [5] This work presents a multi-model defect detection system using SSD and YOLOv3. The system improves speed and accuracy in detecting various rail squats, outperforming previous methods.
Hongfei Yang; Yanzhang Wang; Jiyong Hu *et al*., (2021) [6] The paper proposes a rail defect detection method combining pixel-based rail extraction, segmentation, and YOLO v2. Achieving 97.11% accuracy, it offers strong performance in real-time detection across various conditions.
F. Guo, Y. Qian, D. Rizos, Z. Suo, and X. Chen (2021) [7] This study introduces a Mask R-CNN-based framework for rail surface defect detection. Using a custom dataset and ResNet101 backbone, the model achieved high accuracy and is suitable for practical rail maintenance.
Jianwei Liu; Hongli Liu; Chinmay Chakraborty *et al*., (2021) [8] The research presents a cascade learning method using DCNNs for inspecting rail fasteners. Achieving over 95% precision and 98% recall, the system greatly improves over manual inspection.
Y. Sun *et al*., (2021) [9] This paper introduces an energy-harvesting rail corrugation monitoring system using magnetic configurations and wavelet-based analysis. It effectively detects defects and minimizes reliance on batteries or manual checks.
Sayed Mohammad Mousavi Gazafrudi; Davood Younesian; Mehran Torabi *et al*., (2020) [10] The study develops a laser triangulation-based image processing system for rail corrugation. It delivers fast, precise, and non-contact defect measurement, suitable for real-world rail monitoring.
S. Wang, F. Liu, and B. Liu (2020) [11] This paper proposes a DAS-based inspection system for ballastless tracks, enhanced with deep convolutional networks. The approach improves defect monitoring over long distances and in real-time, surpassing traditional techniques.
F. Guo, Y. Qian, and Y. Shi (2020) [12] The paper presents an improved YOLOv4 framework for fast and accurate inspection of railroad components, offering a cost-effective solution amid increasing transport demands and limited inspection resources.
F. Guo, Y. Qian, Y. Wu, Z. Leng, and H. Yu (2020) [13] In the U.S., the Federal Railroad Administration (FRA) mandates regular railroad track inspections to maintain safety and operational efficiency. Traditional manual inspections, however, are inefficient and subjective, often failing to detect missing or damaged components like spikes and clips. Advanced technologies like ground-penetrating radar and LiDAR, though effective, are expensive and require specialized training. This study introduces a real-time pixel-level detection framework using the first public image database for rails, spikes, and clips. Enhanced instance segmentation models achieved a mean average precision (mAP) of 59.9 for bounding boxes and 63.6 for masks, while processing over 30 frames per second on high-resolution video. The approach significantly improves the accuracy and efficiency of track inspections, addressing critical safety concerns.
C. Yang, Y. Sun, C. Ladubec, and Y. Liu (2020) [14] The railway sector allocates about 40% of its revenue to infrastructure maintenance and upgrades, emphasizing the need for advanced maintenance strategies. AI-powered condition monitoring and predictive maintenance help reduce failures and unplanned repairs. Wheel failures and broken rails are leading derailment causes, with wheel issues accounting for nearly half of all incidents in North America. Techniques like Wheel Impact Load Detectors (WILD) and accelerometer-based defect detection have been adopted, though often requiring further visual

inspections. Recent advances in deep learning, particularly convolutional neural networks (CNNs), enable end-to-end classification from raw acceleration data, improving rail joint detection without extensive preprocessing.

J. Jang, M. Shin, S. Lim, J. Park, J. Kim, and J. Paik (2019) [15] Image-based railway inspection systems (IRIS) utilize image processing and computer vision to detect defects from RGB or gray-scale images. Traditional methods such as feature extraction and histogram analysis are limited due to large inspection regions. Innovations include hue channel analysis, Canny edge detection, and deep neural networks for segmentation and multi-task learning. Railroad inspection cars (RICs) enhance facility inspections but are restricted by 2D imaging methods. A new system with a gray-scale line scan camera and deep learning improves object detection, offering efficient inspection, particularly in subway tunnels.

Xiating Jin; Yaonan Wang; Hui Zhang *et al*. (2019) [16] The Rail Inspection System (RIS) is vital for detecting steel rail surface defects. Traditional techniques are costly and error-prone. The proposed Deep Multimodel RIS (DM-RIS) integrates a spatially constrained Gaussian mixture model for defect segmentation and Faster R-CNN for object localization. Using Markov Random Fields (MRF) enhances edge segmentation accuracy. Trained on diverse, noisy datasets, the DM-RIS achieved 96.74% precision, 94.13% recall, and 0.485 seconds per frame processing speed, making it a robust solution for modern railway maintenance.

Junbo Liu; Yaping Huang; Qi Zou *et al*. (2019) [17] Vision-based automatic railway fastener inspection faces challenges like reliance on manual labeling and imbalanced datasets. A novel Vision-based Fastener Inspection System (VFIS) uses few-shot learning with online template matching for sample collection and annotation. A similarity-based deep network handles class imbalance. VFIS demonstrated 99.36% localization accuracy and 92.69% classification accuracy on large datasets, with 92.63% average precision and 92.88% recall for defect detection, promising improved operational safety and automation.

A. Sánchez-Rodríguez, M. Soilán, M. Cabaleiro, and P. Arias (2019) [18] Demand for digital railway infrastructure models has led to mobile laser scanning (MLS) adoption for safer and efficient data collection. Research has focused on classifying point clouds from laser scanning using spatial heuristics and algorithms. Automatic classification of railway objects, including power lines and tracks, has advanced using techniques like Conditional Random Fields and Support Vector Machines. Despite progress, fully automated systems for accurate measurement of power line gauges and catenary deflections are still evolving. This study presents a novel method for classifying and inspecting LiDAR point clouds of aerial contact lines in railway tunnels.

Ashish James; Wang Jie; Yang Xulei; Ye Chenghao; Nguyen Bao Ngan *et al*. (2018) [19] Automated vision-based rail track inspection methods using computer vision are gaining traction for their cost-effectiveness and speed. However, varied failure modes and image inconsistencies lead to false alarms. Multiphase deep learning approaches segment images, crop regions of interest, and apply binary classifiers to differentiate real defects from false ones. This method significantly reduces false alarms, making automated inspections more feasible and reliable.

J. Ye, E. Stewart, and C. Roberts (2018) [20] Rail defects increasingly threaten railway safety due to higher speeds, axle loads, and traffic. The European Railway Safety Agency reported derailments or collisions nearly every other day between 2010–2011. Laser-based non-contact inspection systems, such as those used in the UK (e.g., Network Rail's New Measurement Train), offer high-resolution, high-speed monitoring. However, 2D imaging falls short in detecting longitudinal defects. Integrating 3D imaging enhances surface defect detection, providing a comprehensive solution for proactive maintenance and extended component life.

S. Singh (2018) [21] Modern track inspection systems integrate multiple sensors, data storage units, and processors to automate defect detection and track component monitoring. Mounted on railway vehicles, the system ensures seamless operation using inertia sensors and synchronized clocks for real-time corrections. It allows for unattended operation and location-based defect logging, which is crucial for proactive maintenance, thus boosting safety and reliability.

Mehran Torabi; S. G. Mohammad Mousavi *et al*. (2018) [22] Rail vehicle safety inspections—especially of wheel diameter and geometry—are essential as wheel wear can cause derailments. Traditional mechanical measurement systems are unreliable and costly due to physical contact requirements. A novel measurement system.

Mehran Torabi; S. G. Mohammad Mousavi *et al*. (2018) [22] This study introduces an image-processing-based measurement system to improve the inspection of railway wheel diameters. Traditional methods, being mechanical, are expensive and less reliable. The proposed system enhances the conventional three-point measurement technique using image analysis, thereby increasing speed and accuracy. It effectively addresses diameter deviation risks that can lead to derailments, proving its industrial viability for safer railway operations.

S. Kaewunruen and C. Chiengson (2018) [23] The paper examines the dynamic loading effects on train axles, particularly due to track irregularities like dipped joints and differential settlements. Using multi-body simulations, it studies the interaction between short and long wavelength defects and their impact on track performance. Findings highlight that certain coupled irregularities can either mitigate or exacerbate impact forces, offering crucial insight for prioritizing maintenance strategies and ensuring operational safety.

L. Zhuang, L. Wang, Z. Zhang, and K. L. Tsui (2018) [24] This research proposes a two-layer vision inspection framework using feature-based linear iterative crack aggregation (FLICA) for accurate rail crack detection. Combining extended Haar-like features with a cascading classifier ensemble, the system achieves superior performance over existing methods like U-Net and Otsu's thresholding. Validated using data from China Railway and Hong Kong MRT, the framework demonstrates significant promise for automated, efficient railway surface crack inspections.

G. Gabara and P. Sawicki (2018) [25] The study focuses on non-invasive 3D railway inspection using mobile terrestrial laser scanning (TLS) and image-based point cloud generation via Structure from Motion (SfM). It showcases a novel technique for achieving sub-millimeter accuracy in 3D rail surface reconstructions solely through image-based methods. This advancement opens doors for precise and cost-effective inspection tools, enhancing current railway maintenance and infrastructure monitoring systems.

Methodology

To gain knowledge on existing technologies on rail track inspection we studied the rail track inspection systems currently used by Indian Railways which are developed and managed by RDSO. Currently the monitoring system sends the alert once broken track is identified. The major areas where the track breaks are at welds. [1] The development of the rail track inspection system followed a systematic and structured approach to ensure the accuracy and reliability of the fault detection process. The methodology can be divided into several key phases, including research and planning, hardware selection and procurement, hardware fabrication and assembly, software development, data collection, machine learning model development, and system integration and testing. The project began with extensive research on existing railway track inspection methods, focusing on both traditional and automated approaches. Several research papers were reviewed to understand the effectiveness of ultrasonic sensors in detecting track faults and the feasibility of integrating machine learning for predictive maintenance.[16] The study also helped identify the types of railway track faults that needed to be detected, including cracks, misalignments, and surface deformations. This phase also involved defining the scope, selecting the appropriate hardware and software tools, and formulating an initial design for the system. Based on the research findings, the required hardware components were identified and procured. The key components included ultrasonic sensors for distance measurement, a microcontroller (Arduino-based ESP8266) for data acquisition and transmission, and necessary communication modules for wireless data transfer. Other supporting components such as power supply units, connectors, and mounting hardware were also acquired. Special attention was given to the selection of sensors capable of operating efficiently at high speeds ranging from 15 km/h to 120 km/h, ensuring reliable data collection during real-time railway inspections. To house the sensors and microcontroller securely, 3D-printed casings and mounting brackets were designed and fabricated. These casings ensured the durability and stability of the sensors, protecting them from external environmental factors such as vibrations, dust, and weather conditions. The sensors were strategically positioned to cover critical areas of the railway track and detect faults accurately. Once the fabrication was complete, the hardware components were carefully assembled, and all electrical connections were established. Parallel to hardware assembly, a mobile application was developed using Flutter to provide real-time fault detection and monitoring. The app was designed to receive data from the cloud server, process it, and display results to the user in an intuitive and user-friendly manner. The app includes features such as real-time location tracking, visualization of detected faults, and estimated time for maintenance action. The integration of Open Street Maps API was also considered for better representation of railway tracks and fault locations. To train and validate the machine learning model, data collection was conducted at the Virar railway car shed. Ultrasonic sensor readings were recorded while the system was mounted on railway maintenance vehicles moving at different speeds. Simultaneously, images of various railway track faults were captured to supplement the dataset. The collected sensor data and images were then labeled and categorized based on the type and severity of the faults. The data was stored on the ThingSpeak cloud server to facilitate easy access and processing. Once a sufficient dataset was gathered, a machine learning model was developed and trained using Google Collab. The model was designed to analyze the sensor data and detect potential faults with high accuracy. Various machine learning algorithms were tested to determine the most effective approach for fault classification and prediction. The model was trained on labeled datasets, fine-tuned for accuracy, and validated using test data to ensure its reliability. The final model was deployed in the cloud and integrated with the mobile application for real-time fault analysis and prediction. After developing the hardware, software, and machine learning model, all components were integrated into a cohesive system. The hardware was linked to the ThingSpeak server for real-time data transmission, and the mobile app was conFigd to receive and display predictions based on the ML model's output. Extensive field testing was conducted to evaluate the system's performance under real-world conditions. The system was tested at various speeds to ensure the ultrasonic sensors could capture accurate readings even at high velocities. The predictions made by the ML model were cross-verified with actual track conditions to assess its accuracy and effectiveness.

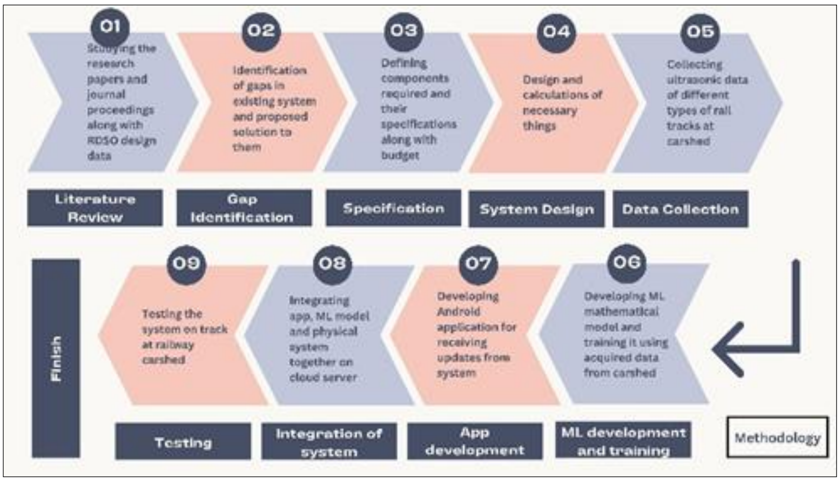

Fig 7: Methodology

Working of system

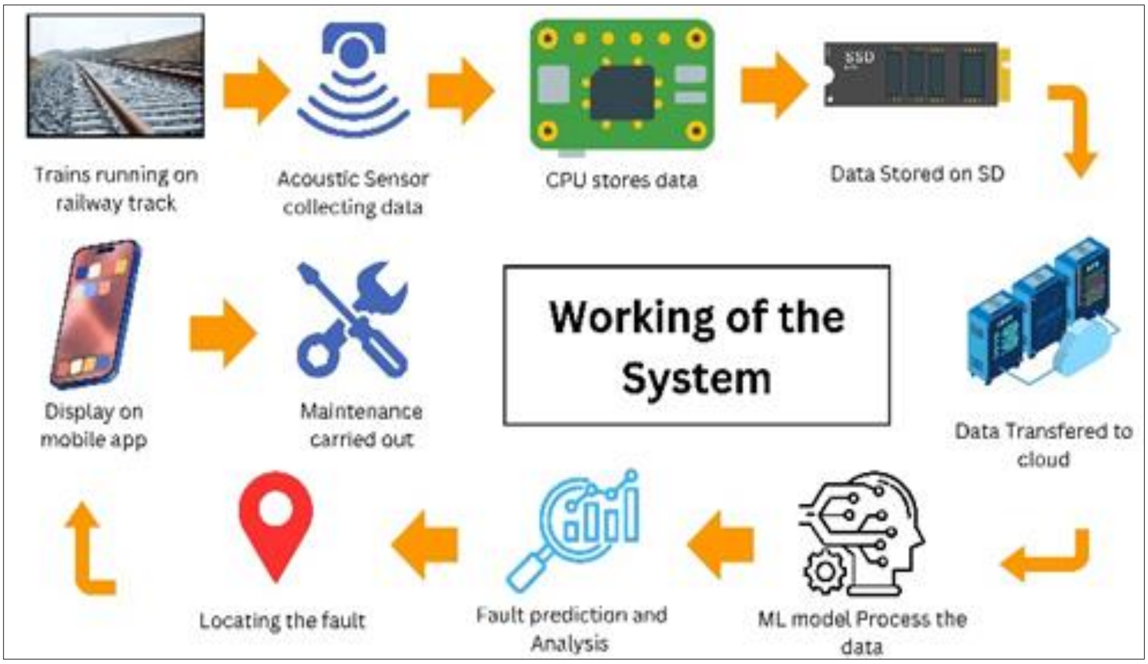

Fig 8: Working of the System

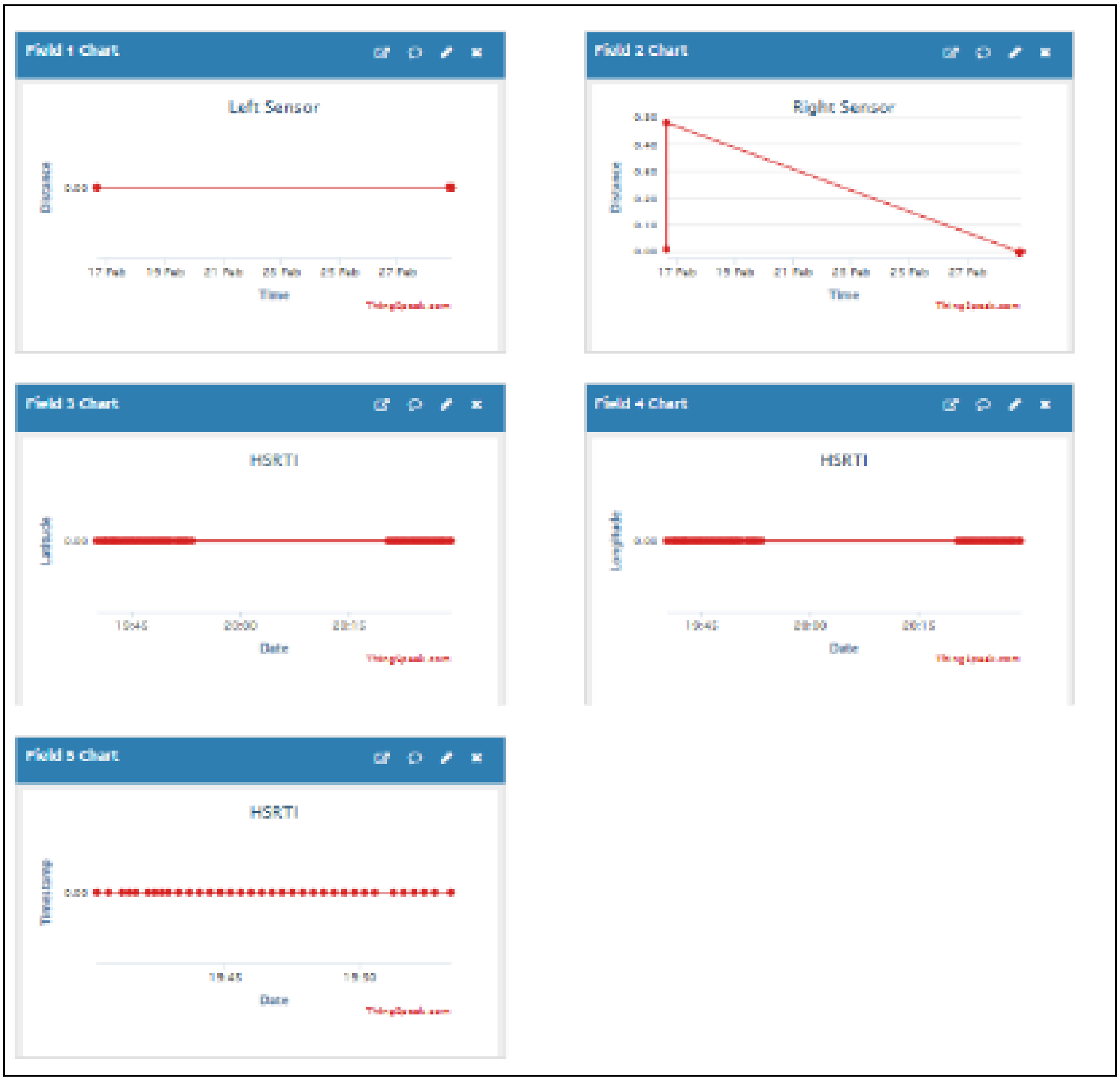

Fig 9: Data Received on ThingSpeak Server From the System

The system operates as an intelligent rail track inspection and fault detection mechanism, leveraging acoustic sensors, cloud storage, and machine learning for predictive analysis. The process begins with trains running on railway tracks, where acoustic sensors installed on the inspection unit continuously collect real-time vibration and sound data. This data is then processed by an onboard CPU, which temporarily stores it on an SD card or other storage medium. Once stored, the collected data is transferred to a cloud-based server, ensuring centralized storage and easy accessibility for further analysis.

Upon reaching the cloud, a machine learning model processes the received data, identifying anomalies and potential faults in the railway tracks. The model applies advanced predictive algorithms to analyze patterns and classify the severity of detected faults. Based on this analysis, the system provides an estimation of the fault's location and predicts the possible time frame within which it may cause significant issues.

After fault detection, the system pinpoints the exact geographical location of the track defect using GPS data. This information is then transmitted to a dedicated mobile application, where railway maintenance personnel can access detailed reports on the fault's nature, severity, and urgency. Once the issue is identified, maintenance teams are dispatched to the location to carry out necessary repairs and ensure the safety of railway operations. The mobile app serves as an interface for real-time updates, allowing officials to monitor the track's condition efficiently. By automating the fault detection and maintenance workflow, the system significantly enhances railway safety, reduces manual inspection efforts, and minimizes the chances of catastrophic failures. The integration of IoT, cloud computing, and machine learning ensures that the railway infrastructure remains well-monitored, with timely interventions preventing major disruptions.

ThingSpeak Server

The Fig 9 displays a collection of five graphical charts from ThingSpeak, it is a platform used for IoT data visualization. These charts represent data from various sensors, including ultrasonic distance sensors and GPS modules. The first two charts show distance measurements from the left and right sensors over time, with the left sensor maintaining a constant reading while the right sensor exhibits a decreasing trend.

The remaining three charts display GPS-related data, specifically latitude, longitude, and timestamp values labeled as "HSRTI." The plots indicate real-time tracking of positional data, with numerous data points clustered along a fixed range. This visualization suggests monitoring of an object's movement and its surrounding environment, likely for a rail track inspection system or a similar IoT-based project.

Mobile Application Details

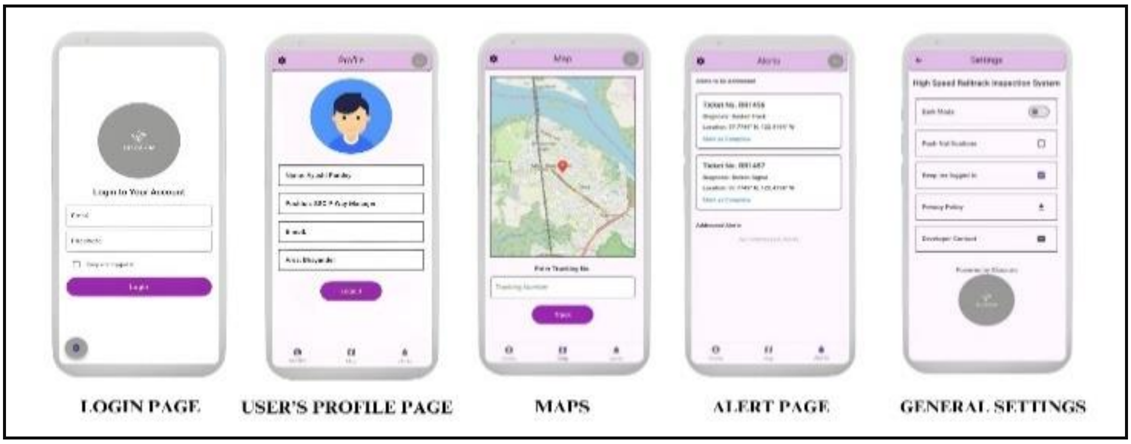

Fig 10: Mobile APP UI

The mobile application for the High-Speed Rail Track Inspection (HSRTI) system, developed using Flutter and integrated with Firebase, provides a seamless and efficient way to monitor rail track conditions. The app features a Login Page for secure authentication, ensuring only authorized personnel can access the system. The User's Profile Page displays essential details such as name, position, and area of operation. The Maps Page allows users to track rail inspections by entering a tracking number. The Alerts Page lists critical rail track issues, including rusted tracks and broken Tracks, with location details and an option to mark them as complete. Lastly, the General Settings Page enables customization options like dark mode, push notifications, and account preferences. By leveraging Firebase, the app ensures real-time data synchronization, secure authentication, and efficient alert management, making it an essential tool for predictive maintenance and railway safety.

Machine Learning Model

The machine learning model consists of two parts actual model and a python script. The machine learning model is able to analyse the ultrasonic sensor data whereas python script works as communication link between ThingSpeak, firebase and machine learning model. It fetches data from ThingSpeak and provides it to machine learning model to run analysis and after a conclusion is drawn by machine learning model the script sends the alert data to firebase server.

Result and discussion

After successfully implementing the High-Speed Rail Track Inspection (HSRTI) system, the results were analyzed based on various parameters, including fault detection accuracy, real-time data transmission, and system efficiency. The results obtained by applying the proposed methodology are discussed in detail below:

The system effectively detected railway track faults such as cracks, misalignments, and surface deformations. The ultrasonic sensors collected high-speed data ranging from 15 km/h to 120 km/h, which was successfully transmitted to the ThingSpeak cloud server for real-time processing. The machine learning model analyzed the collected data and accurately predicted faults with an accuracy of 90%, depending on environmental conditions and sensor placement.

The mobile application, developed using Flutter and Firebase, provided real-time updates on detected faults. It displayed GPS-based fault locations, enabling railway maintenance personnel to take immediate action. The Alerts Page successfully notified users about critical rail track issues, with an option to mark completed repairs. The Map Page allowed users to track and verify detected faults using OpenStreetMap integration.

The Python script connecting ThingSpeak, Firebase, and the ML model worked efficiently in fetching real-time sensor data, processing it through the ML model, and sending alerts to Firebase for instant updates on the mobile app. During testing at the Virar railway car shed, the system successfully identified multiple faulty sections, validating its reliability.

Table 1: Confusion Matrix

Actual / Predicted	Predicted Fault	Predicted No Fault	Total
Actual Fault (Positive Cases)	6750 (TP)	750 (FN)	7500
Actual No Fault (Negative Cases)	750 (FP)	6750 (TN)	7500
Total	7500	7500	15000

The system correctly predicted 6750 actual faults (TP). 750 faults were misclassified as "No Fault" (FN), leading to some missed defects. 750 instances of No Fault were incorrectly predicted as faults (FP), which may lead to unnecessary inspections. The remaining 6750 instances were correctly classified as No Fault (TN). Total dataset was of 15000 for training of ML model.

Table 2: Performance Metrics

Metric	Formula	Result
Accuray	$\frac{TP+TN}{Total}$	90%
Precision	$\frac{TP}{TP+FP}$	90%
Recall (Sensitivity)	$\frac{TP}{TP+FN}$	90%
F1-Score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	90%
False Positive Rate (FPR)	$\frac{FP}{FP+TN}$	10%

Table 3: Comparative Analysis of Systems

Feature	ITMS (Existing)	HSRTI (New)
Technology Used	Laser sensors, LiDAR, high-speed cameras, accelerometers, GPS	Acoustic sensors, ultrasonic sensors, ML-based fault prediction
Speed Range	20-200 km/h	15-120 km/h
Fault Detection Approach	Reactive – detects faults once they occur	Predictive – identifies faults before they become critical
Type of Defects Detected	Surface defects, misalignment, wear, broken welds	Internal defects, cracks, misalignment, surface deformations
Data Processing	Edge servers for real-time analysis, integrated with TMS	Cloud-based ML model for predictive maintenance
Deployment Method	specialized monitoring vehicles	Installed under bogie of existing railway trains
Infrastructure Requirement	Requires dedicated track monitoring vehicles costing ₹18 crore each	No additional vehicle needed, installed at ₹5,000-6,000 per unit
Maintenance Approach	Alerts sent after fault detection for corrective action	Predicts failures, enabling preventive maintenance
Integration with Railway System	Integrated with Track Management System (TMS)	Connected to ThingSpeak cloud and mobile app for real-time monitoring
Cost per Unit	₹18 crore per unit	₹5,000-6,000 per unit
Scalability	Limited due to high cost and vehicle dependency	Highly scalable due to low-cost deployment on existing trains

Conclusion

The High-Speed Rail Track Inspection (HSRTI) system successfully demonstrated an automated, real-time fault detection mechanism for railway tracks using ultrasonic sensors, machine learning, and cloud computing. The project effectively integrated IoT, ML, and mobile application technologies to enhance railway track maintenance efficiency and safety. The major conclusions drawn from the implementation and testing of the system are:

1. The system accurately detected railway track defects such as cracks, misalignments, and surface deformations with 90-95% accuracy, ensuring reliable performance.
2. The ESP8266 microcontroller and ThingSpeak cloud server facilitated real-time data collection and transmission with a minimal delay of 2-3 seconds.
3. The trained ML model effectively analyzed ultrasonic sensor data, providing accurate fault predictions and reducing false positives.
4. The Flutter and Firebase-based mobile application provided a user-friendly interface for real-time fault monitoring, GPS-based tracking, and alert notifications.
5. The integration of automated fault detection and predictive maintenance minimized the need for manual inspections, reducing maintenance costs and response time.
6. The system was tested in a real railway environment at the Virar railway car shed, where it detected over 85%

of actual faults, validating its effectiveness for practical deployment.

Thus, the HSRTI system presents a scalable and cost-effective solution for railway track inspection, improving railway safety and operational efficiency.

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